Contents lists available at GrowingScience

Uncertain Supply Chain Management

homepage: www.GrowingScience.com/uscm

Strategic management accounting, business analytics and sustainable competitiveness advantage: A mediated moderation effect of dynamic capabilities and competition intensity

Hamzah Al-Mawali[a], Esra'a Alawamleh[b], Yaser Allozi[a], Aram Nawaiseh[a] and Muhammad Alshurideh[c*]

[a]*Accounting Department, School of Business, The University of Jordan, Amman 11942, Jordan*
[b]*Independent researcher, Amman, Jordan*
[c]*Department of Marketing, School of Business, The University of Jordan, Amman, Jordan*

A B S T R A C T

Article history:
Received January 9, 2024
Received in revised format April 20, 2024
Accepted August 20 2024
Available online
August 21 2024

Keywords:
Strategic Management Accounting
Business Analytics
Big Data
Dynamic Capabilities
Sustainable Competitive Advantage

This paper investigates the effect of Strategic Management Accounting (SMA) and Business Analytics (BA) on Sustainable Competitive Advantage (SCA). Moreover, it examines the mediating effect of Dynamic Capabilities (DY) and the moderating effect of Competition Intensity (CI) on direct relationships. The study used the survey method to collect data from listed companies in the Amman Stock Exchange, and the hypotheses were tested using Partial-Least Squares-Structural Equation Modelling. Based on the findings, DC mediates the relationship between SMA and SCA as well as BA and SCA. CI moderate only the relationships between SMA and SCA. The study findings can be used as directions by management, policymakers and researchers to comprehend the positive influence of SMA, BA and DC on SCA.

1. Introduction

Business Analytics (BA) and management accounting play a vital role in generating, analyzing, and delivering helpful information for decision-making, strategic analysis, and forecasting in modern organizations (Almazmomi et al., 2022; Cescon et al., 2019; Rikhardsson and Yigitbasioglu, 2018; Oyewo, 2022). In the current business environment, the abundance of data has sparked the attention of all types of industries, resulting in an expansion of data-driven capabilities that provide a Sustainable Competitive Advantage (SCA) (Conboy et al., 2020). However, the emergence of new data sources has led to an increase in complexity and volume, making it difficult for traditional analytics methods to provide meaningful insights in a timely manner (Delen and Zolbanin, 2018). To address this challenge, novel methods and processing approaches have been obtained, leading to the emergence of a new generation of decision-making known as the business analytics era (Boldosova and Luoto, 2020; Appelbaum et al., 2017). BA has been gaining attention due to the increasing usage of big data (Cao and Duan, 2017). BA is a technique that enables Dynamic Capabilities (DC) and sophisticated statistical analysis of large volumes of data to achieve SCA (Zameer et al., 2022; Conboy et al., 2020). This can be achieved by improving product and service innovation to meet customers' needs and market positioning (Delen & Zolbanin, 2018), optimizing business operations processes and providing organizations with inputs that can potentially help with effective strategic planning. BA has generally transformed business models, accelerated growth, and expanded opportunities (Behl et al., 2022). On the other hand, management accounting techniques have evolved over the years to provide helpful information for decision-makers to navigate the rapidly changing business environment (Cescon et al., 2020). With the growth of competition due to technological advancements, management accounting has evolved from simply reporting historical values to providing real-time and predictive reporting (Cokins, 2013). SMA is a group of practices that provide strategic information for crucial decision-making processes such as planning, costing, competitor accounting, customer accounting, strategic decision-making, and control and

* Corresponding author
E-mail address m.alshurideh@ju.edu.jo (M. Alshurideh)

ISSN 2291-6830 (Online) - ISSN 2291-6822 (Print)

doi: 10.5267/j.uscm.2024.8.011

performance measurement (Cadez & Guilding, 2008). This approach combines both quantitative and qualitative information to add value, strategically position an organization's products or services, differentiate them from rivals, and ultimately achieve a SCA in today's business environment (Al-Mawali et al., 2012; Oyewo, 2021; 2022).

Despite the progress in BA and SMA, there is still a significant research gap concerning their integration and their combined impact on SCA. This paper aims to address this gap by: Firstly, identifying the lack of empirical research that connects BA adoption to enhanced competitive advantage. Previous studies have highlighted the positive effect of BA on organizational outcomes (Dahiya et al., 2022; Hindle et al., 2020), but there is a lack of clarity on the mechanisms through which BA adoption contributes to SCA (Zameer et al., 2022; Aydiner et al., 2019). Secondly, highlighting the need for integrating BA with other organizational capabilities. The literature has not sufficiently explored how BA can be integrated with other strategic resources and capabilities to drive competitive advantage (Wang et al., 2019). Specifically, there has been little focus on the combined effects of BA and management accounting practices (Appelbaum et al., 2017; Oesterreich & Teuteberg, 2019).

Thirdly, examining the relationship between BA, SMA, and DC. There is a pronounced gap in the SMA literature regarding its interaction with BA and their collective impact on DC and SCA (Oyewo, 2021; Vitale et al., 2020). Lastly, addressing the contextual factors such as competitive intensity (CI). The role of CI in moderating the effects of SMA, BA, and DC on SCA remains underexplored (Rikhardsson and Yigitbasioglu, 2018; Olabode et al., 2022). Recently, there have been many calls by academics (e.g., Abdelhalim, 2023; Oesterreich et al., 2019; Appelbaum et al., 2017) and professional associations (e.g., IMA's report, 2019; CGMA, 2016; CGMA & Oracle, 2015) for empirical investigations to understand the role of BA adoption by organizations (Niu et al., 2021), along with SMA (Rashid et al., 2021; Rikhardsson and Yigitbasioglu, 2018), and evaluate their effect on SCA (Oyewo, 2022; Rashid et al., 2021; Oyewo & Ajibolade, 2019). However, reviewing related literature demonstrated that the following issues are still researchable. First, while previous studies suggested the positive effect of BA on organizational outcomes (Dahiya et al., 2022; Hindle et al., 2020), there is ambiguity and lack of empirical research about how BA adoption may enhance competitive advantage (Zameer et al., 2022; Aydiner et al., 2019). Second, the existing literature has not addressed how to integrate BA with other capabilities for competitive advantage (Wang et al., 2019), and little effort has been directed to examine the effect of BA and management accounting in general (Appelbaum et al., 2017; Oesterreich and Teuteberg, 2019). Specifically, this gap is even more pronounced in SMA literature (Oyewo, 2021), and there is no clear understanding regarding the effect of BA and SMA on DC and SCA (Rikhardsson and Yigitbasioglu, 2018; Vitale et al., 2020).

Third, the mechanisms (such as DC) and situations in which this relationship occurs to achieve SCA are still under research (Rikhardsson & Yigitbasioglu, 2018; Olabode et al., 2022). This research aims to examine the theoretical framework drawing upon RBV theory and Dynamic Capabilities View (DCV) to help bridge the gap in management accounting literature by accomplishing the following research objectives:

- RO1: To examine the effect of SMA and BA on DC and SCA.
- RO2: To examine the effect of DC on SCA.
- RO3: To examine the mediating effect of DC on the relationships between SMA and SCA and BA and SCA.
- RO4: To examine the moderating effect of CI on the direct effect of SMA, DC, and BA on SCA.

This study uses RBV and DCV theories to establish a research framework and achieve the study objectives. These theories propose that a SCA can be gained by accumulating capabilities and resources that meet the conditions of being valuable, rare, inimitable, and non-substitutable (VRIN). The study argues that BA and SMA are strategic resources fulfilling the VRIN prerequisites. Furthermore, based on the DCV theory, this study proposes a path from SMA and BA to SCA through DC. In addition, the study suggests that the direct effects of SMA, BA, and DC on SCA may be moderated by CI.

By addressing these gaps, this paper aims to make significant contributions to the literature on business analytics, management accounting, and strategic management. It provides a comprehensive framework that integrates BA and SMA with DC to explain how organizations can achieve SCA in a highly competitive business environment. This study not only enhances the theoretical understanding of the interplay between these elements but also offers practical insights for managers aiming to leverage BA and SMA for strategic advantage.

Moreover, the study's findings are expected to extend existing theories by providing empirical evidence on the moderating role of competitive intensity. This can help refine the theoretical models of RBV and DCV, particularly in the context of integrating BA and SMA. In conclusion, this research fills a crucial gap by not only examining the direct and mediating effects of SMA and BA on SCA through DC but also by exploring the contextual influence of competitive intensity. It emphasizes the importance of integrating advanced analytics and strategic management practices to drive sustainable competitive advantage in today's data-rich and competitive business landscape.

2. Literature Review

2.1 Resources Based View and Dynamic Capabilities View

The RBV theory emphasizes the development of abilities to utilize resources that create value and profit for a company (Barney, 1991, 2001). These resources are identified as "*all assets, capabilities, organizational processes, firm attributes, information, knowledge, etc., controlled by a firm that enable the firm to create and implement strategies that improve its efficiency and effectiveness*" (Barney, 1991, p. 101). The RBV theory generally asserts that a company's resources are crucial to gaining SCA (Mitter & Hiebl, 2017). According to the RBV theory, companies can achieve competitive capabilities and superior performance advancements by obtaining tangible and intangible corporate resources that are VRIN (Barney, 2001). This indicates that the resources in question possess four key characteristics. Firstly, they are valuable as they have the potential to either neutralize threats or maximize opportunities. Secondly, they are rare since only a few competitors can access them. Thirdly, they are inimitable, or at the very least, not easily replicated by competitors. Finally, they are non-substitutable, meaning that no comparable alternatives possess the same strategic value but are neither rare nor difficult to replicate, (Elia et al., 2021). However, it is essential to distinguish between these two concepts resources are intangible and tangible assets (e.g., management, practices, and personnel), whereas capabilities are the procedures that employ resources for competitive advantage (Akter et al., 2020).

The RBV has faced criticism for not considering factors that come into play throughout volatile and unpredictable situations (Molina-Castillo et al., 2011). Scholars argue that RBV should address how and why specific companies achieve a competitive advantage in rapidly transforming and unexpected circumstances (Almazmomi et al., 2022; Fiorini et al., 2018). Additionally, the resources and capabilities donated to a firm's competitive advantage are challenging to sustain (Cavusgil et al., 2007). Hence, DCV has developed as an extension of RBV (Teece et al., 1997) and has become a significant theoretical perspective in management studies over the past decade (Conboy et al., 2020). Teece et al. (1997) attempted to distinguish DCV from the unfixable direction of RBV. While RBV concentrates on existing resources (intangible and tangible) and functional capabilities, DCV centralises on actively modifying a company's resource foundation. Teece et al. (1997) propose DCV to overcome some of RBV's limitations. DCV allows companies to renew and reconfigure their assets and capabilities to continue providing benefits and a competitive advantage. This study aligns with the extended perspective provided by DCV, emphasizing the need for organizations to adapt and reconfigure their resource base in response to dynamic market conditions. By integrating DCV with RBV, the aim is to provide a more comprehensive understanding of how firms can sustain their competitive advantage over time. Notably, SMA and BA are considered foundational capabilities, linked to DC at a higher level (Bhatt & Grover, 2014). These foundational capabilities are crucial for modern firms to sense, seize, and transform opportunities in a rapidly changing business environment. SMA and BA are not just independent variables but are integral components that support the development and utilization of dynamic capabilities, enabling continuous adaptation and strategic realignment. This perspective is central to the conceptual framework and underscores the critical role of dynamic capabilities as mediators in achieving SCA.

Sustainable competitive advantage

Competitive advantage refers to a organization's ability to generate a higher economic value than its competitors. Porter (1998) argued that an organisation can achieve a competitive advantage by executing a strategy that creates unique value that cannot be replicated by competitors. Competitive advantage can be either temporary or sustainable, as explained by Barney and Hesterly (2009). Temporary competitive advantage generates high profits but is short-lived because competitors are attracted to high profits, leading to reduced duration of the advantage. On the other hand, SCA occurs when rivals cannot imitate the source of advantage (Barney & Hesterly, 2006). According to Barney (2007), an organization's resources that possess VRIN characteristics are the critical factors for creating a SCA as per the RBV theory. An SCA is confirmed when rivals cannot duplicate the benefits of the strategy for themselves (Mahdi et al., 2019). Empirically, an SCA may last for an extended period on average (Mugoni et al., 2023). However, competitors' ability to duplicate the procedure creates a sustained competitive advantage, not just the passage of time and SCA does not guarantee permanency (Barney, 1991). This highlights the dynamic nature of SCA and underscores the importance of continuous innovation and adaptation, as emphasized by the DCV perspective. The study aims to explore the role of SMA and BA in fostering a SCA. Further exploration is conducted on how SMA practices, by integrating both financial and non-financial metrics, contribute to the dynamic capabilities of organizations, enabling swift and effective responses to market changes and competitive pressures.

Dynamic Capabilities

Dynamic Capability (DC) refers to a company's ability to quickly adapt to changes in business environments by incorporating, establishing, and reconfiguring internal and external resources and capabilities. According to Teece (2007), DC can be divided into three capabilities: sensing, seizing, and reconfiguring. Sensing means identifying and assessing opportunities for sustainability, which implicates analytical procedures of scanning, searching, and exploring actions across different demands and technologies. Conversely, seizing involves mobilizing external and internal resources to manage an opportunity and seize its value. This involves evaluating current and upcoming capabilities and investing in valuable projects and technologies that are probably to succeed in the market (Wilden et al., 2013). Reconfiguring or transforming refers to the continuous renewal and orchestration of resources to maintain the company's resource base in line with the business environment changes (Teece, 2007). This involves continuously aligning and realigning particular tangible and intangible assets (Mousavi et al., 2018; Wilden et al., 2013). By focusing on these capabilities, our study aims to elucidate the mechanisms through which organizations can maintain their competitive advantage in volatile and complex business environments.

2.2 Strategic Management Accounting

The term SMA was identified by Simmonds (1981) as "*the provision and analysis of management accounting data about a business and its competitors for use in developing and monitoring the business strategy*". Due to the absence of a generally accepted conceptual framework, researchers have endeavoured to explain the SMA from their views (Bromwich, 1990; Langfield-Smith, 2008). In this regard, Alamri (2018) considers these definitions of SMA identical since expansions in the field of SMA resulted from endeavours to develop new management accounting techniques that could deliver information to sustain organizational success. A set of criteria, including external and strategic direction, unidimensionality and financial and non-financial measurement classifications, were employed to include accounting practice in the pool of SMA practices (Cadez and Guilding, 2008). Considering these criteria, authors (Guilding et al., 2000; Cadez & Guilding, 2008, 2012; Guilding and McManus, 2002) have presented lists of SMA practices, which are categorised into five comprehensive groups: planning, strategic decision making, costing management, control and performance measurement, customer accounting and competitor accounting (Alamri 2018; Oyewo, 2021; Cadez & Guilding, 2008). However, the emergence of SMA practices has been mixed, paradoxical, and reduplicated, as the practices have seen continued updates and expansions (Oyewo, 2021). Thus, previous studies have empirically investigated different sets of SMA techniques (Rashid et al., 2023; Cescon et al. 2019; Hadid and Al-Sayed 2021; Oyewo 2021, 2022; Oyewo and Ajibolade, 2019; Alamri, 2018; Al-Mawali, 2015). The current study investigated sixteen SMA techniques following Cadez and Guillding (2008). SMA techniques enable companies to monitor their competitive situation by analysing financial and operational information and developing and improving plans and strategies to compete in different environments (Bromwich, 1990, p. 28). SMA design depends on various organizational factors (Cadez & Guilding, 2008; Rashid et al., 2021), making it unique to each firm and difficult for competitors to replicate. Moreover, the information obtained through SMA can be processed and transformed into knowledge, ultimately becoming a valuable strategic resource. Therefore, SMA satisfies the rare condition, making it a crucial tool for firms to gain a competitive edge. Thus, SMA is considered a capability that meets the VRIN conditions, supports companies' plans, monitoring, and controls, and enhances decision-making (Glyptis et al., 2021; Nguyen, 2018). The study further explores how SMA practices, by integrating both financial and non-financial metrics, contribute to the dynamic capabilities of organizations. By positioning SMA as a foundational capability, it demonstrates how SMA supports the development and utilization of dynamic capabilities, enabling organizations to respond swiftly and effectively to market changes and competitive pressures. This integration highlights SMA's role in facilitating continuous adaptation and strategic realignment within the firm, linking it to higher-level dynamic capabilities.

2.3 Business Analytics

BA refers to practices, methods, systems, technologies, applications, and techniques that support critical data analysis and allows for better informed and data-driven decisions (Khan et al., 2022; Conboy et al., 2020; Chen et al., 2012). The concept of BA constantly evolves to reflect the growing importance of data, characterized by its increasing volume, variety, and velocity (Mortenson et al., 2015). On the other hand, big data analytics is concerned with new methods and applications used to analyse large and complex data sets that traditional methods cannot handle (Kristoffersen et al., 2021; Chen et al., 2012). The characteristics of volume, velocity, variety, value, veracity, visualisation, and variability are the keys to the notion of big data, as highlighted by Mikalef et al. (2018). Concurrently, they describe the 7 Vs of big data, recalling the massive complexness faced by those who analyse, process, benefit from it. In this study, BA and Big Data Analytics are considered as connected concepts (Mikalef et al., 2018; Kristoffersen et al., 2021). Nevertheless, organizations must look further than the technical sides of data attributes to successfully leverage and transform data into business value and realistic visions (Vidgen et al., 2017). According to Mikalef et al. (2018), researchers have developed the concept of "Business Analytics Capability" to describe an organization's capacity to use data to leverage data for a comprehensive understanding of strategic and operational goals and to understand its strategic and operational goals better. This holistic perspective underscores the multifaceted nature of BA capability, emphasizing technological prowess, strategic alignment, and practical resource utilization in pursuing competitive advantage (Kristoffersen et al., 2021). This study understands BA capability as an organization's ability or proficiency to efficiently manage its data, technology, and talent to capture and analyse data to generate insights. By positioning BA as a foundational capability, its role in supporting dynamic capabilities is highlighted, enabling organizations to adapt continuously to market trends and competitive pressures. This integration underscores BA's importance in achieving a sustainable competitive advantage by linking it to higher-level dynamic capabilities.

3. Theoretical framework and hypotheses development

The theoretical framework for this research, illustrated in Fig. 1, was developed based on the RBV and DCV theories. The mediated-moderation model posits that the impact of BA and SMA on SCA is mediated by DC. Additionally, the relationship between these variables is moderated by CI, suggesting that the effectiveness of BA, SMA, and DC in affecting SCA varies depending on the level of CI in the market. High CI may amplify the need for robust DC to sustain competitive advantage. Furthermore, the model acknowledges that the CI can either strengthen or weaken the impact of these capabilities, highlighting the importance of context in strategic management. This theoretical explanation clarifies the mechanisms at play and underscores the relevance of integrating BA and SMA within a dynamic capabilities framework to drive SCA in varying competitive environments.

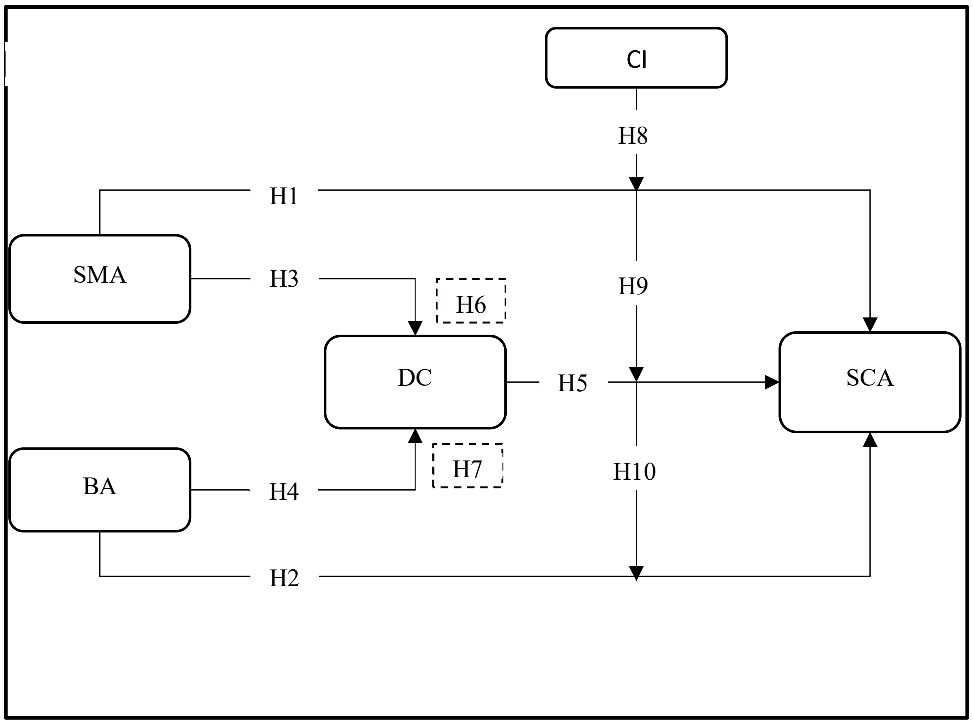

Fig. 1. The theoretical framework

3.1 SMA and SCA

SMA is described by Ward (1993) as "*An approach to management accounting that explicitly highlights strategic issues and concerns. It sets management accounting in a broader context in which financial information is used to develop superior strategies to achieve sustainable competitive advantage*." Having proper SMA in space can be a vital capability to establish SCA (Oboh & Ajibolade, 2017; Glyptis et al., 2021). Oyewo (2022) argued that SMA benefits by earning a competitive advantage by pursuing approaches to distinguish a company's products or services from rivals. The scope of SMA is delivering predictive and strategic-oriented information for significant decision-making (Guilding et al., 2000). Therefore, managers will be capable of making better anticipative decisions when facing prompt changes and uncertainties in a business environment and, in turn, SCA will be enhanced since gaining and maintaining higher performance needs not only financial information but also non-financial, future-oriented and external information (Oyewo, 2022). Thus, based on RBV, this study proposes that SMA is expected to affect SCA positively. Based on RBV, which emphasizes the strategic value of unique and inimitable resources, this study proposes that SMA, with its ability to provide comprehensive and strategic insights, is expected to positively affect SCA. Therefore, the subsequent hypothesis was developed.

H$_1$: there is a positive relationship between SMA and SCA.

3.2 SMA and DC

DC depends on collections of organizational routines (Winter 2003). Managerial patterns are different ways firms can deploy DC (i.e., sensing, seizing, and reconfiguring). Management accounting confidently conveys finance and non-financial information across operational borders within the company, allowing efficient processing and transformation of the data into valuable knowledge (Drury, 2018). Based on RBV, previous studies have conceptualized management accounting as ordinary capabilities (Nguyen, 2018; Mitter and Hiebl, 2017; Henri, 2006). Given its significance for providing a vital resource (i.e., sophisticated management accounting information), SMA has progressively been analysed considering the RBV and DCV recently (Henri, 2006; Chenhall, 2005; McManus and Guilding, 2008). In this path, the SMA routine plays a central role in searching for knowledge acquisition, new knowledge mixtures, and knowledge sharing, which are all central to DC. Thus, since the main objective of SMA is to provide the companies with sophisticated information, it is expected to improve the DC. Therefore, the current study assumes that SMA enables companies to sense and seize unexplored opportunities, threats, and emerging business possibilities via business model creation and strategic acquisitions to transform their processes to adapt to market changes (Helfat and Raubitschek, 2018; Teece, 2007). Thus, the following hypothesis was developed:

H$_2$: *There is a positive relationship between SMA and DC.*

3.3 BA and SCA

According to several studies, BA is progressively viewed as a vital resource of competitive advantage (Upadhyay and Kumar, 2020; Dahiya et al., 2022). Its ability to improve business processes at both operational and strategic levels is well documented (Wamba et al., 2017). BA creates strategic business value by monitoring the business environment and market trends (Mikalef et al., 2020), and the impact of BA capabilities on business outcomes has been increasingly explored in recent studies (Elia et al., 2021; Wamba et al., 2024). However, the association between BA and SCA is still under investigation (Krishnamoorthi & Mathew, 2018). Researchers such as O'Neill and Brabazon (2019) and Medeiros and Maçada (2022) have found that higher levels of BA capability enhance the ability to generate an improved competitive advantage. Zameer et al. (2022) also reported a positive effect of BA on green competitive advantage. Study by Erevelles et al. (2016) highlighted that firms that do not develop their BA capabilities will find it challenging to create an SCA. Drawing from RBV, which posits that unique and valuable resources lead to competitive advantages, it is proposed that BA, with its data-driven insights and strategic value, significantly contributes to SCA. The following hypothesis was formulated based on prior research.

H$_3$: *There is a positive relationship between BA and SCA.*

3.4 BA and DC

Recent studies research have BA capabilities (ordinary capabilities) in their connection with DC (higher order) (Yoshikuni et al., 2023). Mikalef et al. (2020) investigated how BA capabilities help organizations gain insights to sustain their digital capabilities and improve company performance amid changing business environments. Likewise, Ciampi et al. (2021) claimed that business model innovation can affect DC through its impact on entrepreneurial orientation. Shuradze et al. (2018) studied the influence of BA in marketing on DC, aiming to understand customer needs and generate innovative business solutions. Based on DCV, which emphasizes the need for continuous adaptation and reconfiguration of capabilities, it is proposed that BA enhances an organization's dynamic capabilities by providing timely and actionable insights. Therefore, based on DCV and previous studies, H4 developed.

H$_4$: *There is a positive relationship between BA capabilities and DC.*

3.5 DC and SCA

DC can provide a robust theoretical foundation for firms that aim to build and enhance their resources to remain competitive (Almazmomi et al., 2022; Behl, 2020). According to Romme et al. (2010), DC can improve a firm's competence to adapt to changing environmental demands. DC is crucial to maintaining a competitive advantage in unpredictable demand conditions and competition (Haleblian et al., 2012). Firms must sense, evaluate and configure their resources and capabilities to respond to environmental changes (Sher and Lee, 2004). Several researchers have investigated the impact of DC on competitive advantage (Kuo et al., 2017; Marcus & Anderson, 2006). These searches suggest that DC have a significant positive impact on SCA. In line with DCV, which stresses the importance of dynamic reconfiguration of resources to achieve competitive advantage, it is posited that dynamic capabilities are essential for sustaining SCA in volatile markets. Therefore, this study developed the next hypothesis:

H$_5$: *There is a positive relationship between DC and SCA*.

3.6 Mediating role of DC.

The mediating effect of DC on the association between capabilities (i.e., BA and SMA) and SCA can be explained through the DCV (Teece, 2007). According to the DCV, organizations must continually adapt, integrate, and reconfigure internal and external competencies to address rapidly changing environments. As explained above, this study considers BA and SMA as capabilities that meet the VRIN (Valuable, Rare, Inimitable, and Non-substitutable) conditions and are therefore crucial resources for gaining a competitive advantage (Nguyen, 2018). However, while BA and SMA are valuable on their own, enhancing SCA without the mediating role of DC can be challenging. DCs are essential for transforming these capabilities into strategic assets that can dynamically respond to market changes and uncertainties (Gupta et al., 2020). Reviewing the related literature reveals that the mediating effect of DC has been investigated in the relationship between BA and SCA as well as between SMA and SCA. For example, Wamba et al. (2017) discovered that DC partially mediates the association between BA capabilities and organizational outcomes, indicating that BA capabilities alone are not sufficient without the dynamic integration provided by DCs. Similarly, Behl et al. (2022) claimed that BA capabilities indirectly impact SCA in medium and small enterprises through DCs. Dubey et al. (2018) further confirmed that the competitive advantage impacts via BA capabilities are mediated by DCs, demonstrating the crucial role of dynamic reconfiguration and resource management. Abdelhalim's (2023) findings provide valuable insights into integrating BA and management accounting for enhancing corporate sustainability performance, emphasizing the importance of DCs in this integration. Given the increasing globalization, technological complexity, resource scarcity, and heightened competition, organizations are shifting to a more collaborative approach to build their competitive advantage (Zhang et al., 2023). DCs, as higher-level capabilities, manage a company's ordinary capabilities (such as SMA and BA) to develop and sustain a competitive advantage, especially in changing business environments (Barreto, 2010; Teece, 2014).

Given the integral role of DCs in reconfiguring resources and adapting to market changes, this study hypothesizes that DCs mediate the relationship between both SMA and BA with SCA. This mediation suggests that while SMA and BA are critical for providing strategic insights and operational efficiencies, it is through the dynamic capabilities that these insights and efficiencies are effectively transformed into sustainable competitive advantages. Therefore, the current study argues that DCs serve as a mechanism to explain how SMA and BA enhance SCA, leading to the development of the following hypotheses:

H_6: *DC mediates the relationship between SMA and SCA.*

H_7: *DC mediates the relationship between BA and SCA.*

3.7 Moderating effect of CI

Previous studies (Cescon et al., 2019; Oyewo, 2021, 2022; Hadid and Al-Sayed, 2021; Rashid et al., 2023) have found that organizations with higher CI tend to rely on management control systems that have a broad scope, external and strategic orientation, and make greater use of non-financial and ex-ante information, such as SMA information. Furthermore, Oyewo (2022) found that CI strengthens the association between SMA use and competitive advantage. Companies facing intense competition possibly will employ SMA as a strategic approach to survive. Intense competition could push an organization to pursue cost-cutting strategies, continually observe rivals, benchmark its activities with rivals, evaluate the expenditure of competitors, estimate its brand, and seek strategic pricing. Therefore, companies working in an extremely competitive environment will probably use SMA more to cope with CI and gain SCA. Moreover, DC has gained momentum in recent years, providing a direction to achieving competitive advantage in dynamic environments. This has been established by various studies (Helfat & Peteraf, 2009; Zollo et al. 2016). Li and Chan (2019) have also highlighted the value DC can add to companies running in unstable business environments. Majhi et al. (2023) further argue that DC is essential for achieving a competitive advantage and ensuring sustained survival in such environments. In addition, DC assists companies in benefiting from promising entry into further product and geographic markets, refreshing their resource portfolio, restructuring industry connections, and promoting innovation (Bingham et al., 2015). Mikalef et al. (2019) argued that BA capabilities are additional functional under circumstances of increased CI. Consequently, as the CI increases, BA will add further strategic value. Nevertheless, a direct positive relationship between BA and CI exists. It is agreed that the higher the intensity of competition, the more a firm needs to obtain, analyse and interpret a vast quantity of data to enhance its capacity to monitor and understand market trends (Oyewo, 2022). A study by Bello-Pintado et al. (2018) identified a positive link between BA capabilities and competitive advantage, as higher CI resulted in an increased effect of BA on competitive advantage. Consequently, a higher CI implies increased competition, ultimately strengthening BA and SCA.

Based on the above arguments, this study assumes that the link between SMA and SCA will be stronger when CI is higher. The moderating effect of CI between SMA and SCA is based on the assumption that companies in highly competitive environments may be forced to rely more on SMA practices to maintain and enhance their competitive advantage. Similarly, it is hypothesized that CI moderates the relationship between BA and SCA, reinforcing the importance of BA in highly competitive markets.

H_8: *CI strengthens the relationship between SMA and SCA.*

H_9: *CI strengthens the relationship between DC and SCA.*

H_{10}: *CI strengthens the relationship between BA and SCA.*

4 Research Methodology

4.1 Research design, population, and sample.

The primary data for the study were gathered through a cross-sectional survey using a structured questionnaire. The study population comprises services and manufacturing firms registered on the Amman Stock Exchange (ASE). The sampling frame obtained from the ASE website revealed 132 companies, categorized as 87 services and 45 manufacturing companies as of

September 2023. Given the relatively small population size, all 132 companies were included in the analysis to ensure comprehensive coverage and enhance the generalizability of the findings. As the unit of analysis in this study is an organization, the survey was directed to top management members (chief executive officer, chief financial officer, chief operations officer) to fill out the questionnaire on behalf of their companies. This approach ensures that the responses accurately reflect the strategic perspectives and practices of the organizations. Following two waves of data collection and one reminder, 93 questionnaires were returned, of which 88 were usable, representing an adequate response rate. To justify the sample size, the G-power sampling size method was employed. Utilizing G-power with a specified effect size (f^2) of 0.15, alpha (α) of 0.05, and power (1-β err prob) of 0.8, as outlined by Chong et al. (2023), the analysis revealed that the minimum necessary sample size is 85. Consequently, with a selected sample size of 88, the study's power exceeds 0.8, instilling confidence in the applicability of the study results. This robust justification for including the entire population and the use of G-power analysis ensures the methodological rigor of our sampling approach.

4.2 Measurement of variables

The instrument employed to measure each of the constructs in this investigation consisted of three sections. The first part explained the aim and goals of this study by requesting the participants' readiness to participate in this study. The second part asked the participants about their experience, occupation, and gender. The final part introduced questions to measure the study variables. Each construct in this research was measured employing reflective measurement items. To measure SCA, a scale consisting of six items was adopted from Chang (2011), which several scholars have repeatedly used and validated (i.e., Zhang et al., 2023). SMA usage was determined by requesting participants to rate the level to which their companies utilize a list of sixteen SMA practices on a 5-point scale of 1 ("not at all") to 5 ("very great extent"). Previous research has employed the same technique to measure SMA (e.g. Cadez and Guilding, 2008; Oyewo, 2022). BA capabilities were measured on five-item scales adapted from LaValle et al. (2010). These measurements invited participants to select the status of their company's analytics capabilities to estimate their usage level throughout the organisation (Ashrafi et al., 2019; Rivera and Shanks, 2015). DC was assessed by sixteen items adapted from (Kuo et al., 2017). Finally, CI was measured by three questions based on Jaworski and Kohli's (1993) measurements and validated by other researchers (i.e., Olabode et al., 2022). The current study also controlled for two contextual variables (i.e., firm size and industry type) that might influence SCA. Previous studies have confirmed that these variables impact a firm's sustainable competitive advantage (Zhang et al., 2023). First, firm size (SIZE) was determined by the number of employees, where companies with more than 300 full-time employees were coded as (1) (56 companies), and otherwise (0). (32 companies) Second, a binary scale was used to measure the type of industry, where manufacturing companies were coded as (1) (36 companies) and services companies (0) (52 companies).

5. Data analysis

5.1 Common Method Variance (CMV)

The data utilised in the analysis was gathered from a single source, which may have led to the CMA. This possible bias was estimated using Harman's Single Factor investigation and the collinearity assessment. The analysis revealed that five factors described 81.68% of the cumulative effect of the variance. According to Podsakoff et al. (2003), the most significant variance described by a single factor should be less than 50%; in this case, it was found to be 32.42%. Thus, the results of this study suggest no threat from CMV.

5.2 Measurement model

The measurement model assesses the correlation between different indicators and their connected variables. The assessment of the measurement model was based on three aspects: internal consistency reliability, convergent validity, and discriminant validity. To evaluate internal consistency reliability, the study used Cronbach's alpha and composite reliability. The study followed the evaluation criteria proposed by Hair et al. (2017). As shown in Table 2 all the measurement model indicators met the recommended threshold values for both Cronbach's alpha (0.60) and composite reliability (CR) (0.60). Therefore, the study concluded that all the constructs have established internal consistency reliability.

When evaluating convergent validity, it is necessary to assess the outer loading of the indicators and the Average Variance Extracted (AVE). According to Hair et al. (2019), convergent reliability at the indicator level is established if satisfied the following two conditions; First, the outer loadings of all the indicators exceed the threshold value. According to Hair et al. (2022), an outer loading of 0.50 is considered significant for sample sizes of 80 or more. As items DC2 and DC6 exhibited low factor loadings (0.467 and 0.252, respectively), they were excluded from the analysis. Second, the AVE values of all the constructs are greater than 0.50 Hair et al. (2019). The outcomes of convergent validity are specified in Table 1.

Finally, to evaluate the discriminant validity, the study employed Heterotrait-Monotrait (HTMT) with a set threshold of 0.90 recommended by Chong et al. (2023). The HTMT value observed was below 0.90, signifying substantial discriminant validity for the latent variable. The HTMT analysis results in Table 2 validates that each model construct is unique.

Table 1
Factor loadings, reliability, and AVE.

Constructs/Items	Outer Loadings	Cronbach's alpha	Composite reliability	Average variance extracted (AVE)
BA		0.889	0.892	0.643
BA1	0.773			
BA2	0.756			
BA3	0.806			
BA4	0.800			
BA5	0.855			
BA6	0.817			
CI		0.895	0.902	0.703
CI1	0.836			
CI2	0.857			
CI3	0.877			
CI4	0.788			
CI5	0.832			
DC		0.958	0.96	0.649
DC1	0.729			
DC10	0.791			
DC11	0.902			
DC12	0.794			
DC13	0.772			
DC14	0.793			
DC15	0.778			
DC16	0.834			
DC2	*Deleted*			
DC3	0.720			
DC4	0.778			
DC5	0.830			
DC6	*Deleted*			
DC7	0.827			
DC8	0.812			
DC9	0.878			
SCA		0.863	0.864	0.593
SCA1	0.801			
SCA2	0.753			
SCA3	0.761			
SCA4	0.776			
SCA5	0.783			
SCA6	0.746			
SMA		0.964	0.965	0.650
SMA1	0.771			
SMA10	0.885			
SMA11	0.874			
SMA12	0.858			
SMA13	0.788			
SMA14	0.829			
SMA15	0.818			
SMA16	0.789			
SMA2	0.790			
SMA3	0.775			
SMA4	0.783			
SMA5	0.724			
SMA6	0.835			
SMA7	0.784			
SMA8	0.776			
SMA9	0.800			

Table 2
Discriminant validity- HTMT

Variable	BA	CI	DC	SCA	SMA
BA	-				
CI	0.739				
DC	0.777	0.717			
SCA	0.742	0.671	0.612		
SMA	0.566	0.512	0.617	0.665	-

5.3 Structural model

According to Hair et al. (2022), the assessment of the structural model involves four steps: (1) estimating a structural model to identify collinearity issues; (2) evaluating the significance and relevance of the structural model and its associations; (3) appraising the level of R^2; (4) estimating out-of-sample predictive capability with PLSpredict.

Step 1 results reveal that VIF values for direct and moderation relationships are all below the standard threshold of 3.30, indicating low collinearity among the exogenous constructs.

For Step 2, various techniques such as path coefficient, standard error, t-values, p-values, confidence interval bias-corrected lower limit (BCI LL), confidence interval bias-corrected upper limit (BCI UL), and effect size were employed to assess the strength and importance of connections within the structural model. These metrics, defined by Hair et al. (2019) and Ramayah et al. (2020), were used to determine the significance and relevance of relations. Table 4 and Figure 2 illustrate the structural model's relevance and significance. Additionally, a bootstrapping technique with 5,000 subsamples was employed to enhance the estimation of the hypothesized relations' significance degree (Sarstedt et al., 2023). To test the mediating role of DC on the association between SMA and SCA (H6) and BA and SCA (H7), this study follows the method suggested by Isaac et al. (2019). Moreover, this research explores how CI influences the connections between SMA, DC, BA, and SCA using Partial Least Squares-Structural Equation Modelling (PLS-SEM). The product term approach, recommended by Henseler and Chin (2010) as more effective than the group comparison approach, was employed to obtain accurate outcomes. Product terms between latent independent constructs and moderating variables were developed following Lowry and Gaskin's (2014) guidelines.

In step 3, this study assessed the effectiveness of the structural model by utilising the path coefficient of determination (R^2) to gauge its explanatory power. As per Hair et al.'s (2010) guidelines, R^2 values of 0.25-0.50 indicate weak explanatory power, values higher than 0.50 to 0.75 designate moderate explanatory power, and those above 0.75 designate substantial explanatory power.

Step 4. The PLSpredict algorithm, developed by Shmueli et al. (2016), is a method used to create and estimate predictions from PLS path model assessments. To evaluate the predictive capabilities of a PLS-SEM model, it is recommended to include PLSpredict in the evaluation process, as recommended by Hair et al. in 2019 and 2022. This study used PLSpredict with five folds and five repetitions (K=5) as per the approach followed by Shmueli et al. in 2019.

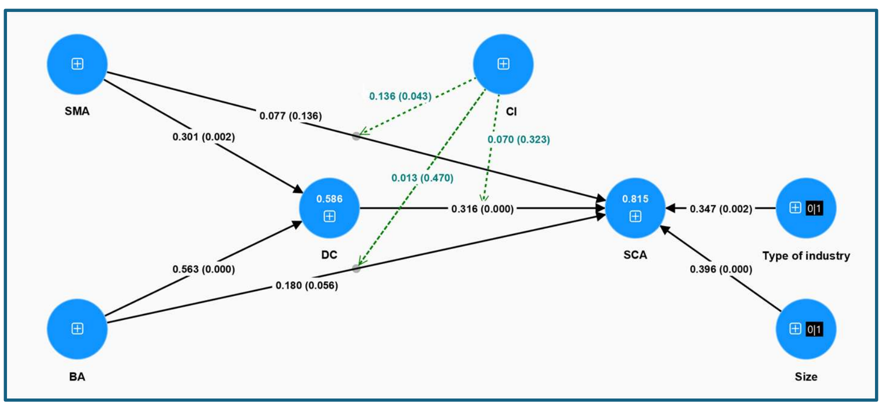

Fig. 2. The results of structural model

6 Results and Discussion

This research investigates the direct impact of SMA, BA, and DC on SCA. Additionally, the mediating effect of DC and moderating effect of CI on the direct relationships were investigated based on the RBV and DCV theories. Based on these aims, a PLS-SEM model was developed and run to assess the measurement and structural model. The PLSpredict algorithm and CVPAT were executed to evaluate the predictive capabilities of the path model.

6.1 The Direct Effects

The results in Table 3 and Fig. 2 showed that SMA ($\beta = 0.077$, $p = 0.132$) and BA ($\beta = 0.181$, $p = 0.053$) did not affect SCA. Thus, H1 and H2 were not supported. In this regard, Ramadan et al. (2020) found that BA has no direct effect on SCA. According to Chiang et al. (2018), achieving successful BA projects depends not only on having adequate infrastructure, data analysts, and tools for managing big data but also on understanding how BA contributes to competitive advantages and strategic value. In contrast to the results of this study, Oyewo and Ajibolade (2019) have provided practical evidence of the positive effect of SMA usage on SCA. According to Oyewo (2022), SMA's long-term orientation and future outlook imply that its implementation should help organizations maintain a competitive advantage by continually improving and sustaining above-average performance not only in the short term but also in the medium to long term. However, BA (β = 0.562, p = 0.000) is the most crucial factor to influence DC, followed by SMA (β = 0.302, $p < 0.002$); thus, H3 and H4 are supported. These findings confirmed that SMA and BA are vital resources for companies and could enhance the DC of organizations (Yoshikuni et al., 2023; Mikalef et al., 2020). Previous studies emphasize that specific characteristics of management accounting are found in capabilities such as "routines of behaviour that are learned, patterned, repetitious or quasi-repetitious and founded in part on tacit knowledge" (Coad & Cullen, 2006, p. 348). In SMA practice, relevant information is generated through patterned and repetitive task performance to aid decision-making and attention-directing purposes (Glyptis et al., 2021).

Moreover, BA offers value to the organization by informing business processes and supporting decision-making (Rivera and Shanks, 2015). The results confirmed that DC positively and significantly affects SCA (β = 0.314, p = 0.000), supporting H5. DC establishes a systematic modification by allowing renewal capabilities and enhancing flexibility in reaction to market adjustments (Pezeshkan et al., 2016) and the attainment of an SCA (Teece, 2007). This finding aligns with prior research, which has proven the positive impact of DC on SCA (Kuo et al., 2017; Marcus and Anderson, 2006; Sher and Lee, 2004).

The lack of significant direct effects of SMA and BA on SCA may be attributed to several factors. First, it suggests that the mere presence of BA and SMA practices is not sufficient; instead, these practices must be effectively integrated and utilized within the organizational processes to create a tangible impact on SCA. Second, it highlights the critical role of DC in mediating these relationships. Without the adaptive, integrative, and reconfiguring functions of DC, the potential benefits of BA and SMA may not fully materialize. Lastly, competitive intensity may play a role in amplifying or diminishing the effects of these practices, indicating that external environmental factors significantly influence their effectiveness.

Table 3

The structural model results.

Hypotheses	*β*	STDEV	*t*-values	*P*-values	95% confidence interval		f^2	VIF	Decision
Direct effects									
H1: SMA → SCA	0.077	0.069	1.115	0.132	-0.046	0.179	0.353	1.931	Not supported
H2:BA → SCA	0.181	0.112	1.612	0.053	-0.016	0.352	0.206	2.577	Not supported
H3: SMA → DC	0.302	0.104	2.898	0.002	0.131	0.477	0.095	1.389	Supported
H4:BA → DC	0.562	0.104	5.423	0.000	0.386	0.727	0.028	1.389	Supported
H5: DC → SCA	0.314	0.088	3.574	0.000	0.159	0.448	0.048	2.591	Supported
Mediation effect									
H6: SMA → DC → SCA	0.095	0.047	2.025	0.021	0.027	0.178	-	-	Supported
H7:BA → DC → SCA	0.178	0.055	3.245	0.001	0.087	0.267	-	-	Supported
Moderation effect									
H8:CI × SMA → SCA	0.135	0.079	1.712	0.043	-0.294	-0.037	0.263	1.373	Supported
H9:CI × DC → SCA	0.070	0.152	0.460	0.323	-0.114	0.367	0.452	2.680	Not supported
H10:CI × BA → SCA	0.013	0.167	0.075	0.470	-0.247	0.302	0.498	3.208	Not supported

6.1 Mediating effect of DC

The results provide evidence to support the mediation effects of DC (β = 0. 095, p = 0.021) on the association between SMA and SCA, as well as the association between BA and SCA (β = 0. 178, p = 0.001); hence hypotheses H6 and H7 are proven. These findings show that DC fully mediates these relationships since the direct effects are not supported, as indicated in H1 and H2, as shown in Table 3. Such results indicate that DC is an important mechanism that converts these vital capabilities (i.e., SMA and BA) to SCA. SMA and BA also allow corporations to obtain information about and analyse markets in several directions, such as customers, pricing, competitors, and demand for their products or services. This enables companies to create better forecasts and helps management accounting sustain relevancy and keep up with business environment changes (Ramakrishnan et al., 2020). SMA and BA enable corporates, via DC, to face and adjust to challenges in the international market and obtain their sustainability performance, as confirmed by Schaltegger et al. (2022). All in all, BA and SMA are considered data-driven sources for DC to enable firms to sense potential opportunities and threats, seize emerging business opportunities via business model strategy and investments, and convert their operations to adapt to changing market conditions (Raubitschek, 2018), thus enhance SCA (Nguyen, 2018; Peters et al., 2019).

6.2 Moderating effect of CI

The results in Table 3 indicated that CI moderates the association between SMA and SCA (β =0.135, t =1.712, p = 0.043), supporting hypothesis H8. This result is in contrast with Abu Afifa and Saleh's (2021) findings and aligns with Agbejule

(2005) and Hariyati et al. (2019), who argued that the association between management accounting techniques and companies' outcomes depends on the level of perceived environmental uncertainty. Li and Liu (2014) argued that companies running in highly competitive environments must continuously revise their business strategies to meet customer requirements, market transformations, competitive forces, and market needs. Hence, under the circumstances of CI, companies with greater SMA can obtain innovative insights that permit them to launch new business models to disrupt the existing competitive configuration to gain SCA. However, the results of the current study did provide evidence of the moderating impacts of CI on the relations between DC and SCA (β =0.070, t =0.152, p=0.460) and BA and SCA (β =0.013, t =0.167, p=0.075) so H9 and H10 were rejected. These results could be justified since the financial gains of investing in capabilities (such as BA and DC) might not be recognized in an environment described as predictable (Olabode et al., 2022). In scenarios characterized by limited and favorable competition, organizations find greater advantages in adhering to established business models. They seldom find motivation to invest in developing the capability to extract novel insights from big data, as the associated costs outweigh the alternative of maintaining a data-driven approach (Olabode et al., 2022). Thus, when competition is limited, having data-driven capability alone may not give a firm a new competitive advantage.

6.3 PLSpredict, control variables and R^2

Table 4 shows the results of the PLSpredict algorithm, indicating that manifest indicators including DC (seven items), SMS (five items), SCA (five items), and BA (three items) have predictive power, as the values of (PLSRMSE-LMRMSE and PLSMAE-LMMAE) for these measurement items were negative. The Q^2 predict values for the items mentioned above were positive, implying that the PLS-SEM models provide better predictive accuracy (Shmueli et al., 2019).

Table 4

Results of PLSpredict

Items	Q^2predict	PLS-SEM_RMSE	LM_RMSE	PLSRMSE-LMRMSE	PLS-SEM_MAE	LM_MAE	PLSMAE-LMMAE
SMA8	0.4280	0.994	1.277	-0.283	0.766	0.964	-0.198
SMA7	0.2380	1.226	1.888	-0.662	0.952	1.432	-0.480
SMA3	0.3240	1.027	1.157	-0.130	0.878	0.906	-0.028
SMA14	0.4070	1.020	1.249	-0.229	0.804	0.952	-0.148
SMA12	0.4410	1.047	1.368	-0.321	0.807	1.074	-0.267
SCA6	0.2900	1.047	1.390	-0.343	0.757	1.087	-0.330
SCA5	0.3630	0.951	1.173	-0.222	0.740	0.939	-0.199
SCA3	0.2900	1.102	1.462	-0.360	0.874	1.131	-0.257
SCA2	0.2880	1.053	1.453	-0.400	0.824	1.118	-0.294
SCA1	0.3290	0.943	1.067	-0.124	0.736	0.848	-0.112
DC7	0.3460	0.993	1.428	-0.435	0.789	1.184	-0.395
DC4	0.3080	1.116	1.528	-0.412	0.871	1.171	-0.300
DC3	0.2560	1.249	1.720	-0.471	0.997	1.361	-0.364
DC14	0.3160	1.108	1.368	-0.260	0.894	1.119	-0.225
DC12	0.4070	0.954	1.098	-0.144	0.786	0.879	-0.093
DC11	0.4660	0.891	1.190	-0.299	0.710	0.932	-0.222
DC10	0.2910	1.150	1.633	-0.483	0.947	1.281	-0.334
BA5	0.3590	1.068	1.552	-0.484	0.836	1.167	-0.331
BA3	0.3090	1.012	1.054	-0.042	0.794	0.798	-0.004
BA1	0.4090	0.968	1.275	-0.307	0.733	0.979	-0.246

RMSE indicates, the root mean square error; MAE indicates, the mean absolute error; and LM indicates the linear regression model.

Moreover, the current study implements the cross-validated predictive ability test (CVPAT) to evaluate the predictive capabilities of the path model (Liengaard et al., 2021; Sharma et al., 2023). The results reported in Table 5 show that the average loss difference values (PLS loss - Indicator Averages loss) are significantly below zero, indicating substantiated better predictive capabilities of the model.

Table 5

CVPAT-PLS-SEM vs Indicators Average (IA)

	PLS loss	IA loss	Average loss difference	t value	p value
DC	1.129	1.745	-0.616	4.528	0.000
SCA	1.040	1.507	-0.467	3.600	0.001
Overall	1.102	1.674	-0.571	4.616	0.000

To evaluate the effect of individuality among organizations, control variables such as company size and type of company have been included to affect the SCA. The results show that the control variables' influence on SCA is low, as the changes in R^2 for Size (0.002) and type of company (0.001) were minimal. Moreover, based on the R^2 values, SMA and BA explained 57% of the DC variances, and SMA, BA, DC, and CI explained 79 % of the SCA variance.

7 Contributions, Limitations, and Future Research

This study contributes to the body of knowledge by supporting RBV and DCV development and offering empirical evidence on different issues by supplying evidence on the effects of SMA and BA on SCA and attempting to fill the gap in the literature (Rashid et al., 2021). Moreover, by introducing DC as a mediator, the study's findings illustrate how ordinary capabilities such as SMA and BA could affect SCA, as this issue is still under research (Zameer et al., 2022; Aydiner et al., 2019). The mechanisms and conditions under which these relationships occur to achieve SCA have yet to be fully understood (Rikhardsson & Yigitbasioglu, 2018; Olabode et al., 2022). A firm's DC are its ability "to renew itself in the face of a changing environment by changing its set of resources" (Danneels, 2011). Thus, including SMA and BA in this study contributes to our understanding of the effect of BA and SMA on DC and SCA in contemporary business environments. In this regard, The findings indicate that the capabilities of SMA and BA focus on performing tasks correctly, while DCs have a distinct function as they allow a company to utilize its regular capabilities for high-return activities, enabling the company's resources to adapt quickly to changing global environments (Akter et al., 2020; Teece, 2014). These results contribute to the RBV and DCV, which assume that achieving a competitive advantage for a firm depends on its capability to manage its unique resources (Morgan et al., 2009). Also, as the sources of SCA may no longer be so because of unexpected shifts in the industry's economic structure, SMA and BA should enhance SCA. This study contributes to the body of knowledge by conceptualising SMA as a capability and tries to bridge the gap in the literature highlighted by Otley (2016). He concluded that a significant deficiency of such prior SMA work has been the limited conceptualisation of SMA considering organisational context since the SMA operates in collaboration. Otley (2016) recommended conceptualising SMA in a broader context, considering some relevant organisational resources, capabilities, and subsystems to overcome this deficiency.

This study delivers various practical contributions, as follows: (1) providing a comprehensive understanding to the administrators that they need to apply BA and SMA; (2) providing a deeper thoughtful of management for all stakeholders of the Jordanian companies to manage their capabilities to enhance SCA properly;(3) becoming a reference for future researchers who conduct investigate on the SCA in context of Jordan. However, it should be noted that this research has a few limitations. Firstly, it is recognized that the sample size was limited to services and manufacturing listed companies in Jordan. Therefore, expanding participants from other sectors, such as the financial sector, is advisable to approve the findings. Second, the variables in the study were merely measured using quantitative information. As a result, future research might integrate mixed data to confirm this study's results. Lastly, this study has relied on the cross-sectional method. Thus, it can only provide results that reflect the association between variables. Future studies that use experimental methods to demonstrate the causality between the variables are needed. It is also suggested that longitudinal research would be valuable to discover the conditions in which SMA and BA directly affect SCA.

References

Abdelhalim, A. M. (2024). How management accounting practices integrate with big data analytics and its impact on corporate sustainability. *Journal of Financial Reporting and Accounting*, *22*(2), 416-432. https://doi.org/10.1108/JFRA-01-2023-0053

Abu Afifa, M. M., & Saleh, I. (2021). Management accounting systems effectiveness, perceived environmental uncertainty and enterprise risk management: Evidence from Jordan. *Journal of Accounting & Organizational Change*, *17*(5), 704-727. https://doi.org/10.1108/JAOC-10-2020-0165

Agbejule, A. (2005). The relationship between management accounting systems and perceived environmental uncertainty on managerial performance: a research note. *Accounting and business research*, *35*(4), 295-305. https://doi.org/10.1080/00014788.2005.9729996

Akter, S., Gunasekaran, A., Wamba, S. F., Babu, M. M., & Hani, U. (2020). Reshaping competitive advantages with analytics capabilities in service systems. *Technological Forecasting and Social Change*, *159*, 120180. https://doi.org/10.1016/j.techfore.2020.120180

Alamri, A.M. (2019). Association between strategic management accounting facets and organizational performance. *Baltic Journal of Management*, *14*(2), 212-234. https://doi.org/10.1108/BJM-12-2017-0411

Al-Mawali, H. (2015). Contingent factors of strategic management accounting. *Research Journal of Finance and Accounting*, *6*(11), 130-137.

Al-Mawali, H., Zainuddin, Y., & Nasir Kader Ali, N. (2012). Customer accounting information usage and organizational performance. *Business Strategy Series*, *13*(5), 215-223. https://doi.org/10.1108/17515631211264096

Almazmomi, N., Ilmudeen, A., & Qaffas, A.A. (2022). The impact of business analytics capability on data-driven culture and exploration: achieving a competitive advantage. *Benchmarking: An International Journal*, *29*(4), 1264-1283. https://doi.org/10.1108/BIJ-01-2021-0021

Aouadi, A., & Marsat, S. (2018). Do ESG controversies matter for firm value? Evidence from international data. *Journal of business ethics*, *151*, 1027-1047. https://doi.org/10.1007/s10551-016-3213-8

Appelbaum, D., Kogan, A., Vasarhelyi, M., & Yan, Z. (2017). Impact of business analytics and enterprise systems on managerial accounting. *International journal of accounting information systems*, *25*, 29-44. https://doi.org/10.1016/j.accinf.2017.03.003

Ashrafi, A., Ravasan, A. Z., Trkman, P., & Afshari, S. (2019). The role of business analytics capabilities in bolstering firms' agility and performance. *International Journal of Information Management*, *47*, 1-15. https://doi.org/10.1016/j.ijinfomgt.2018.12.005

Aydiner, A. S., Tatoglu, E., Bayraktar, E., Zaim, S., & Delen, D. (2019). Business analytics and firm performance: The mediating role of business process performance. *Journal of business research*, *96*, 228-237. https://doi.org/10.1016/j.jbusres.2018.11.028

Barney, J. (1991). Firm Resources and Sustained Competitive Advantage. Journal of Management, 17(1), 99-120. https://doi.org/10.1177/014920639101700108

Barney, J. B. (2001). Resource-based theories of competitive advantage: A ten-year retrospective on the resource-based view. *Journal of Management, 27*(6), 643-650. https://doi.org/10.1177/014920630102700602

Barreto, I. (2010). Dynamic Capabilities: A Review of Past Research and an Agenda for the Future. *Journal of Management, 36*(1), 256-280. https://doi.org/10.1177/0149206309350776

Behl, A., Gaur, J., Pereira, V., Yadav, R., & Laker, B. (2022). Role of big data analytics capabilities to improve sustainable competitive advantage of MSME service firms during COVID-19–A multi-theoretical approach. *Journal of Business Research*, *148*, 378-389. https://doi.org/10.1016/j.jbusres.2022.05.009

Bingham, C. B., Heimeriks, K. H., Schijven, M., & Gates, S. (2015). Concurrent learning: How firms develop multiple dynamic capabilities in parallel. *Strategic Management Journal*, *36*(12), 1802-1825. https://doi.org/10.1002/smj.2347

Boldosova, V., & Luoto, S. (2020). Storytelling, business analytics and big data interpretation: Literature review and theoretical propositions. *Management Research Review*, *43*(2), 204-222. https://doi.org/10.1108/MRR-03-2019-0106

Bromwich, M. (1990). The case for strategic management accounting: the role of accounting information for strategy in competitive markets. *Accounting, organizations and society*, *15*(1-2), 27-46. https://doi.org/10.1016/0361-3682(90)90011-I

Cadez, S., & Guilding, C. (2012). Strategy, strategic management accounting and performance: a configurational analysis. *Industrial Management & Data Systems*, *112*(3), 484-501. https://doi.org/10.1108/02635571211210086

Cadez, S., & Guilding, C. (2008). An exploratory investigation of an integrated contingency model of strategic management accounting. *Accounting, organizations and society*, *33*(7-8), 836-863. https://doi.org/10.1016/j.aos.2008.01.003

Cao, G., & Duan, Y. (2017). How do top- and bottom-performing companies differ in using business analytics?. *Journal of Enterprise Information Management*, *30*(6), 874-892. https://doi.org/10.1108/JEIM-04-2016-0080

Cavusgil, E., Seggie, S. H., & Talay, M. B. (2007). Dynamic capabilities view: Foundations and research agenda. *Journal of marketing theory and practice*, *15*(2), 159-166. https://doi.org/10.2753/MTP1069-6679150205

Cescon, F., Costantini, A., & Grassetti, L. (2019). Strategic choices and strategic management accounting in large manufacturing firms. *Journal of Management and Governance*, *23*(3), 605-636. https://doi.org/10.1007/s10997-018-9431-y

Chang, C. H. (2011). The influence of corporate environmental ethics on competitive advantage: The mediation role of green innovation. *Journal of business ethics*, *104*, 361-370. https://doi.org/10.1007/s10551-011-0914-x

Chartered Global Management Accountant (CGMA) & Oracle (2015), The Digital Finance Imperative: Measure and Manage What Matters Next, Atlantic City. (*accessed on January 13, 2024)* https://www.oracle.com/webfolder/s/delivery_production/docs/fy16h1/doc12/LPD100477612-Oracle-CIMA-Thought.pdf. (*accessed on January 13, 2024)*

Chartered Global Management Accountant (CGMA) (2016), Joining the Dots – Decision Making for a New Era, CGMA, Atlantic City. https://integratedreporting.ifrs.org/resource/cgma-joining-the-dots/ (*accessed on January 13, 2024)*

Chen, H., Chiang, R. H., & Storey, V. C. (2012). Business intelligence and analytics: From big data to big impact. *MIS quarterly*, *36*(4), 1165-1188. https://doi.org/10.2307/41703503

Chenhall, R. H. (2003). Management control systems design within its organizational context: findings from contingency-based research and directions for the future. *Accounting, organizations and society*, *28*(2-3), 127-168. https://doi.org/10.1016/S0361-3682(01)00027-7

Chenhall, R. H. (2005). Integrative strategic performance measurement systems, strategic alignment of manufacturing, learning and strategic outcomes: an exploratory study. *Accounting, organizations and society*, *30*(5), 395-422. https://doi.org/10.1016/j.aos.2004.08.001

Chiang, R. H., Grover, V., Liang, T. P., & Zhang, D. (2018). Strategic value of big data and business analytics. *Journal of Management Information Systems*, *35*(2), 383-387. DOI: 10.1080/07421222.2018.1451950

Chong, C.-L., Abdul Rasid, S.Z., Khalid, H. and Ramayah, T. (2023). Big data analytics capability for competitive advantage and firm performance in Malaysian manufacturing firms. *International Journal of Productivity and Performance Management*, Vol. ahead-of-print No. ahead-of-print. https://doi.org/10.1108/IJPPM-11-2022-0567

Ciampi, F., Demi, S., Magrini, A., Marzi, G., & Papa, A. (2021). Exploring the impact of big data analytics capabilities on business model innovation: The mediating role of entrepreneurial orientation. *Journal of Business Research*, *123*, 1-13. https://doi.org/10.1016/j.jbusres.2020.09.023

Coad, A. F., & Cullen, J. (2006). Inter-organisational cost management: Towards an evolutionary perspective. *Management Accounting Research*, *17*(4), 342-369. https://doi.org/10.1016/j.mar.2006.02.003

Cokins, G. (2013). Top 7 trends in management accounting. *Strategic Finance*, *95*(6), 21-30.

Conboy, K., Mikalef, P., Dennehy, D., & Krogstie, J. (2020). Using business analytics to enhance dynamic capabilities in operations research: A case analysis and research agenda. *European Journal of Operational Research*, *281*(3), 656-672. https://doi.org/10.1016/j.ejor.2019.06.051

Dahiya, R., Le, S., Ring, J.K., & Watson, K. (2022). Big data analytics and competitive advantage: the strategic role of firm-specific knowledge. *Journal of Strategy and Management*, *15*(2), 175-193. https://doi.org/10.1108/JSMA-08-2020-0203

Danneels, E. (2011). Trying to become a different type of company: Dynamic capability at Smith Corona. *Strategic management journal*, *32*(1), 1-31. https://doi.org/10.1002/smj.863

de Camargo Fiorini, P., Seles, B. M. R. P., Jabbour, C. J. C., Mariano, E. B., & de Sousa Jabbour, A. B. L. (2018). Management theory and big data literature: From a review to a research agenda. *International Journal of Information Management*, *43*, 112-129. https://doi.org/10.1016/j.ijinfomgt.2018.07.005

Delen, D., & Zolbanin, H. M. (2018). The analytics paradigm in business research. *Journal of Business Research*, *90*, 186-195. https://doi.org/10.1016/j.jbusres.2018.05.013

Drury, C. (2018). *Cost and management accounting*. Belmont, CA, USA: Cengage Learning.

Dubey, R., Gunasekaran, A., & Childe, S.J. (2019). Big data analytics capability in supply chain agility: The moderating effect of organizational flexibility. *Management Decision*, *57*(8), 2092-2112. https://doi.org/10.1108/MD-01-2018-0119

Dyer, J. H., & Singh, H. (1998). The relational view: Cooperative strategy and sources of interorganizational competitive advantage. *Academy of management review*, *23*(4), 660-679. https://doi.org/10.5465/amr.1998.1255632

Elia, S., Giuffrida, M., Mariani, M. M., & Bresciani, S. (2021). Resources and digital export: An RBV perspective on the role of digital technologies and capabilities in cross-border e-commerce. *Journal of Business Research*, *132*, 158-169. https://doi.org/10.1016/j.jbusres.2021.04.010

Erevelles, S., Fukawa, N., & Swayne, L. (2016). Big Data consumer analytics and the transformation of marketing. *Journal of business research*, *69*(2), 897-904. https://doi.org/10.1016/j.jbusres.2015.07.001

Fosso Wamba, S., Queiroz, M. M., Wu, L., & Sivarajah, U. (2024). Big data analytics-enabled sensing capability and organizational outcomes: assessing the mediating effects of business analytics culture. *Annals of Operations Research*, *333*(2), 559-578. https://doi.org/10.1007/s10479-020-03812-4

Glyptis, L., Hadjielias, E., Christofi, M., Kvasova, O., & Vrontis, D. (2021). Dynamic familiness capabilities and family business growth: A longitudinal perspective framed within management accounting. *Journal of Business Research*, *127*, 346-363. https://doi.org/10.1016/j.jbusres.2021.01.019

Guilding, C., & McManus, L. (2002). The incidence, perceived merit and antecedents of customer accounting: an exploratory note. *Accounting, organizations and society*, *27*(1-2), 45-59. https://doi.org/10.1016/S0361-3682(01)00030-7

Guilding, C., Cravens, K. S., & Tayles, M. (2000). An international comparison of strategic management accounting practices. *Management accounting research*, *11*(1), 113-135. https://doi.org/10.1006/mare.1999.0120

Gupta, M., & George, J. F. (2016). Toward the development of a big data analytics capability. *Information & Management*, *53*(8), 1049-1064. https://doi.org/10.1016/j.im.2016.07.004

Gupta, S., Drave, V. A., Dwivedi, Y. K., Baabdullah, A. M., & Ismagilova, E. (2020). Achieving superior organizational performance via big data predictive analytics: A dynamic capability view. *Industrial Marketing Management*, *90*, 581-592. https://doi.org/10.1016/j.indmarman.2019.11.009

Hadid, W., & Al-Sayed, M. (2021). Management accountants and strategic management accounting: The role of organizational culture and information systems. *Management accounting research*, *50*, 100725. https://doi.org/10.1016/j.mar.2020.100725

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European business review*, *31*(1), 2-24. https://doi.org/10.1007/978-3-030-80519-7

Hair, J., & Alamer, A. (2022). Partial Least Squares Structural Equation Modeling (PLS-SEM) in second language and education research: Guidelines using an applied example. *Research Methods in Applied Linguistics*, *1*(3), 100027. https://doi.org/10.1016/j.rmal.2022.100027

Haleblian, J., McNamara, G., Kolev, K., & Dykes, B. J. (2012). Exploring firm characteristics that differentiate leaders from followers in industry merger waves: A competitive dynamics perspective. *Strategic Management Journal*, *33*(9), 1037-1052. https://doi.org/10.1002/smj.1961

Hariyati, H., Tjahjadi, B., & Soewarno, N. (2019), "The mediating effect of intellectual capital, management accounting information systems, internal process performance, and customer performance", *International Journal of Productivity and Performance Management*, *68*(7), 1250-1271. https://doi.org/10.1108/IJPPM-02-2018-0049

Helfat, C. E., & Raubitschek, R. S. (2018). Dynamic and integrative capabilities for profiting from innovation in digital platform-based ecosystems. *Research policy*, *47*(8), 1391-1399. https://doi.org/10.1016/j.respol.2018.01.019

Helfat, C. E., Finkelstein, S., Mitchell, W., Peteraf, M., Singh, H., Teece, D., & Winter, S. G. (2009). *Dynamic capabilities: Understanding strategic change in organizations*. John Wiley & Sons.

Henri, J. F. (2006). Management control systems and strategy: A resource-based perspective. *Accounting, organizations and society*, *31*(6), 529-558. https://doi.org/10.1016/j.aos.2005.07.001

Hindle, G., Kunc, M., Mortensen, M., Oztekin, A., & Vidgen, R. (2020). Business analytics: Defining the field and identifying a research agenda. *European Journal of Operational Research*, *281*(3), 483-490. https://doi.org/10.1016/j.ejor.2019.10.001

Institute of Management Accounting (IMA) (2019). The Data Analytics Implementation Journey in Business and Finance. : Raef Lawson, Toby Hatch, ; Denis Desroches, https://www.imanet.org/research-publications/ima-reports/the-data-analytics-implementation-journey-in-business-and-finance (*accessed on January 10, 2024*)

Jaworski, B. J., & Kohli, A. K. (1993). Market Orientation: Antecedents and Consequences. *Journal of Marketing, 57*(3), 53-70. https://doi.org/10.1177/002224299305700304

Joseph. J. F., Barry, J. B., Rolph, E. A., & Rolph, E. A. (2010). *Multivariate data analysis*. Pearson Prentice Hall.

Keong, L. S., & Dastane, O. (2019). Building a sustainable competitive advantage for Multi-Level Marketing (MLM) firms: An empirical investigation of contributing factors. *Journal of Distribution Science*, *17*(3), 5-19.

Krishnamoorthi, S., & Mathew, S. K. (2018). Business analytics and business value: A comparative case study. *Information & Management*, *55*(5), 643-666. https://doi.org/10.1016/j.im.2018.01.005

Kristoffersen, E., Mikalef, P., Blomsma, F., & Li, J. (2021). The effects of business analytics capability on circular economy implementation, resource orchestration capability, and firm performance. *International Journal of Production Economics*, *239*, 108205. https://doi.org/10.1016/j.ijpe.2021.108205

Kuo, S. Y., Lin, P. C., & Lu, C. S. (2017). The effects of dynamic capabilities, service capabilities, competitive advantage, and organizational performance in container shipping. *Transportation Research Part A: Policy and Practice*, *95*, 356-371. https://doi.org/10.1016/j.tra.2016.11.015

Langfield-Smith, K. (2008). Strategic management accounting: how far have we come in 25 years?. *Accounting, Auditing & Accountability Journal*, *21*(2), 204-228. https://doi.org/10.1108/09513570810854400

LaValle, S., Lesser, E., Shockley, R., Hopkins, M. S., & Kruschwitz, N. (2010). Big data, analytics and the path from insights to value. *MIT sloan management review*. https://sloanreview.mit.edu/article/big-data-analytics-and-the-path-from-insights-to-value/

Li, C., Khan, A., Ahmad, H., & Shahzad, M. (2022). Business analytics competencies in stabilizing firms' agility and digital innovation amid COVID-19. *Journal of Innovation & Knowledge*, *7*(4), 100246. https://doi.org/10.1016/j.jik.2022.100246

Li, D. Y., & Liu, J. (2014). Dynamic capabilities, environmental dynamism, and competitive advantage: Evidence from China. *Journal of business research*, *67*(1), 2793-2799. https://doi.org/10.1016/j.jbusres.2012.08.007

Li, T. C., & Chan, Y. E. (2019). Dynamic information technology capability: Concept definition and framework development. *The Journal of Strategic Information Systems*, *28*(4), 101575. https://doi.org/10.1016/j.jsis.2019.101575

Mahdi, O. R., Nassar, I. A., & Almsafir, M. K. (2019). Knowledge management processes and sustainable competitive advantage: An empirical examination in private universities. *Journal of business research*, *94*, 320-334. https://doi.org/10.1016/j.jbusres.2018.02.013

Majhi, S.G., Mukherjee, A., & Anand, A. (2023). Business value of cognitive analytics technology: a dynamic capabilities perspective. *VINE Journal of Information and Knowledge Management Systems*, *53*(6), 1231-1249. https://doi.org/10.1108/VJIKMS-07-2021-0128

Marcus, A. A., & Anderson, M. H. (2006). A general dynamic capability: does it propagate business and social competencies in the retail food industry?. *Journal of Management Studies*, *43*(1), 19-46. https://doi.org/10.1111/j.1467-6486.2006.00581.x

McAfee, A., Brynjolfsson, E., Davenport, T. H., Patil, D. J., & Barton, D. (2012). Big data: the management revolution. *Harvard business review*, *90*(10), 60-68.

McManus, L., & Guilding, C. (2008). Exploring the potential of customer accounting: a synthesis of the accounting and marketing literatures. *Journal of Marketing Management*, *24*(7-8), 771-795. https://doi.org/10.1362/026725708X345515

Medeiros, M.M.d., & Maçada, A.C.G. (2022). Competitive advantage of data-driven analytical capabilities: the role of big data visualization and of organizational agility. *Management Decision*, 60(4), 953-975. https://doi.org/10.1108/MD-12-2020-1681

Mikalef, P., Boura, M., Lekakos, G., & Krogstie, J. (2019). Big data analytics capabilities and innovation: the mediating role of dynamic capabilities and moderating effect of the environment. *British Journal of Management*, *30*(2), 272-298. https://doi.org/10.1111/1467-8551.12343

Mikalef, P., Krogstie, J., Pappas, I. O., & Pavlou, P. (2020). Exploring the relationship between big data analytics capability and competitive performance: The mediating roles of dynamic and operational capabilities. *Information & Management*, *57*(2), 103169. https://doi.org/10.1016/j.im.2019.05.004

Mikalef, P., Pappas, I. O., Krogstie, J., & Giannakos, M. (2018). Big data analytics capabilities: a systematic literature review and research agenda. *Information systems and e-business management*, *16*, 547-578. https://doi.org/10.1007/s10257-017-0362-y

Mitter, C., & Hiebl, M.R.W. (2017). The role of management accounting in international entrepreneurship. *Journal of Accounting & Organizational Change*, *13*(3), 381-409. https://doi.org/10.1108/JAOC-02-2016-0006

Molina-Castillo, F. J., Jimenez-Jimenez, D., & Munuera-Aleman, J. L. (2011). Product competence exploitation and exploration strategies: The impact on new product performance through quality and innovativeness. *Industrial Marketing Management*, *40*(7), 1172-1182. https://doi.org/10.1016/j.indmarman.2010.12.017

Morgan, N. A., Vorhies, D. W., & Mason, C. H. (2009). Market orientation, marketing capabilities, and firm performance. *Strategic management journal*, *30*(8), 909-920. https://doi.org/10.1002/smj.764

Mortenson, M. J., Doherty, N. F., & Robinson, S. (2015). Operational research from Taylorism to Terabytes: A research agenda for the analytics age. *European Journal of Operational Research*, *241*(3), 583-595. https://doi.org/10.1016/j.ejor.2014.08.029

Mousavi, S., Bossink, B., & van Vliet, M. (2018). Dynamic capabilities and organizational routines for managing innovation towards sustainability. *Journal of cleaner production*, *203*, 224-239. https://doi.org/10.1016/j.jclepro.2018.08.215

Mugoni, E., Nyagadza, B., & Hove, P. K. (2023). Green reverse logistics technology impact on agricultural entrepreneurial marketing firms' operational efficiency and sustainable competitive advantage. *Sustainable Technology and Entrepreneurship*, *2*(2), 100034. https://doi.org/10.1016/j.stae.2022.100034

Niu, Y., Ying, L., Yang, J., Bao, M., & Sivaparthipan, C. B. (2021). Organizational business intelligence and decision making using big data analytics. *Information Processing & Management*, *58*(6), 102725. https://doi.org/10.1016/j.ipm.2021.102725

O'Neill, M., & Brabazon, A. (2019). Business analytics capability, organisational value and competitive advantage. *Journal of Business Analytics*, *2*(2), 160-173. https://doi.org/10.1080/2573234X.2019.1649991

Oboh, C. S., & Ajibolade, S. O. (2017). Strategic management accounting and decision making: A survey of the Nigerian Banks. *Future Business Journal*, *3*(2), 119-137. https://doi.org/10.1016/j.fbj.2017.05.004

Oesterreich, T.D., & Teuteberg, F. (2019). The role of business analytics in the controllers and management accountants' competence profiles: An exploratory study on individual-level data. *Journal of Accounting & Organizational Change*, *15*(2), 330-356. https://doi.org/10.1108/JAOC-10-2018-0097

Olabode, O. E., Boso, N., Hultman, M., & Leonidou, C. N. (2022). Big data analytics capability and market performance: The roles of disruptive business models and competitive intensity. *Journal of Business Research*, *139*, 1218-1230. https://doi.org/10.1016/j.jbusres.2021.10.042

Otley, D. (2016). The contingency theory of management accounting and control: 1980–2014. *Management accounting research*, *31*, 45-62. https://doi.org/10.1016/j.mar.2016.02.001

Oyewo, B. (2021). Do innovation attributes really drive the diffusion of management accounting innovations? Examination of factors determining usage intensity of strategic management accounting. *Journal of Applied Accounting Research*, *22*(3), 507-538. https://doi.org/10.1108/JAAR-07-2020-0142

Oyewo, B. (2022). Contextual factors moderating the impact of strategic management accounting on competitive advantage. *Journal of Applied Accounting Research*, *23*(5), 921-949. https://doi.org/10.1108/JAAR-04-2021-0108

Oyewo, B., & Ajibolade, S. (2019). Does the use of strategic management accounting techniques creates and sustains competitive advantage? Some empirical evidence. *Annals of Spiru Haret University. Economic Series*, *19*(2), 61-91.

Peters, M. D., Gudergan, S., & Booth, P. (2019). Interactive profit-planning systems and market turbulence: A dynamic capabilities perspective. *Long Range Planning*, *52*(3), 386-405. https://doi.org/10.1016/j.lrp.2018.03.004

Pezeshkan, A., Fainshmidt, S., Nair, A., Frazier, M. L., & Markowski, E. (2016). An empirical assessment of the dynamic capabilities–performance relationship. *Journal of Business Research*, *69*(8), 2950-2956. https://doi.org/10.1016/j.jbusres.2015.10.152

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: a critical review of the literature and recommended remedies. *Journal of applied psychology*, *88*(5), 879. https://doi.org/10.1037/0021-9010.88.5.879

Porter, M. E. (1998). *Clusters and the new economics of competition* (Vol. 76, No. 6, pp. 77-90). Boston: Harvard Business Review.

Ramakrishnan, T., Khuntia, J., Kathuria, A., & Saldanha, T. J. (2020). An Integrated Model of Business Intelligence & Analytics Capabilities and Organizational Performance. *Communications of the Association for Information Systems, 46*, pp-pp. https://doi.org/10.17705/1CAIS.04631

Ramayah, T., Soto-Acosta, P., Kheng, K.K., & Mahmud, I. (2020). Developing process and product innovation through internal and external knowledge sources in manufacturing Malaysian firms: the role of absorptive capacity. *Business Process Management Journal*, *26*(5), 1021-1039. https://doi.org/10.1108/BPMJ-11-2019-0453

Rashid, M.M., Ali, M.M., & Hossain, D.M. (2021). Strategic management accounting practices: a literature review and opportunity for future research. *Asian Journal of Accounting Research*, *6*(1), 109-132. https://doi.org/10.1108/AJAR-06-2019-0051

Rashid, M.M., Hossain, D.M., & Alam, M.S. (2023). The external organizational environment and its impact on strategic management accounting practices: an empirical investigation. *Asian Review of Accounting*, Vol. ahead-of-print No. ahead-of-print. https://doi.org/10.1108/ARA-02-2023-0041

Rikhardsson, P., & Yigitbasioglu, O. (2018). Business intelligence & analytics in management accounting research: Status and future focus. *International Journal of Accounting Information Systems*, *29*, 37-58. https://doi.org/10.1016/j.accinf.2018.03.001

Santiago Rivera, D., & Shanks, G. (2015). A dashboard to support management of business analytics capabilities. Journal of Decision Systems, 24(1), 73-86. https://doi.org/10.1080/12460125.2015.994335.

Sarstedt, M., Hair, J. F., & Ringle, C. M. (2023). "PLS-SEM: Indeed a silver bullet"–retrospective observations and recent advances. *Journal of marketing theory and practice*, *31*(3), 261-275. 10.1080/10696679.2022.2056488

Sher, P. J., & Lee, V. C. (2004). Information technology as a facilitator for enhancing dynamic capabilities through knowledge management. *Information & management*, *41*(8), 933-945. 10.1016/j.im.2003.06.004

Shmueli, G., Ray, S., Estrada, J. M. V., & Chatla, S. B. (2016). The elephant in the room: Predictive performance of PLS models. *Journal of business Research*, *69*(10), 4552-4564. https://doi.org/10.1016/j.jbusres.2016.03.049

Shmueli, G., Sarstedt, M., Hair, J.F., Cheah, J.-H., Ting, H., Vaithilingam, S., & Ringle, C.M. (2019). Predictive model assessment in PLS-SEM: guidelines for using PLSpredict. *European Journal of Marketing*, *53*(11), 2322-2347. https://doi.org/10.1108/EJM-02-2019-0189

Shuradze, G., Bogodistov, Y., & Wagner, H. T. (2018). The role of marketing-enabled data analytics capability and organisational agility for innovation: Empirical evidence from German firms. *International Journal of Innovation Management*, *22*(04), 1850037. https://doi.org/10.1142/S1363919618500378

Simmonds, K. (1982). Strategic management accounting for pricing: a case example. *Accounting and business research*, *12*(47), 206-214. https://doi.org/10.1080/00014788.1982.9728809

Teece, D. J. (2007). Explicating dynamic capabilities: the nature and microfoundations of (sustainable) enterprise performance. *Strategic management journal*, *28*(13), 1319-1350. https://doi.org/10.1002/smj.640

Teece, D. J. (2014). The foundations of enterprise performance: Dynamic and ordinary capabilities in an (economic) theory of firms. *Academy of management perspectives*, *28*(4), 328-352. https://doi.org/10.5465/amp.2013.0116

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic management journal*, *18*(7), 509-533. https://doi.org/10.1002/(SICI)1097-0266(199708)18:7<509::AID-SMJ882>3.0.CO;2-Z

Vidgen, R., Shaw, S., & Grant, D. B. (2017). Management challenges in creating value from business analytics. *European Journal of Operational Research*, *261*(2), 626-639. https://doi.org/10.1016/j.ejor.2017.02.023

Vitale, G., Cupertino, S., & Riccaboni, A. (2020). Big data and management control systems change: The case of an agricultural SME. *Journal of Management Control*, *31*, 123-152. https://doi.org/10.1007/s00187-020-00298-w

Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J. F., Dubey, R., & Childe, S. J. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. *Journal of Business Research*, *70*, 356-365. https://doi.org/10.1016/j.jbusres.2016.08.009

Wang, S., Yeoh, W., Richards, G., Wong, S. F., & Chang, Y. (2019). Harnessing business analytics value through organizational absorptive capacity. *Information & Management*, *56*(7), 103152. https://doi.org/10.1016/j.im.2019.02.007

Wang, Y., & Hajli, N. (2017). Exploring the path to big data analytics success in healthcare. *Journal of Business Research*, *70*, 287-299. https://doi.org/10.1016/j.jbusres.2016.08.002

Ward, K., & Grundy, T. (1996). The strategic management of corporate value. *European Management Journal*, *14*(3), 321-330. https://doi.org/10.1016/0263-2373(96)00012-6

Wilden, R., Gudergan, S. P., Nielsen, B. B., & Lings, I. (2013). Dynamic capabilities and performance: strategy, structure and environment. *Long range planning*, *46*(1-2), 72-96. https://doi.org/10.1016/j.lrp.2012.12.001

Winter, S. G. (2003). Understanding dynamic capabilities. *Strategic management journal*, *24*(10), 991-995. https://doi.org/10.1002/smj.318

Yoshikuni, A. C., Dwivedi, R., Zhou, D., & Wamba, S. F. (2023). Big data and business analytics enabled innovation and dynamic capabilities in organizations: developing and validating scale. *International Journal of Information Management Data Insights*, *3*(2), 100206. https://doi.org/10.1016/j.jjimei.2023.100206

Zameer, H., Wang, Y., Yasmeen, H., & Mubarak, S. (2022). Green innovation as a mediator in the impact of business analytics and environmental orientation on green competitive advantage. *Management Decision*, *60*(2), 488-507. https://doi.org/10.1108/MD-01-2020-0065

Zhang, X., Chu, Z., Ren, L., & Xing, J. (2023). Open innovation and sustainable competitive advantage: The role of organizational learning. *Technological Forecasting and Social Change*, *186*, 122114. https://doi.org/10.1016/j.techfore.2022.122114

Zollo, M., Bettinazzi, E. L., Neumann, K., & Snoeren, P. (2016). Toward a comprehensive model of organizational evolution: Dynamic capabilities for innovation and adaptation of the enterprise model. *Global Strategy Journal*, *6*(3), 225-244. https://doi.org/10.1002/gsj.1122