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Examining the role of big data and marketing analytics in SMEs innovation and competitive advantage: A knowledge integration perspective☆

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ABSTRACT

The age of digitisation has resulted in an explosion of studies investigating the benefits of Big Data Analytics (BDA) as a means to enhance competitive advantage in organisations. However, the best way to leverage BDA is still inconclusive. Moreover, there is paucity of studies investigating how SMEs, who are recognised as having high levels of entrepreneurial orientation, can utilise big data and marketing analytics to support innovation and competitive advantage in dynamic environments. This study employs dynamic capabilities as a lens to investigate the nuanced relationships. Adopting a partial least squares (PLS) path modelling method with 194 UK SMEs, this study finds that knowledge integration mechanisms are particularly critical value creation enablers by transforming EO and BDA into organisational wide capabilities in support of innovation and competitive advantage. These novel and nuanced insights are of value to both practitioner and researchers.

1. Introduction

Small and Medium Enterprises (SMEs) represent over 90% of enterprises worldwide (The World Bank, 2022), and are credited as a major force in driving economic growth and innovation in many OECD countries (Coltorti and Venanzi, 2017; Genc et al., 2020; Thrassou et al., 2020). Yet, increasing global uncertainty and competition, changing customer demands, rapidly evolving technologies, and global events such as Covid-19 and the war in Ukraine, have had a major impact on the competitiveness and survival of SMEs (Adam and Alarifi, 2021; Ciampi et al., 2021; Dubey et al., 2020 Gurría, 2020). SME's have long since been recognised as a hotbed of entrepreneurship and innovation and having key advantages over larger firms, such as being more agile and responsive due to their flatter structures and size and having higher levels of entrepreneurial orientation (EO) capabilities (Hervé et al., 2020; Miroshnychenko et al., 2020; Miller et al., 2021). EO capabilities typically include a culture of innovativeness, proactiveness and risk taking (Hervé et al., 2020; Lumpkin and Dess, 1996). Yet, it appears that possessing a set of higher-level EO capabilities alone does not always translate into increased innovation or competitive advantage for SMEs (Ozer and Dayan, 2015; Thrassou et al., 2020). It is estimated that almost 50% of global SMEs currently are not translating their EO capabilities into some aspect of innovation, and this in turn is having a negative impact on their competitive position (Genc et al., 2019).

This has resulted in SME's having to reassess their businesses to find ways to try to solve this innovation conundrum in order to enhance their competitive position (Miroshnychenko et al., 2020). One area that is showing promise in unlocking the entrepreneurial and innovation potential of SMEs is the development of big data analytics capabilities (BDAC) (Del Vecchio, 2018; Miller et al., 2021; Trabucchi and Buganza, T, 2019). In an era of digitisation, the emergence of big data analytics (BDA) has resulted in much higher volumes and variety of data than ever before being readily accessible to firms (Brintrup et al., 2020). Big data comprises data sets whose size is beyond the capacity of standard database software tools to capture, manage and analyse (Hoffmann, 2017). BDA has evolved from capturing and interpreting vast volumes and variety of data that exist today to providing timely and accurate knowledge to support strategic decision making. New BDA tools and software, such as Cloudera and Rapidminer are transforming this previously untapped information and knowledge into clear and

☆ **An SME data driven innovation capabilities model: the role of knowledge integration.**

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concise customer behaviours, patterns and trends in support of innovation (Del Vecchio et al., 2018; Trabucchi and Buganza, 2019) and enhanced competitive advantage (Dubey et al., 2019a; Gupta and George, 2016; Maheshwari et al., 2021; Wamba et al., 2017).

A seminal paper by Gupta and George (2016) examined the resources required to build BDAC and provided an architecture and theoretical framework for researchers and practitioners alike to further explore and conduct empirical research into BDAC. This framework has since become a fundamental foundation and inspiration for many scholars investigating BDAC across different sectors and organisational settings (refer to Cadden et al., 2020; Wamba et al., 2017; Wamba and Akter, 2019). The framework proposed three categories of big data resources (BDR's) that supports the development of BDAC namely: tangible resources (resources that are easily replicable or purchased), for example, basic resources, data resources and technology, human resources (such as technical and management skills), and intangible resources (resources that are difficult to replicate and are 'deep rooted' such as intellectual capital, knowledge, culture and organisational learning).

Whilst it is argued in the literature that all three categories of BDR's are included in developing a holistic set of BDACs, it the strategic differentiator of the BDAC framework that lies within the intangible BDAC's. Intangible capabilities are much more challenging to understand, measure and develop due to a lack of clear boundaries (Teece 2007) and are 'highly context dependent' (Gupta and George, 2016: 1053), but are recognised as an elixir of competitive advantage if these capabilities can be developed and utilised by the firm (Teece 2014; Gupta and George, 2016).

However, whilst there is much promise through the lens of intangible capability development in support of competitive advantage, the SME data driven innovation capabilities literature is currently inconclusive and a neglected area of academic enquiry in this regard (Ciampi et al., 2021; Genc et al., 2019; Hervé et al., 2020; Miller et al., 2021; Miroshnychenko et al., 2020). This paper attempts to address this much needed research gap by investigating the salient literature in this domain and empirically testing an SME data driven innovation capabilities model that has intangible capabilities at the heart of the model to support competitive advantage.

This paper addresses the following central research question: *How can SMEs develop a set of data driven innovation capabilities in support of competitive advantage in turbulent environments*?

Dynamic capability theory (DCT) is the underpinning theoretical basis for this study. DCT is defined as the "*ability to integrate, build, and reconfigure internal and external resources/competencies to address, and possibly shape, rapidly changing business environments*" (Teece, 2012, p135). In particular, DCT is an important theoretical lens for understanding the key DCT orchestration processes: '*sense, seize* and *transformation'* for SMEs in a data driven world who are recognised as possessing entrepreneurship and innovation capabilities, and the ability to adapt much more quickly than their larger counterparts (Heider et al., 2020).

This paper makes a number of important contributions. Firstly, this paper provides a theoretical contribution by developing an SME Data Driven Innovation Capabilities Model for enhanced innovation and competitive advantage. The theoretical model is underpinned by DCT and charts the *sense, seize* and *transformation* orchestration processes by highlighting the key capabilities and interrelationships required at each stage in an SME Data Driven Innovation context to promote enhanced competitive advantage. SMEs level of innovation, globally, is still relatively low which is surprising given the level of EO reported in SMEs (Genc et al. 2019). This study investigates this innovation deficit from EO to innovation by providing additional insights and a pathway to increased innovation for SMEs.

Secondly, current studies on SMEs fail to investigate the interrelated mechanisms through which innovation can thrive in a changing global environment with increasing digitisation. This paper explores the influence EO has in an age of digitisation. Moreover, the research provides important insights into how this knowledge can be exploited and embedded through big data, marketing analytics and knowledge integration to drive innovation and ultimately competitive advantage (Canakoglu et al., 2018; Ciampi et al. 2021; Dubey et al., 2019b). This study applies a moderating methodology to study and address these interrelationships and, therefore extends the current literature beyond linear relationships to provide SMEs with a roadmap to enhanced innovation and competitive advantage. These issues are particularly pertinent to SMEs that are the lifeblood of the global economy.

Employing DCT at the technology-innovation interface is a further contribution of this study. It is posited in this study that SMEs will only thrive and survive if they possess the capabilities to sense, seize, and transform data and information, both external and internal, into knowledge to stimulate innovation (Mikalef et al., 2019; Miller at al, 2021). The theoretical lens employed builds on current studies in the literature through providing an additional framework for deconstructing the complex pathways and mechanisms necessary to assist SMEs with increasing innovation in a dynamic environment.

This paper also aims to provide a number of important managerial insights. Informing SME managers on how best to sense, seize and transform data in a turbulent environment to drive innovation and competitiveness is much needed. An understanding of the importance of knowledge integration as a set of intangible capabilities and how best to integrate and develop these capabilities will aid SME managers decision making and organisational learning and communication strategies to support the development of a data driven culture. Also, the importance of investing in marketing analytics tools to increase market insights and building its internal knowledge base to transform this knowledge into innovation and competitive advantage.

This paper is presented as follows. A theoretical underpinning to the study is presented including the operationalisation of the constructs via the hypotheses development section. Section 4 presents the research methodology section and findings. In section 5, both the theoretical and managerial implications of the findings are discussed. Limitations of the research study, followed by proposed future research directions and conclusions are then presented.

2. Theoretical underpinning and literature review

2.1. Dynamic capability theory

DCT is now a widely accepted theory in strategic management literature as a theory that provides a valuable lens to assess a company's ability to sense, build, and reconfigure both internal and external capabilities and resources to respond to environmental changes (Defee and Fugate, 2010; Teece, 2007). Further, the development of DCT is positioned as having three key elements: (1) *sensing,* (2) *seizing* and (3) *transforming/reconfiguring* (Teece 2014). The sensing capability is a higher-order capability that contributes to competitive advantage by leveraging company resources to identify, capture and proactively assess market changes and customer needs. This foundational ability serves to support the second capability, seizing, whereby firms leverage their resources to interpret key market knowledge and information to inform strategic decision-making. The third element builds on the seizing capability through transforming and reconfiguring the firm dynamically to position its resources to proactively respond to changing customer requirements. These three elements combine to result in value creation and competitive advantage (Ciampi et al. 2021; Mikalef and Pateli, 2017). The more quickly firms can develop these capabilities and integrate this knowledge within their strategic decision-making process, the more proactive and successful a firm can become in responding to dynamically changing environments (Dubey et al., 2019b).

The seizing capability term coined by Teece (2014) was extended in a study by Wilhelm et al. (2015) to refer to learning. The ability of a firm to learn in a dynamic and volatile marketplace is central to mitigating challenges and exploiting opportunities. The result of this learning capability will enable firms to sense key changes in customer demands and translate and act on this knowledge rapidly resulting in superior performance (Dubey et al. 2020; Mikalef and Pateli, 2017). Firms that possess and utilise the capabilities to be proactive and agile in such marketplaces have reported increased profits, improved service, improved quality, more efficient processes, better strategic decision-making and increased customer satisfaction (Ciampi et al., 2020; Dubey et al., 2019a; Lokshina et al. 2018). A range of studies employing DCT have demonstrated and reported that such capabilities may be created and developed over time (Mikalef et al., 2019; Wilhelm et al., 2015), thus maximising both technical and human resources necessary for surviving and thriving in the external environment (Mikalef et al., 2020). DCT, therefore, is a suitable theoretical lens for investigating the key mechanisms through which the use of BDA enables EO to stimulate innovation in SMEs.

2.2. Entrepreneurial orientation

EO has been employed as a construct in academic research since the early 1980 s (Miller, 1983; Genc et al., 2019). It has been operationalised as a construct to comprise three key sub-elements including innovativeness, proactiveness and risk-taking. The first element, innovativeness, suggests that firms with high levels of innovation capabilities, such as having the research skills to capture customer requirements and swiftly translate this knowledge into new value-added products and services to reach the market before their competitors, will typically result in improved competitive advantage (Shepherd and Rudd, 2013). The proactiveness component refers to a firm's capability to adopt a first mover advantage approach and have the practices and processes to rapidly identify and respond proactively to market needs (Nwankpa and Datta, 2017). Firms that can adopt the latest technologies to support their proactiveness approach should attain competitive advantage (Hervé et al., 2020). Risk taking is the third element of the EO construct. Within this element firms that thrive have a culture of risk taking. A firm tends to embrace higher risk projects and have an organisational structure, and a set of results-based decision-making processes and practices that makes it more responsive to changing market needs (Covin and Slevin, 1989; Wiklund and Shephard, 2005; Ciampi et al., 2021; Dai et al., 2014).

EO has endured in academic discourse and remains a relevant and much valued construct across different sectors (Dubey et al., 2019b; Hervé et al., 2020). For example, Basco et al. (2020) found that EO has a direct impact on firm performance irrespective of context. Whereas Genc et al. (2019) found that EO significantly impacts innovation performance in emerging SMEs. EO continues to be at the heart of corporate strategy and firms that nurture EO capability development appear to be better prepared to exploit market opportunities, have a high level of variety and volume of innovations (market, production, process or managerial; Weerawardena et al., 2015), and achieve higher levels of competitive advantage (Ciampi et al. 2021; Nwankpa and Datta, 2017).

EO represents the firm's policies and practices that guide entrepreneurial decisions and actions (Pérez-Luño et al., 2011). Possessing EO is regarded as a higher order dynamic capability as it shapes and directs the firm towards transformational activities, such as structural and cultural change in support of high-performance outcomes (Dubey et al. 2020).

2.3. Environmental dynamism

ED refers to the rate and unpredictability of change in a business context (Dubey et al., 2020; Eisenhardt and Martin, 2000; Mitchell et al., 2021). It is well recognized that organisations should bring new products and services to market to meet the challenge of constantly changing customer requirements in a dynamic business environment (Pérez-Luño et al., 2011). ED as a construct has been widely used in association with studies that have employed DCT as a theoretical basis (Chen et al., 2015; Dubey et al., 2019b; Baum and Wally, 2003; Rai and Tang, 2010), and has been reported as making a significant contribution to operational performance (Dubey et al., 2020).

ED is a construct also prevalent in innovation management research (Mitchell et al., 2021; Miller et al., 2021) as many firms face strong competition in a rapidly changing business environment characterised by high uncertainty and complexity. Therefore, firms need to actively engage in innovation activities in response to changes in the business environment (Ciampi et al. 2021). This is especially relevant for SMEs that often have the flexibility to adapt very quickly, but lack the resources of larger firms. Exhibiting these unique compositions of capabilities, such as learning orientation capabilities, entrepreneurial capabilities and communication skills could be a very attractive selling point for larger firms that are typically less entrepreneurial and such cultures are difficult to imitate and can lead to competitive advantage. Joint asset specificity is one such technique larger firms adopt in supply chain management in order to engage with SMEs and benefit from SMEs capabilities to swiftly adapt and respond to market needs (Cadden et al., 2020; Gupta and George, 2016; Miller et al., 2021).

2.4. Big data and big data analytics

There are three widely recognised characteristics that form big data: volume, variety, and velocity (Johnston et al., 2017; Cadden et al., 2022). These three BDC's lay the foundation for BDA value creation (Hofman et al., 2017). Volume refers to every piece of data that is obtainable, internally or externally. Variety comprises of the differing types of information and data available to firms, this could be changes in customer demands, or buying patterns, or new way to collect data such as RFID, Blockchain, cloud computing or AI (Hoffmann 2017; Dubey et al., 2022; Mikalef et al., 2023). Velocity is the speed that collected data can be processed (Wamba & Akter, 2019; Maheshwari et al, 2021; Talwar et al, 2021).

Increasingly firms are turning to BDA as a potential source of competitive advantage in today's volatile and changing marketplace (Cadden et al, 2022; Dubey et al., 2019; Gupta and George, 2016; Wamba et al, 2017). BDA is generally accepted as a term that comprises two elements namely big data and analytics. Big data is recognised as "data sets whose size is beyond the ability of typical database software tools to capture, store, manage and analyse" (Hoffmann, 2017: 5109). These rich data assets that firms have at their disposal are largely due to increasing digitisation and cloud computing technologies. The analytics element of big data has emerged almost as a separate element, whereby a range of tools have appeared on the market. Such tools enable firms to analyse huge volumes and varieties of data much more quickly than ever before to reveal hidden patterns, trends, and correlations (Gupta and George, 2016; Wamba et al., 2017; Cadden et al., 2022). Advanced BDA tools such as Rapid Minor and Apache Flink, supported by data driven practices, allow companies to create value through timely knowledge that informs strategic decision-making (Chae et al., 2014; Duan et al., 2020; Mikalef et al., 2020). However, investing in BDA resources alone, such as hardware and software can be easily imitated by competing firms, and therefore access to such resources does not automatically lead to competitive advantage (Cadden et al., 2022). Value creation and inimitability is derived through having a set of knowledge and learning capabilities within the firm to transform data that can contribute to competitive advantage (Brinch, 2018; Gupta and George, 2016).

The development of BDA not only focuses on the internal organisational, but also across the supply chain. It has been reported that firms with successfully developed BDA capabilities, both technical and human can achieve superior supply chain performance (Chen et al., 2015, Gupta and George, 2016; Wamba et al., 2017; Wamba et al., 2020). Cadden et al. (2022) presented a framework for exploring the role of supply chain intangible capabilities, such as human resources and a data driven culture as an enabler of value creation and supply chain agility. Similarly, Wamba et al. (2020) found that BDA has a significant impact on supply chain capabilities, such as agility, adaptability in support of performance enhancement. BDA has the potential to provide a platform for novel innovative approaches across supply chain practices and processes in support of SC innovation and collaboration (Conboy et al., 2020; Sanders, 2014). Whilst BDA has shown much promise inside the firm and across the supply chain, it is not proving to be a panacea or 'magic pill' in enhancing competitive advantage. More empirical research into the nuances and interrelationships are required to provide deeper and richer insights (Ben-Daya et al., 2019; Cadden et al., 2021; Dubey et al., 2019b).

2.5. Marketing analytics usage

Marketing analytics has evolved within big data analytics literature as a specific strategic activity for the collection, management, and analysis of data to extract useful insights to support marketing decision-making (Germann et al. 2013). Through the focused deployment of big data analytics, firms can sense emerging market opportunities and threats, generate critical insights, and adapt their operations based on trends observed in the competitive environment (Chen et al. 2012; Mikalef et al. 2019).

Marketing analytics aims to transform large amounts of unstructured market data to derive valuable insights (Cao et al., 2019). Deployment of customer analytics has a positive effect on firm performance (Germann et al. 2014; Wamba et al. 2017). It is increasingly argued that marketing analytics enable effective firm-level decision-making by generating useful insights and knowledge about the market and competition in real-time (Xu et al., 2016) and allows organizations to create more idiosyncratic customer value enabling competitive advantage (Cao et al., 2019).

2.6. Knowledge integration

Knowledge integration is regarded as a fundamental process through which firms can gain the benefits of newly acquired knowledge for competitive advantage (Jarrahi & Sutherland, 2019; O'Dell & Davenport, 2019). Rather than relying on knowledge acquisition alone some researchers have argued that such knowledge should be integrated with existing firm knowledge to enable firms to explore new market opportunities (Salunke et al., 2019). This will involve having formal structures and processes to acquire and integrate knowledge from multiple sources into and across distinct business units in the firm (Davenport, 2019; Jarrahi & Sutherland, 2019; Salunke et al., 2019). This includes converting tacit knowledge into explicit and actionable knowledge (Yang, 2005: Narayanan et al., 2009). Knowledge integration supports the competitive strategy of the firm in two ways. Firstly, integrating superior knowledge sets can create stronger value-adding innovations that allow a firm to obtain an advantage over its competitors (Bhatt, 2001; Prusak and Cranefield, 2016). Secondly, novel knowledge configurations diffused into organizational routines, that are difficult to imitate by a firm's closest competitors, enable firms to achieve competitive advantage (Salunke et al., 2019).

2.7. Innovation

Innovation is generally defined as a new product or service, a new production technology, a new process, or a new management or marketing innovation (Weerawardena et al., 2015), and has been shown to reduce costs, and provide increased product differentiation and in turn competitive advantage (Duan et al., 2020; Heider et al., 2020).

Typically, SMEs are more resource limited, both in financial and human terms, than their larger counterparts (Miller et al., 2021) and therefore, innovation capabilities are critical capabilities for SMEs in competitive and volatile environments (Heider et al., 2020). Product and process innovation together constitute technical innovation in the widely adopted organizational innovation typology by Damanpour et al., 1989 (Miller et al., 2021; Rosenbusch et al., 2011). While product innovation is defined as the adoption of a new idea pertaining to a new product or service, process innovation is defined as the introduction of new elements in an organization's production process or service operations (Damanpour et al., 1989). The latter may aim for reduction of labor costs or improved manufacturing flexibility (Leiponen and Helfat, 2010). Based on newness and value addition criteria that have been widely used to determine the degree of innovation, product innovations may range from incremental to radical (Weerawardena et al. 2015). The degree of innovation indicates the extent of new knowledge embedded in an innovation (Verona 1999) The organizational subsystem view that has been used in the literature to explain sources of innovation suggests that technical innovation stems from the socio-technical subsystem of the organization, which includes R&D and other experimental learning activities (Weerawardena et al. 2015).

2.8. Sustained competitive advantage

Sustained competitive advantage (SCA) occurs '*when current and potential competitors are unable to duplicate the value creating strategy adopted by the firm and the benefits of such a strategy*' (Barney 1991, 102). Central to this is the notion of durability or inimitability. The concept of 'competitive duplication' has been used for capabilities or innovations of the focal firm where the inimitability of distinctiveness of firm capabilities is suggested as the key source of sustainability (Day and Wensley 1988; Cao et al., 2019). Similarly, the 'capability differential' on which competitive strategy is founded is at the core of competitive advantage (Teece et al., 1997). There is general agreement that a measure for SCA, includes both financial and financial indicators, such as market penetration, increased market share, increased customer satisfaction, a higher return on investment and higher than average gross profits (Anning-Dorson 2016; Lee and Falahat 2019; Swink and Song 2007).

2.9. Hypothesis development

Based on the theoretical discussion in section 2, a research model was developed from the current literature as shown in Fig. 1. Based on the key concepts of DCT we suggest that SMEs can sense and seize opportunities using big data and marketing analytic capabilities to respond to the dynamic external environment and combine existing knowledge with new knowledge. The new knowledge resources developed through this process enable SMEs to pursue greater innovation and in turn achieve competitive advantage.

The following sections will operationalise the constructs under study and present testable hypotheses.

2.10. EO and big data

Having an EO is critical for business survival and success, especially for SMEs (Covin and Wales, 2019). A highly entrepreneurially oriented firm often adopts a more proactive approach for identifying and exploiting opportunities for innovation that leads to better performance. Such a firm will continuously direct its attention to scanning and monitoring the business environment in order to identify any market opportunities (Keh et al., 2007), and this follows closely the logic of sensing in DCT (Mikalef et al., 2021). Therefore, SMEs in a rapidly changing environment must expand their capabilities to embrace big data and marketing analytics (Chen et al., 2012). Whilst resource scarcity is the norm in many SMEs, higher levels of engrained entrepreneurial orientation traits within SMEs are a platform for identifying and employing contemporary digital technologies (Gupta et al., 2016; Pérez-Luño et al., 2011). In our research context, it is argued that entrepreneurial-oriented SMEs will actively engage in employing big data technologies and marketing analytics to scan the market environment for improved innovation, which in turn can be a source of dynamic capabilities. For example, Gupta et al. (2016) analysed the role of EO in influencing technology adoption and found that individual EO has a

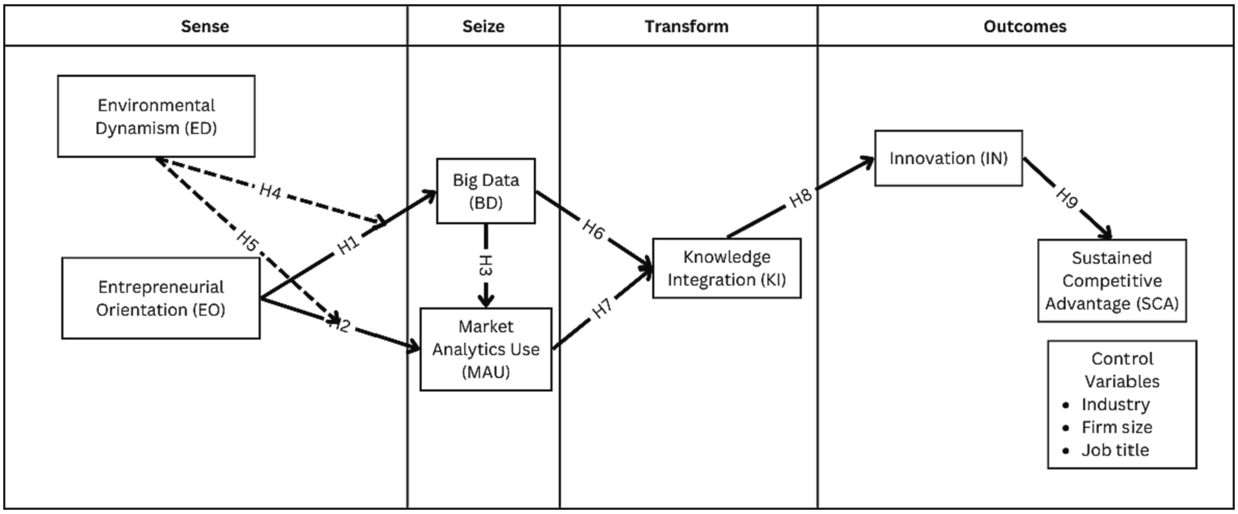

Fig. 1. Research model.

significant role in employee acceptance and engagement with new technologies. Therefore, this study presents the following hypotheses:

H1: EO is positively related to big data.

H2: EO is positively related to MAU.

Big data is often referred to as data with high volume, variety, and velocity (Johnston et al., 2017; Hoffman, 2017). With the increasing use of accessible digital technologies, such as the Internet of Things, organisations of all sizes can collect big data. However, to make sense of big data, companies have to use various analytical technologies as the value of big data can only be realised through the use of relevant and effective analytics (Brinch, 2018). Adopting BDA technologies can facilitate rapid decision-making which is necessary for competing in many industry contexts for SMEs (Matarazzo et al., 2021; Maroufkhani et al., 2020) and for improving overall supply chain and operational performance (Dubey et al., 2019a). In this research context, the use of marketing analytics can transform big data into valuable business and marketing insights, and this in turn is related to the sensing process of DCT where SMEs can mobilise resources to avail of market opportunities and capture value (Mikalef et al., 2021). Data availability has been found to be a critical foundation for an SME when using marketing analytics (Cao et al., 2019). Therefore, this study proposes that:

H3. Big data is positively related to MAU.

2.11. Role of Environmental dynamism

Extant literature shows that ED has been especially potent when considered an important moderator in relevant studies such as innovation tendency (e.g. Pérez-Luño et al., 2011), firm performance (Wiklund and Shepherd, 2005; Covin and Wales, 2019), strategic decision-making, (Shepherd and Rudd, 2014; Rajagopalan et al., 1993), exploration and exploitation (Wang and Li, 2008; Jansen et al., 2009), and in analytics studies (e.g. Mikalef et al., 2019; Srinivasan and Swink, 2018).

Engelen et al. (2014) conducted a comprehensive analysis of moderating variables including EO relationship to performance and revealed that numerous studies have examined the moderating role of ED between EO and firms' performance. Yet, there have been mixed results. For example, Pérez-Luño et al. (2011) have revealed that ED moderates the relationship between proactivity and innovative tendency. Wiklund and Shepherd (2005) suggest that the relationship between EO and SME performance is positively moderated by ED in that performance increases when an EO is present, albeit at a more rapid pace than in dynamic environments. However, the findings on the moderating effect of dynamic environments on EO and firm performance are inconclusive (Engelen et al. 2014).

SMEs operate in dynamic and rapidly changing environments, and have to be more active in utilizing available BDA technologies to scan and monitor their market environment to find opportunities for new or improved products, services or processes. Further, this will be especially true for SMEs who possess higher levels of EO and a high degree of flexibility in their modus operandi (Herhausen et al., 2020; Thrassou et al., 2020; Coltorti and Venanzi, 2017). Moreover, the logic of DCT is that when entrepreneurial-oriented SMEs have to deal with a higher level of ED, they will be more active in sensing environmental changes and seizing opportunities by using BDA. Therefore, this study proposes the following hypotheses:

H4. ED moderates the positive relationship between EO and big data.

H5. ED moderates the positive relationship between EO and marketing analytics.

2.12. Big data and marketing analytics to knowledge integration

Knowledge integration capability (KIC) refers to an SME's ability to obtain, process and apply knowledge to exploit opportunities in the market. KIC can also include the ability of an SME to develop new knowledge from disparate knowledge, integrate this knowledge into value creating activities (Kogut and Zander, 1992; Salunke et al., 2019; 2011). This will allow the SME to continuously adapt and refresh this knowledge in order to respond to changes in its product and service markets. This involves developing knowledge generated from BDA and marketing analytics into the SME's value creating activities to continuously deliver new and value-adding innovations, which is aligned with the logic of the transforming process of DCT. However, the knowledge generated from BDA and marketing analytics must already be present in the SME. As an SME acquires new knowledge, particularly through external sources, it may not be aligned with existing knowledge and therefore such knowledge has to be processed and integrated with current knowledge (Davenport, 2019; Jarrahi & Sutherland, 2019). Moreover, some acquired knowledge may not be relevant for dealing with customer needs, and vary across different projects. Such new knowledge combinations will facilitate entrepreneurial SMEs gaining competitive advantage through the delivery of high-value-adding innovations that cannot be easily replicated by their competitors (Mitchell et al., 2021). Therefore, this study proposes the following hypothesis:

H6: Big data is positively related to knowledge integration.

Marketing analytics has its origins in business analytics and is concerned with collecting, managing and analysing data to develop insights to enhance decision-making in a marketing context (Germann et al., 2013). The integrative nature of BDA allows entrepreneurial managers to build dynamic capabilities to effect internal changes and address external market opportunities (Defee and Fugate, 2010; Rojo et al., 2018). Business analytics helps SMEs establish knowledge creation routines to capture new market opportunities that facilitates learning about customer and competitor behaviour in the wider market environment and these have a stronger sensing capacity (Cao et al., 2019; Chen et al., 2015; Wilden and Gudergan, 2014). Such knowledge routines will enable an SME to rapidly meet customer needs and highlight new business opportunities, whilst at the same time redesigning their business processes to improve performance (Wamba et al., 2020). Customer knowledge gained from marketing analytics has to be integrated with existing knowledge inside the SME to allow this to happen. We therefore hypothesize:

H7: Marketing analytics is positively related to knowledge integration.

2.13. Knowledge integration to innovation

The knowledge-based view of innovation suggests that new knowledge forms the foundation for innovation (Davenport, 2019; Jarrahi & Sutherland, 2019; Zhou and Li, 2012, Nonaka and Takeuchi 1995). The accumulation and integration of disparate knowledge in innovation has attracted a lot of attention in the innovation literature (Almeida et al., 2002; Baker et al., 2022; Brown and Eisenhardt, 1997; Menon and Pfeffer, 2003). However, as argued by Salunke et al., (2019) and Kennedy (2019), knowledge generation on its own is not sufficient but has to be combined along with existing knowledge to address high-value adding market opportunities. (Leiponen, 2006; Okhuysen and Eisenhardt, 2002). Adhering to the logic of the sensing and seizing processes of DCT, we posit that the knowledge generated through BDA and marketing analytics should be integrated to pursue value creating strategies. Similarly, as noted earlier, dynamic capabilities can allow an SME to develop new knowledge to enhance its competitive position. We therefore theorize that BDA and marketing analytics represent strategic knowledge acquisition capabilities through which the SME senses market opportunities and seizes such opportunities through knowledge integration for greater innovation. We therefore hypothesize:

H8: Knowledge integration is positively related to organizational innovation.

2.14. Innovation to competitive advantage

Innovation is widely accepted as a gateway to competitive advantage (Amarakoon et al., 2018 Damanpour & Aravind, 2012; Datta et al., 2015; Hullova et al., 2016). Many studies on innovation have reported that having a high degree of innovation capability results in superior operational and financial performance (Baker et al., 2022; Datta et al., 2015). Today's markets are increasingly volatile and unpredictable. Firms that have higher levels of innovation and can respond and adapt to customer needs can outperform their competitors. Firms require the ability to sense market trends, absorb this knowledge and transform information into new innovations. For example, a study by Amarakoon et al., (2018) highlighted how firms who have a learning orientation towards innovation can achieve increased performance. Further, a systematic literature review by Baker et al., (2022) reported thirty six studies that reported where innovation lead to competitive advantage. However, many studies investigate innovation through a generic construct lens; whereas increasingly innovation is recognised as more complex; and includes multiple facets including product, process, managerial and marketing (Weerawardena et al., 2015). Innovation includes product innovations and improvements; process innovations, both incremental and radical, and managerial, both incremental and radical, and marketing innovations (Baker et al., 2022; Weerawardena et al., 2015).

Further, work by Kahn (2018) suggests innovation is a culture and a process leading to an outcome. With much work being focused on the technical aspects of innovation, this study is underpinned by DCT, and deconstructs innovation into its constituent parts to identify which elements are most important in driving innovation and capturing value in an era of digitisation. Therefore, we posit:

H9: Innovation is positively related to competitive advantage.

3. Research methodology

The partial least squares (PLS) path modelling method was used, and implemented in the SmartPLS3 software, to test our hypotheses empirically. PLS is suggested as suitable for testing research models where relevant theories are not well refined (Gefen et al., 2011; Hair et al., 2013). Although all our constructs are well developed in the literature, their relationships examined in this research are original. Thus, PLS path modelling is appropriate for this study.

3.1. Measures of constructs

All the constructs were measured reflectively using indicators modified from the literature (Table 1), while all their indicators were five-point Likert scales, anchored from 1 = strongly disagree to 5 = strongly agree. The indicators used to measure big data were adopted from Johnson et al. (2017), including three lower-order constructs volume, variety, and velocity. The indicators used to measure ED were adopted from Baum and Wally (2003) and Rai and Tang (2010). EO was measured via three lower-order constructs: innovativeness, responsiveness, and risk-taking (Covin and Slevin, 1989; Dai et al., 2014). Knowledge integration was measured in terms of four indicators adapted from Salunke et al. (2019). The indicators used to measure MAU were adapted from Germann et al. (2013) and Cao et al. (2019). The indicators used to measure innovation were adopted from Weerawardena (2003) and Weerawardena et al. (2015), using four lower-order constructs: product innovation, product process innovation, managerial innovation, and marketing innovation. To measure sustained competitive advantage, five indicators were adopted from Day and Wensley (1988). Moreover, based on prior studies (Cao et al., 2019; Duan et al., 2020; Weerawardena et al., 2020), firm size (number of employees), industry type, and job title were controlled for in the present research as they might influence informants' perceptions of sustained competitive advantage.

To measure the research constructs, a questionnaire survey was used to collect data in the UK, which is summarized in Table 1. The survey was developed from the literature review, examined by five domain experts, and revised six times. The survey was then piloted with a sample of 10 marketing and innovation academics, 30 senior marketing managers, and 50 students studying MSc Marketing and MSc Innovation programmes. As a result, amendments were made to improve the appropriateness of the scale items.

600 SMEs were chosen randomly from 1,946 companies across the sectors included in a UK national database. The survey was forwarded to SME senior managers using an online-based survey platform, Qualtrics. The total design method suggested by Dillman's (1978) was followed to build trust with the recipients and improve the response rate. The first electronic survey included a cover letter summarizing the aim of the study and the social usefulness, assuring anonymity and confidentiality, a clear instruction guide, and evidence that the survey was administrated by three professors from universities in the UK, UAE, and Australia. After four follow-ups, 199 respondents returned the questionnaires and 194 were usable, with a response rate of 32%.

3.2. Respondents

Of 194 respondents, 42.3% of them were senior managers, while the rest of them included operations, marketing, IT and other middle managers; 68% of the managers were from small companies, and the rest of them were from medium-sized companies; while 24.7% of the

Table 1
Constructs and indicators of the study.

Construct	Indicator (using a five-point Likert scale with 1 = strongly disagree and 5 = strongly agree)	Reference
Big Data (BD)	BD1-Volume My company analyses large amounts of data The quantity of data we explore is substantial We use a great deal of data We scrutinize copious volumes of data BD2-Variety We use several different sources of data to gain insights My company analyses many types of data We have many databases from which we can run data We examine data from a multitude of sources BD3-Velocity We analyze data as soon as we receive it The time period between us getting and analyzing data is short My company is lightning fast in exploring our dataMy company analyses data speedily	Johnson et al. (2017)
Environmental Dynamism (ED)	• ED1-Products and services in our industry become obsolete very quickly ED2-The product/services technologies in our industry change very quickly ED3-The rate of change of customer preferences cannot be predicted^ ED4-We can't predict what our competitors are going to do next ED5-Our industry is experiencing tough price competition^	Rai and Xinlin (2010); Baum and Wally (2003)
Entrepreneurial Orientation (EO)	DEO1-InnovativenessOur firm is very often the first to introduce innovative (new and value adding) products and services Our firm actively invests in research to provide customers with new and value adding products and services DEO2-Proactiveness In dealing with competition, our firm initiates actions to which competitors respond Our firm believes in adopting modern digital technologies in products and services if we are remaining competitive DEO3-Risk-taking In dealing with competition, our firm adopts a 'beat the competitor' approach Our firm tends to invest in high-risk projectsOur firm raises finance by using external borrowings	Covin and Slevin (1989); Dai et al. (2014); Nwankpa and Datta (2017)
Knowledge Integration (KI)	• KI1- Our firm uses existing know-how in different ways to create new products or services KI2- Our firm creates new opportunities by combining new knowledge with existing knowledgeKI3- Our firm identifies further use(s) for existing resources by blending technological knowledge with market knowledgeKI4- Our firm improves current products and services by using knowledge gained through combining diverse knowledge resources	Salunke et al. (2019)
Marketing Analytics Use (MAU)	• MAU1-We extensively use marketing analytics to make sense of market information (customer preferences, competitor behavior) MAU2-Our employees are very good at identifying and employing the appropriate marketing analysis tool given the problem at handMAU3-Our employees master many different quantitative marketing analysis tools and techniques	(Germann et al., 2013); Cao et al. (2019)
Innovation (IN)	IN1-Production innovationProduct innovations introduced by our firm during the last five years have been (from 1- limited to 5-extensive)Product improvements have been mainly (from 1 to incremental to 5-radical) IN2-Production process innovationProcess innovations introduced by our firm during the last five years have been (from 1- limited to 5-extensive)Process innovations have been mainly (from 1 to incremental to 5-radical) IN3-Managerial innovationsManagerial innovations introduced by our firm during the last five years have been (from 1- limited to 5-extensive)Managerial innovations have been mainly (from 1 to incremental to 5-radical) IN4-Marketing innovationsMarketing innovations introduced by our firm during the last five years have been (from 1- limited to 5-extensive)Marketing innovations have been mainly (from 1 to incremental to 5-radical)	Weerawardena (2003); Weerawardena et al. (2015)
Sustained Competitive Advantage (SCA)	Our firm has gained the following advantages over competitors for the last three years (from 1-not all to 5-a great deal): CA1-Entering new markets CA2-Increased market share CA3-Increased customer satisfaction CA4-Gain a higher return on investmentsCA5-Gross profits higher than our industry average	Day and Wensley (1988)

^ dropped after the measurement evaluation.

informants worked below five-years, 36% worked five to 15 years, and the rest 39.2% had over 15 years; 36.6% of respondents came from manufacturing, 28.9% from finance and professional services, and 34.5% from other business services. Thus, each informant was seen to have the relevant background and expertise to answer the survey questions (Bagozzi et al., 1991). Table 2 summarises the respondents' demographic characteristics.

3.3. Common method and non-respondent bias

In order to mitigate common method bias, both procedural and statistical remedies were used, in line with the recommendations of Tehseen et al. (2017). Three procedural approaches were used to minimize common method bias when data was collected, including assuring respondents' complete anonymity to reduce the need for making socially desirable responses (Podsakoff et al., 2003), defining scale items clearly (Podsakoff et al., 2003), and separating scale items from the reported constructs so that respondents were less likely to guess and match the link between variables (Parkhe, 1993). Additionally, two statistical remedies were performed to assess potential common method bias in the research, including (a) the partial correlation procedure (Lindell and Whitney, 2001) using job tenure as the marker variable and (b) checking if there were any highly correlated factors ($r > 0.90$) in the correlation matrix (Pavlou et al., 2007). The results summarized in Table 4 indicated that common method bias did not occur in this study.

To determine whether there was non-response bias, a *t*-test was performed to contrast early ($n = 100$) and late ($n = 94$) respondent groups on each of the measures. The result suggested that the present study had no serious non-response bias (Armstrong and Overton, 1977) as there were no significant variances between the early and late groups.

3.4. Model testing and findings

3.4.1. Evaluation of the measurement model and the structural model

First, the measurement model was evaluated in terms of the widely-accepted internal consistency (composite reliability), indicator reliability, convergent validity and discriminant validity (Hair et al., 2014). The results were satisfactory as summarized in Tables 3 and 4. Recently, Henseler et al. (2015) proposed that the heterotrait-monotrait ratio of correlations (HTMT) is a more suitable approach to assess discriminant validity in variance-based SEM. Thus, this research also checked the HTMT scores, summarized in Table 5, which confirmed discriminant validity as all the scores came in below the strictest threshold of 0.85 (Benitez et al., 2020).

Second, following Hair et al. (2014), we assessed the structural model in terms of collinearity and the significance and relevance of the structural model relationships. The structural model had no collinearity issues since the VIF (variance inflation factor) value for all constructs in this research, generated from SmartPLS3, ranged from 1.01 to 1.65, below the threshold of 5 (Hair et al., 2014; Benitez et al., 2020). The significance and relevance of the path coefficients were also satisfactory, as shown in Fig. 2.

The predictive power of the research model was assessed and confirmed by the amount of variance attributed to the latent variables (i.e., R^2) and the value of the predictive relevance Q^2 that should be larger than zero (Hair et al., 2014). The full model explained 31% in sustainable competitive advantage (SCA) with a Q2 value of 17, 29% in innovation (IN) with a Q^2 value of 0.19, 41% in marketing analytics use (MAU) with a Q^2 value of 0.31, 38% in big data with a Q^2 value of 0.25, 17% in knowledge integration (KI) with a Q^2 value of 0.12. According to Wetzels et al. (2009) the effect size of KI was between small and medium; the effect sizes of BD and MAU were large; and the effect sizes of IN and SCA were between medium and large.

3.5. Hypothesis testing

H1 and H2 propose that EO has a positive influence on big data and MAU, respectively. Both are supported, with path coefficients of 0.57 ($p < 0.001$) and 0.31 ($p < 0.001$). H3 proposes that big data has a positive influence on MAU, supported with path coefficient of 0.37 ($p < 0.001$). H4 and H5 posit that ED moderates the relationships between EO and (a) MAU and (b) big data. These moderation effects were tested based on bootstrapping (5,000 samples) (Hair et al., 2014; Hayes, 2009; Preacher and Hayes, 2004), using a two-stage method provided by SmartPLS3, with ED as a moderator and big data and MAU as predictor variables. H4 is rejected as the moderation effect is not statistically significant, whereas H5 is supported as the moderation effect is 0.13 ($p < 0.05$), as shown in Figure 3.

H6 posit that big data has a positive influence on knowledge integration, supported with a path coefficient of 0.18 ($p < 0.01$). H7 assumes that MAU has a positive influence on knowledge integration, which is confirmed with a path coefficient of 0.28 ($p < 0.001$). H8 postulates that knowledge integration has a positive influence on innovation, which is supported, with a path coefficient of 0.54 ($p < 0.001$). H9 assumes that innovation positively influences sustained competitive advantage, which is supported with the path coefficient of 0.51 ($p < 0.001$).

3.6. Discussion

This study examines the mechanisms through which SMEs leverage the benefit of big data and marketing analytics to support innovation and competitive advantage via knowledge integration. The motivation for this study was influenced by several gaps in the BDA literature, a strand of literature that has grown in significance over the last two decades. First, there is significant evidence that information and insights generated by BDA supports innovation and competitive advantage. Second, a further gap in the BDA literature includes the suggested direct link between BDA and competitive advantage, which remains inconclusive. As a result of this gap academics have turned their attention to the mediating mechanisms where innovation has become prominent. Third, the research supports the growing view that BDA will particularly be helpful to SMEs that have resource constraints.

Underpinned by the key concepts of DCT, a research model was developed and tested to help understand if and to what extent EO enables the use of big data and marketing analytics to stimulate innovation in SMEs. It examines several hypotheses that link the SMEs' dynamic capability building and deploying process of *sensing, seizing* and *transforming* of capabilities (Teece, 2004; 2007) for innovation through knowledge integration. The findings, based on the responses from 194 SMEs in the UK broadly support our hypothesized relationships. Table 6 summarises the results of the hypotheses tests and shows that seven of eight hypotheses are supported.

3.7. Entrepreneurial orientation and capability development

The results have shown that EO has a positive influence on BD (H1) and marketing analytics capabilities (H2), suggesting that firms that are entrepreneurial in their strategic decision-making tend to engage in sensing market opportunities through BD and marketing analytics capabilities (Covin and Wales, 2019). As a foundational capability BD facilitates marketing analytics capability. Consistent with DCT, EO emerges as the driver of organizational capability development and deployment, and in turn innovation-based competitive advantage. This supports the view in DCT that capabilities that provide the foundation for firm competitive advantage are built on the conscious efforts of entrepreneurial managers (Dubey et al., 2020). Therefore, our findings extend DCT literature through applying such theories to a BDA context (e.g., Gupta and George, 2016; Pérez-Luño et al., 2011).

Table 2
Respondent profiles ($n = 194$).

Job title	No (%)	Tenure (x)	No (%)	Company size (y)	No (%)	Industry type	No (%)
CEO or equivalent	82 (42.3)	$x < 5$	48 (24.7)	$y < 10$	65 (33.5)	Manufacturing	71 (36.6)
Operations managers	29 (15.0)	$5 \leq x < 10$	48 (24.7)	$10 \leq y < 50$	67 (34.5)	Financial and Professional services	56 (28.9)
Marketing managers	4 (2.1)	$10 \leq x < 15$	22 (11.3)	$50 \leq y < 249$	62 (32.0)	Other services	67 (34.5)
IT managers	6 (3.1)	$15 \leq x < 20$	21 (10.8)				
Other managers	73 (37.6)	$20 \leq x$	55 (28.4)				

Table 3
Convergent validity and internal consistency reliability.

Construct	Indicators	Loading	Indicator Reliability	Cronbach's α	Composite Reliability	AVE
BD	BD1	0.87	0.76			
	BD2BD3	0.820.86	0.670.74			
ED	ED1	0.51	0.26			
	ED2ED4	0.980.50	0.960.25			
EO	DEO1	0.86	0.74	075	0.85	0.66
	DEO2DEO3	0.860.71	0.740.50			
IN	IN1	0.81	0.66	0.84	0.89	0.68
	IN2	0.84	0.71			
	IN3IN4	0.840.79	0.710.62			
KI	KI1	0.87	0.76	0.88	0.92	0.74
	KI2	0.91	0.83			
	Ki3KI4	0.780.88	0.610.77			
(MAU)	MAU1	0.91	0.83			
	MAU2MAU3	0.810.92	0.660.85			
SCA	SCA1	0.78	0.61	0.84	0.89	0.62
	SCA2	0.90	0.81			
	SCA3	0.76	0.58			
	SCA4SCA5	0.840.62	0.710.38			

Table 4
Inter-Construct Correlations and Summary Statistics.

	1	2	3	4	5	6	7	8
1. BD	**0.85**							
2. ED	0.29**	**0.70**						
3. EO	0.59**	0.34**	**0.81**					
4. IN	0.34**	0.29**	0.52**	**0.82**				
5. KI	0.34**	0.24**	0.53**	0.54**	**0.86**			
6. MAU	0.58**	0.28**	0.55**	0.53**	0.39**	**0.88**		
7. SCA	0.37**	0.32**	0.53**	0.53**	0.41**	0.48**	**0.79**	
8. Tenureˆ	−0.02^{ns}	−0.04^{ns}	−0.02^{ns}	−0.07^{ns}	−0.10^{ns}	−0.00^{ns}	0.06^{ns}	**1**

ˆmarker variable.

Table 5
HTMT Result.

	BD	ED	EO	IN	KI	MAU	SCA
BD	–						
ED	0.24	–					
EO	0.72	0.45	–				
IN	0.39	0.37	0.62	–			
KI	0.39	0.33	0.62	0.62	–		
MAU	0.68	0.21	0.64	0.61	0.41	–	
SCA	0.43	0.39	0.63	0.61	0.45	0.52	–

3.8. *Capability development and ED*

This study theorized that the entrepreneurial capability development does not occur in isolation but is also influenced by external factors. As discussed in section 3.2, the moderating role of ED has been considered in studies related to firm performance (e.g., Dubey et al., 2020; Wiklund and Shepherd, 2005), innovation strategy (Wang and Wang, 2012), exploration and exploitation (e.g., Jansen et al., 2009; Wang and Li, 2008), and analytics. However, the suggested relationship has escaped empirical scrutiny in a BDA context. Broadly the literature suggests that entrepreneurs who perceive their operating environment as uncertain tend to be more entrepreneurial and innovative in their competitive strategies (Miller et al., 2021). Accordingly, ED was placed as a moderator influencing relationships from EO to BD capability (H4) and marketing analytics capability (H5).

Interestingly, results reject the hypothesis H4 that ED moderates the relationship between EO and MAU (H4). The rejection of this hypothesis is unexpected, yet on reflection perhaps not surprising. First, an explanation could be that big data has a significant effect on the use of marketing analytics, and the moderating role of ED may become less effective in moderating the relationship between EO and MAU. Second, an explanation may be that BDA is independently driven by entrepreneurial SME managers in their pursuit of outperforming competitors through greater innovation. SMEs have been shown repeatedly to possess high levels of EO and it may be that the traits of risk taking, proactiveness and proactiveness result in higher levels of flexibility and responsiveness to market demands (Herhausen et al., 2020; Miller et al., 2021; Genc et al., 2019).

Results support H5 that BDA capability and marketing analytics capability (H5) indicating that when the markets are perceived to be dynamic, entrepreneurially oriented SME managers tend to engage in extensive market learning through a marketing analytics capability. Overall, our study represents the first attempt to examine the moderating role of ED in the context of SMEs' use of big data and marketing analytics. The findings demonstrate that the positive influence of EO on the use of big data will become stronger when the level of ED is higher. This suggests that entrepreneurially oriented SMEs operating in a highly dynamic environment will be more proactive in sensing and seizing opportunities, thus strengthening their dynamic capabilities.

3.9. *Capability deployment, knowledge integration and innovation*

Following Salunke, (2011, 2019) we theorized that knowledge acquisition per se will not be helpful in firm competitive strategy and such integrated knowledge addresses the needs of the incumbent firm to create new knowledge sets to take advantage of innovation opportunities. As noted earlier, this acquired knowledge in its original form may not be useful for addressing customer needs and vary across different projects (Baker et al., 2022; Grant, 1996; Kogut and Zander, 1992). Supporting this theorization, we find that both BDA capability (H6) and marketing analytics capability (H7) leads to knowledge integration capability.

Similarly, we hypothesized that knowledge integration can result in

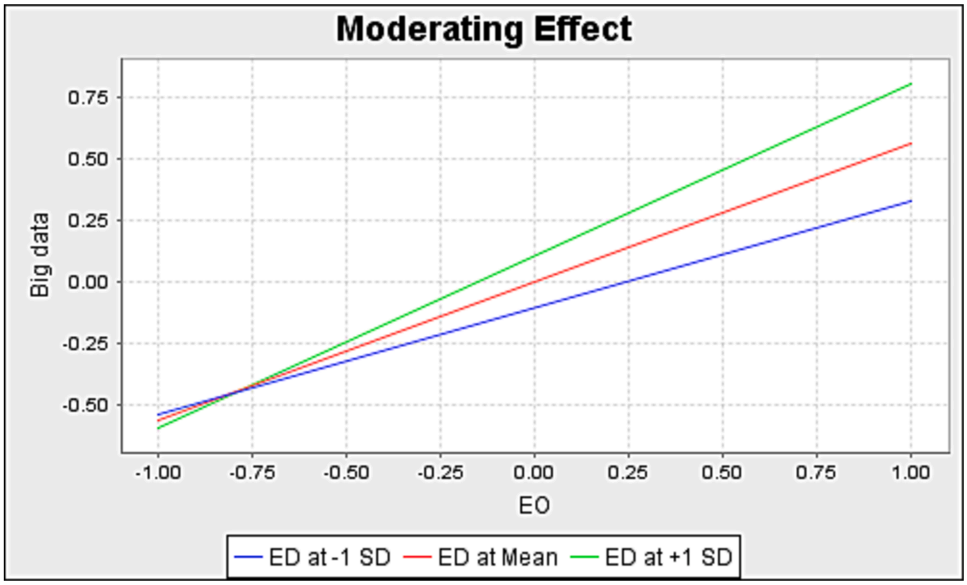

Fig. 2. Moderation role of ED.

Table 6
Summary Results of Hypotheses Testing.

Hypothesis	Hypothesized Path	Path coefficient (or Moderating) effect	Empirical evidence
H1	Entrepreneurial orientation -> Big data	0.57***	Supported
H2	Entrepreneurial orientation -> Marketing analytics use	0.31***	Supported
H3	Big data -> Marketing analytics use	0.37***	Supported
H4	Environmental dynamism × Entrepreneurial orientation -> Marketing analytics use	0.07 ns(moderating)	Rejected
H5	Environmental dynamism × Entrepreneurial orientation -> Big data	0.13* (moderating)	Supported
H6	Big data -> Knowledge integration	0.18**	Supported
H7	Marketing analytics use -> Knowledge integration	0.28***	Supported
H8	Knowledge integration -> Innovation	0.54***	Supported
H9	Innovation -> Sustainable competitive advantage	0.51***	Supported

greater innovation. This is supported by (H8) indicating that integrated BDA and market learning knowledge enable entrepreneurial SMES to achieve greater innovation. This is in line with the current literature on the knowledge-based view of innovation that suggests that new knowledge configurations are requirements for innovation (Jarrahi & Sutherland 2019; Nonaka and Takeuchi, 1995; O'Dell & Davenport, 2019; Powell et al., 1996). However, this view has escaped empirical scrutiny in BDA-based competitive advantage literature. Broadly, H6, H7 and H8 represent the *seize* (Teece, 2004, 2007) stage of the dynamic capability process for greater competitive advantage thereby providing empirical support for DCT in a BDA context.

3.10. *Innovation and competitive advantage*

The findings support H9 that innovation leads to competitive advantage, thereby indicating SMEs that undertake new and value adding innovations are well-positioned to outperform their competitors. Further insights can be gained from how the two constructs are conceptualized. Innovation is suggested as the integration of knowledge resources in the value creating activities of the firm. Accordingly, the new knowledge configurations that are built through the interplay of BDA, marketing analytics and knowledge integration capabilities facilitates innovation in technical, for example, product, process and non-technical, for example, managerial and marketing activities (Amarakoon et al., 2018; Damanpour & Aravind, 2012; Datta et al., 2015; Hullova et al., 2016). On the other hand, competitive advantage can be in the form of financial and non-financial market advantages and competitors' inability to replicate the market advantages of their competitors (Datta et al., 2015).

In summary, our study addresses the knowledge gaps that were identified earlier. It contributes to advancing the BDA and innovation-based competitive advantage literature in an SME context which is fragmented and at an early stage of development. By considering the inconclusive literature on BDA and competitive advantage our findings indicate that the suggested link occurs through several knowledge-based capabilities and innovation. As we theorized EO drives this process.

3.11. *Theoretical contributions*

This paper provides a number of useful theoretical insights. Firstly, underpinned by DCT and the three key orchestration processes that underpin DCT, namely sensing, seizing and transformation, a theoretical SME data driven innovation capabilities model was presented. This model was empirically tested and highlights the significance of employing DCT in this context to develop key capabilities to enable innovation and sustained competitive advantage. The DCT theory was further extended in the model through the deconstruction of the transformation orchestration into transformation and outcomes to recognise and unveil the results of 'transformation' in this context. Key outcomes identified in a SME data driven capabilities context in this study are innovation and competitive advantage.

Secondly, the paper provided new insights into the pathway and interrelationships that are required to support SMEs in a data driven context to enable innovation and competitive advantage. SMEs are subject to 'bounded rationality 'by virtue of their size and resources. In particular, this study highlights and identifies the key role and positioning of intangible capabilities in enabling innovation and competitive advantage for SMEs. For example, entrepreneurial orientation and knowledge integration are the two key intangible capabilities found to have significant impact in supporting SMEs develop data driven innovation and competitive advantage. It is interesting that entrepreneurial orientation is a set of intangible capabilities that are positioned at the sensing phase of the DCT orchestration process in an SME data driven innovation context. Whilst there are a number of studies that have investigated the relationship between entrepreneurial orientation and big data (e.g. Ciampi et al., 2021; Dubey et al., (2020), there are few studies that have provided valuable insights into the role of entrepreneurial orientation in an SME data driven context. Entrepreneurial orientation is recognised as a first order intangible capability which supports the shaping and informing of the firm's organisational routines and behaviours in respect of entrepreneurial decisions and actions (Pérez-Luño et al., 2011), and supports structural and cultural change in support of high-performance outcomes (Dubey et al. 2020). Therefore, the proactiveness, risk taking and innovative characteristics of an SME with high levels of entrepreneurial orientation provide a fundamental platform for SMEs in an era of digitisation to swiftly adapt, embrace and exploit data and information supported by the latest BD technologies and tools.

Knowledge integration was the second key intangible capability and was found to be positioned at the transformation phase of dynamic capabilities in this study. Possessing tangible capabilities such as basic resources and data, and human skills, such as technical and managerial skills (Teece et al., 2014; Gupta and George, 2016; Wamba et al., 2017) are all important in developing a set of BDAC's, but a firm's pathway to enhanced competitive advantage lies in its non-imitable and non-substitutable characteristics (Teece et al., 2014; Gupta ang George, 2016). Knowledge integration is recognised as a key enabler to achieving innovation and higher levels of competitive advantage (Davenport, 2019; Jarrahi, 2019). This study provides a theoretical contribution through demonstrating the role and positioning of knowledge integration as a transforming set of capabilities. A knowledge creation and knowledge sharing culture appears to create a set of routines and behaviours that enable the value of big data to drive innovation and be a source of dynamic capabilities in dynamic environments.

Companies are increasingly under pressure trying to understand and interpret the huge swathes and variety of marketing data that currently exists (Day, 2011; Erevelles et al., 2016). Data on customer patterns and trends, an ever-increasing number of customer contact points, increased market segmentation and explosion of social media outlets have all resulted in an overwhelming amount of information that companies are wrestling with (Cao et al., 2019; Faruk et al., 2021; Herhausen et al., 2020). The disruptive and changing nature of this information is both a challenge and an opportunity for SMEs. Herhausen et al., (2020) refers to two marketing analytics capabilities gaps that currently exist: the practice gap: which identifies the gap between what marketing analytics capabilities managers currently have and the marketing analytics capabilities they need to have; and the knowledge gap': which is the marketing technology knowledge within firms and the current academic knowledge that underpins this knowledge. This study has helped bridge both these gaps through providing an empirical and theoretical roadmap of how SMEs can realise opportunities by developing their marketing analytics capabilities and embed the external market knowledge to drive innovation.

3.12. Practical implications

The study findings provide a practical pathway for SME managers operating in a dynamic business environment and striving to outperform their competitors through the strategic use of big data for greater innovation and ultimately competitive advantage. Firstly, SMEs managers must not dilute or suppress the entrepreneurial characteristics that are within their business in an era of digitisation. Such traits are a fundamental platform to allow the absorption and transformation of BD knowledge. Traditional entrepreneurial behaviours of innovativeness, proactiveness and risk-taking are a useful antecedent in a digital economy context, and when coupled with a culture of learning through knowledge integration mechanisms, innovation thrives in support of competitive advantage. Employee engagement through cross functional teams, innovation hubs; joint supply chain partners meetings (both formal and informal, such as joint social events) support the development of a data driven innovation culture. Secondly, such entrepreneurial managers should build and nurture organizational capabilities in big data characteristics and marketing analytics, and then integrate such new knowledge with existing knowledge to address market opportunities. Managers should invest in continued training and employee engagement with new technologies to remove the fear of such technologies, build trust of technologies in employees, and promote these tools as part of the innovation toolkit, rather than as a replacement. As our findings have revealed it is the knowledge integration mechanisms that transform the new knowledge resources into a usable form for innovation in support of competitive advantage. Thirdly, managers must deploy these new knowledge configurations to pursue high value adding technical (product and process) and non-technical (managerial and marketing) innovation. It is the combinations of innovation characteristics that will provide an advantage for firms. Further, to address the market insights potential gained through marketing analytics, the firm must invest in these tools and also build its internal knowledge base through internal experimental learning to integrate this knowledge in support of innovation and competitive advantage.

3.13. Limitations and directions for future research

Although the findings offer valuable insights into the role of organizational capabilities in the pursuit of BDA and innovation-based competitive advantage for SMEs, the findings must be considered in the context of the limitations of the research. First, our study examined only two key intangible capabilities in innovation in a BDA context. Further research may consider the contribution of other intangible capabilities, such as data driven culture, knowledge acquisition capabilities, internal organisational learning capability and the external organisational learning capability that that will enrich the new knowledge configurations of the firm. Second, the cross-sectional design in this study prevents us from exploring how these knowledge building processes develop and impact on the role of entrepreneurial managers in the process. Future research may examine how resources allocations and trade-offs are made in determining which capabilities are more important to a firm in the pursuit of competitive strategy. Third, theoretical constructs in our study were measured using single-informant reports. Although the respondents to our survey were the CEOs of SMEs and considered to be most familiar with the strategy formulation activity of the firm, multiple informants could be useful in future studies. Finally, SMEs that we studied provided an appropriate setting for examining how BDA-driven innovation is undertaken in resource-constrained contexts. Other specific industries, such as services, may differ in terms of the pace of technological change and, therefore, require a different set of capabilities for competing.

4. Conclusion

This study was motivated by the growing intertest in understanding the role of BD and marketing analytics usage in supporting firm innovation and competitive advantage. However, the suggested link had received limited empirical scrutiny particularly in an SME context which are resource constrained yet more entrepreneurial than larger firms. In the research model that we developed to address this research gap, we highlight the importance of intangible capabilities, namely entrepreneurial orientation and knowledge integration as essential capabilities in the development of an SME data driven innovation capabilities model. The findings support our research model, underpinned by DCT, and have important implications for both theory and practice. Overall, the importance of BD and marketing analytics in innovation-based firm competitive advantage remains a new and fertile ground for theory development.

CRediT authorship contribution statement

Trevor Cadden: Conceptualization, Writing – original draft, Writing – review & editing, Methodology, Supervision, Project administration, Project management. **Jay Weerawardena:** Conceptualization, Writing – original draft, Writing – review & editing. **Guangming Cao:** Conceptualization, Writing – original draft, Writing – review & editing, Methodology, Formal analysis. **Yanqing Duan:** Writing – original draft, Writing – review & editing. **Ronan McIvor:** Conceptualization, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

References

Adam, N. A., & Alarifi, G. (2021). Innovation practices for survival of small and medium enterprises (SMEs) in the COVID-19 times: The role of external support. *Journal of Innovation and Entrepreneurship, 10*(1). https://doi.org/10.1186/s13731-021-00156-6

Almeida, P., Song, J. and Grant, R.M. (2002) 'Are Firms Superior to Alliances and Markets? An Empirical Test of Cross-Border Knowledge Building', Organization Science, 13(2), pp. 147–161. Available at: https://search.ebscohost.com/login.aspx?direct=true&db=edsjsr&AN=edsjsr.3085990&site=eds-live.

Amarakoon, U., Weerawardena, J., & Verreynne, M.-L. (2018). Learning capabilities, human resource management innovation and competitive advantage. *International Journal of Human Resource Management, 29*(10), 1736–1766. https://doi.org/10.1080/09585192.2016.1209228

Anning-Dorson, T. (2016). Interactivity innovations, competitive intensity, customer demand and performance. *International Journal of Quality and Service Sciences, 8*, 536–554.

Armstrong, J. S., & Overton, T. S. (1977). Estimating Nonresponse Bias in Mail Surveys. *Journal of Marketing Research (JMR), 14*(3), 396–402. https://doi.org/10.2307/3150783

Bagozzi, R. P., Yi, Y., & Phillips, L. W. (1991). Assessing Construct Validity in Organizational Research. *Administrative Science Quarterly, 36*(3), 421–458. https://doi.org/10.2307/2393203

Baker, W. E., Mukherjee, D., & Gattermann Perin, M. (2022). Learning orientation and competitive advantage: A critical synthesis and future directions. *Journal of Business Research, 144*, 863–873. https://doi.org/10.1016/j.jbusres.2022.02.003

Barney, J. (1991). Firm Resources and Sustained Competitive Advantage. *Journal of Management, 17*(1), 99–120.

Basco, R., Hernández-Perlines, F., & Rodríguez-García, M. (2020). 'The effect of entrepreneurial orientation on firm performance: A multigroup analysis comparing China. *Mexico, and Spain', Journal of Business Research, 113*, 409–421. https://doi.org/10.1016/j.jbusres.2019.09.020

Baum, J. R., & Wally, S. (2003). Strategic Decision Speed and Firm Performance. *Strategic Management Journal, 24*(11), 1107–1129. https://doi.org/10.1002/smj.343

Ben-Daya, M., Hassini, E., & Bahroun, Z. (2019). Internet of things and supply chain management: A literature review. *International Journal of Production Research, 57* (15/16), 4719–4742. https://doi.org/10.1080/00207543.2017.1402140

Benitez, J., et al. (2020). How to perform and report an impactful analysis using partial least squares: Guidelines for confirmatory and explanatory IS research. *Information & Management, 57*(2). https://doi.org/10.1016/j.im.2019.05.003

Bhatt, G. D. (2001). Knowledge management in organizations: examining the interaction between technologies, techniques, and people. *Journal of Knowledge Management, 5*(1), 68–75. https://doi.org/10.1108/13673270110384419

Brinch, M. (2018). Understanding the value of big data in supply chain management and its business processes: Towards a conceptual framework. *International Journal of Operations & Production Management, 38*(7), 1589–1614. https://doi.org/10.1108/IJOPM-05-2017-0268

Brintrup, A., et al. (2020). Supply chain data analytics for predicting supplier disruptions: A case study in complex asset manufacturing. *International Journal of Production Research, 58*(11), 3330–3341. https://doi.org/10.1080/00207543.2019.1685705

Brown, S. L., & Eisenhardt, K. M. (1997). The Art of Continuous Change: Linking Complexity Theory and Time-Paced Evolution in Relentlessly Shifting Organizations. *Administrative Science Quarterly, 42*(1), 1–34. https://doi.org/10.2307/2393807

Cadden, T., Cao, G., Treacy, R., Yang, Y. and Onofrei, G. (2021) Dynamic Capability Theory as a Lens to Investigate Big Data Analytics and Supply Chain Agility. Responsible AI and Analytics for an Ethical and Inclusive Digitized Society, pp.467–480. Doi: 10.1007/978-3-030-85447-8_39.

Cadden, T., Cao, G., Yang, Y., McKittrick, A., McIvor, R., & Onofrei, G. (2020). The effect of buyers' socialization efforts on the culture of their key strategic supplier and its impact on supplier operational performance. *Production Planning & Control*, 1–17. https://doi.org/10.1080/09537287.2020.1785574

Cadden, T., McIvor, R., Cao, G., Treacy, R., Yang, Y., Gupta, M., et al. (2022). Unlocking supply chain agility and supply chain performance through the development of intangible supply chain analytical capabilities. *International Journal of Operations & Production Management*. https://doi.org/10.1108/ijopm-06-2021-0383

Canakoglu, E., Erzurumlu, S. S., & Erzurumlu, Y. O. (2018). How data-driven entrepreneur analyzes imperfect information for business opportunity evaluation. *IEEE Transactions on Engineering Management, 65*(4), 604–617. https://doi.org/10.1109/TEM.2018.2826983

Cao, G., Duan, Y., & El Banna, A. (2019). A dynamic capability view of marketing analytics: Evidence from UK firms. *Industrial Marketing Management, 76*, 72–83. https://doi.org/10.1016/j.indmarman.2018.08.002

Chae, H.-C., Koh, C.E. and Prybutok, V.R. (2014) 'Information Technology Capability and Firm Performance : Contradictory Findings and Their Possible Causes', MIS Quarterly, 38(1), pp. 305–326. Available at: https://search.ebscohost.com/login.aspx?direct=true&db=edsjsr&AN=edsjsr.26554879&site=eds-live.

Chen, D. Q., Preston, D. S., & Swink, M. (2015). How the Use of Big Data Analytics Affects Value Creation in Supply Chain Management. *Journal of Management Information Systems, 32*(4), 4–39. https://doi.org/10.1080/07421222.2015.1138364

Chen, Y.-C., Li, P.-C., & Evans, K. R. (2012). Effects of interaction and entrepreneurial orientation on organizational performance: Insights into market driven and market driving. *Industrial Marketing Management, 41*(6), 1019–1034. https://doi.org/10.1016/j.indmarman.2012.01.017

Ciampi, F., et al. (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

Coltorti, F., & Venanzi, D. (2017). Productivity, Competitiveness, and Territories of the Italian Medium-Size Companies. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2900336

Conboy, K., Dennehy, D. and Gleasure, R. (2020) A Design Science Approach to Implementing Flow-Based Information Systems Development (ISD). Progress in IS, pp.105–127. Doi: 10.1007/978-3-030-46781-4_5.

Covin, J.G. and Slevin, D.P. (1989) 'Strategic Management of Small Firms in Hostile and Benign Environments', Strategic Management Journal (John Wiley & Sons, Inc.) - 1980 to 2009, 10(1), pp. 75–87. doi:10.1002/smj.4250100107.

Covin, J. G., & Wales, W. J. (2019). Crafting High-Impact Entrepreneurial Orientation Research: Some Suggested Guidelines. *Entrepreneurship Theory and Practice, 43*(1), 3–18. https://doi.org/10.1177/1042258718773181

Prusak, L., & Cranefield, J. (2016). Managing your own Knowledge: A Personal Perspective. *Taylor and Francis*. https://doi.org/10.4324/9781315600154-6

Dai, L., et al. (2014). Entrepreneurial orientation and international scope: The differential roles of innovativeness, proactiveness, and risk-taking. *Journal of Business Venturing, 29*(4), 511–524. https://doi.org/10.1016/j.jbusvent.2013.07.004

Damanpour, F., Szabat, K. A., & Evan, W. M. (1989). The relationship between types of innovation and organizational performance'. *Journal of Management Studies, 26*(6), 587–602. https://doi.org/10.1111/j.1467-6486.1989.tb00746.x

Damanpour, F., & Aravind, D. (2012). "Managerial Innovation: Conceptions, Processes and Antecedents", Management and Organization Review. *Cambridge University Press, 8*(2), 423–454. https://doi.org/10.1111/j.1740-8784.2011.00233

Datta, A., Mukherjee, D., & Jessup, L. (2015). Understanding commercialization of technological innovation: Taking stock and moving forward. *R and D Management, 45*(3), 215–249. https://doi.org/10.1111/radm.12068

Davenport, T. (2019) Managing support knowledge with AI: Talla helps Toast. Forbes. Available at https://www.forbes.com/sites/tomdavenport/2019/10/10/managing-support-knowledge-with-ai-talla-helps-toast/#4d88ade77267.

Day, G. S., & Wensley, R. (1988). Assessing Advantage: A Framework for Diagnosing Competitive Superiority. *Journal of Marketing, 52*(2), 1–20. https://doi.org/10.1177/002224298805200201

Clifford Defee, C., & Fugate, B. S. (2010). Changing perspective of capabilities in the dynamic supply chain era. *The International Journal of Logistics Management, 21*(2), 180–206. https://doi.org/10.1108/09574091011071915

Del Vecchio, P.(1) et al. (2018) 'Big data for open innovation in SMEs and large corporations: Trends, opportunities, and challenges', Creativity and Innovation Management, 27(1), pp. 6-22–22. doi:10.1111/caim.12224.

Dillman, D. A. (1978). *Mail and telephone surveys: The total design method* (vol. 19). New York, USA: Wiley Publication.

Duan, Y., Cao, G., & Edwards, J. S. (2020). Understanding the impact of business analytics on innovation. *European Journal of Operational Research, 281*(3), 673–686. https://doi.org/10.1016/j.ejor.2018.06.021

Dubey, R., et al. (2019a). Big Data and Predictive Analytics and Manufacturing Performance: Integrating Institutional Theory, Resource-Based View and Big Data Culture. *British Journal of Management, 30*(2), 341–361. https://doi.org/10.1111/1467-8551.12355

Dubey, R., et al. (2019b). Big data analytics and organizational culture as complements to swift trust and collaborative performance in the humanitarian supply chain. *International Journal of Production Economics, 210*, 120–136. https://doi.org/10.1016/j.ijpe.2019.01.023
Dubey, R., et al. (2020). Big data analytics and artificial intelligence pathway to operational performance under the effects of entrepreneurial orientation and environmental dynamism: A study of manufacturing organisations. *International Journal of Production Economics, 226*. https://doi.org/10.1016/j.ijpe.2019.107599
Eisenhardt, K.M. and Martin, J.A. (2000) 'Dynamic Capabilities: What Are They?', Strategic Management Journal (John Wiley & Sons, Inc.) - 1980 to 2009, 21(10/11), p. 1105. doi:10.1002/1097-0266(200010/11)21:10/11<1105::AID-SMJ133>3.0.CO;2-E.
Engelen, A., et al. (2014). Entrepreneurial orientation in turbulent environments: The moderating role of absorptive capacity. *Research Policy, 43*(8), 1353–1369. https://doi.org/10.1016/j.respol.2014.03.002
Erevelles, S., Fukawa, N., & Swayne, L. (2016). Big Data consumer analytics and the transformation of marketing. *Journal of business research, 69*(2), 897–904.
Faruk, M., Rahman, M., & Hasan, S. (2021). How digital marketing evolved over time: A bibliometric analysis on scopus database. *Heliyon*, e08603.
Gefen, D., Rigdon, E.E. and Straub, D. (2011) 'An Update and Extension to SEM Guidelines for Administrative and Social Science Research', MIS Quarterly, 35(2), pp. III–XIV. Available at: https://search.ebscohost.com/login.aspx?direct=true&db=edswsc&AN=000290842900001&site=eds-liv.
Genc, E., Dayan, M., & Genc, O. F. (2019). The impact of SME internationalization on innovation: The mediating role of market and entrepreneurial orientation. *Industrial Marketing Management, 82*, 253–264. https://doi.org/10.1016/j.indmarman.2019.01.008
Germann, F., Lilien, G. L., & Rangaswamy, A. (2013). Performance implications of deploying marketing analytics. *International Journal of Research in Marketing, 30*(2), 114–128. https://doi.org/10.1016/j.ijresmar.2012.10.001
Germann, F., et al. (2014). Do Retailers Benefit from Deploying Customer Analytics? *Journal of Retailing, 90*(4), 587–593. https://doi.org/10.1016/j.jretai.2014.08.002
Grant, R. M. (1996). Toward a Knowledge-Based Theory of the Firm. *Strategic Management Journal, 17*(S2), 109–122. https://doi.org/10.1002/smj.4250171110
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, V. K., et al. (2016). Individual entrepreneurial orientation role in shaping reactions to new technologies. *International Entrepreneurship and Management Journal, 12*(4), 935–961. https://doi.org/10.1007/s11365-015-0373-4
Gurría, A. (2020). *2020 Ministerial Council Meeting: The Path to Recovery: Strong, Resilient, Green and Inclusive*. Paris: OECD. Available from: Https://read.oecd-ilibrary.org/view/?ref=137_137401-xei03hgxmq&title=2020MinisterialCouncilMeetingThepathtorecoveryStrongresilientgreenandinclusive.
Hair, J. F., Hult, G., Ringle, C., & Sarstedt, M. (2014). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*. Thousand Oaks, CA: SAGE Publications Inc.
Hair, J. F., Ringle, C. M., & Sarstedt, M. (2013). Partial Least Squares Structural Equation Modeling: Rigorous Applications, Better Results and Higher Acceptance. *Long Range Planning, 46*(1–2), 1–12. https://doi.org/10.1016/j.lrp.2013.01.001
Hayes, A. F. (2009). Beyond Baron and Kenny: Statistical Mediation Analysis in the New Millennium. *Communication Monographs, 76*(4), 408–420. https://doi.org/10.1080/03637750903310360
Heider, A., Gerken, M., van Dinther, N., & Hülsbeck, M. (2020). Business model innovation through dynamic capabilities in small and medium enterprises – Evidence from the German Mittelstand. *Journal of Business Research, 130*. https://doi.org/10.1016/j.jbusres.2020.04.051
Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science, 43*(1), 115–135.
Herhausen, D., Miočević, D., Morgan, R. E., & Kleijnen, M. H. P. (2020). The digital marketing capabilities gap. *Industrial Marketing Management, [online], 90*(2020), 276–290. https://doi.org/10.1016/j.indmarman.2020.07.022
Hervé, A., Schmitt, C., & Baldegger, R. (2020). Digitalization, Entrepreneurial Orientation & Internationalization of Micro-, Small-, and Medium-Sized Enterprises. *Technology Innovation Management Review, 10*(4), 5–17. https://doi.org/10.22215/timreview/1343
Hoffmann, A. L. (2017). Making Data Valuable: Political, Economic, and Conceptual Bases of Big Data. *Philosophy & Technology, 31*(2), 209–212. https://doi.org/10.1007/s13347-017-0295-x
Hullova, D., Trott, P., & Simms, C. D. (2016). Uncovering the reciprocal complementarity between product and process innovation. *Research Policy, 45*(5), 929–940. https://doi.org/10.1016/j.respol.2016.01.012
Jarrahi, M.H. and Sutherland, W. (2019) Algorithmic Management and Algorithmic Competencies: Understanding and Appropriating Algorithms in Gig Work. Information in Contemporary Society, [online] pp.578–589. Doi: 10.1007/978-3-030-15742-5_55.
Jansen, J. J. P., Vera, D., & Crossan, M. (2009). Strategic leadership for exploration and exploitation: The moderating role of environmental dynamism. *The Leadership Quarterly, [online], 20*(1), 5–18. https://doi.org/10.1016/j.leaqua.2008.11.008
Johnson, J. S., Friend, S. B., & Lee, H. S. (2017). Big Data Facilitation, Utilization, and Monetization: Exploring the 3Vs in a New Product Development Process. *Journal of Product Innovation Management, 34*(5), 640–658. https://doi.org/10.1111/jpim.12397
Keh, H. T., Nguyen, T. T. M., & Ng, H. P. (2007). The effects of entrepreneurial orientation and marketing information on the performance of SMEs. *Journal of Business Venturing, 22*(4), 592–611. https://doi.org/10.1016/j.jbusvent.2006.05.003
Kahn, K. B. (2018). Understanding innovation. *Business Horizons, [online], 61*(3), 453–460. https://doi.org/10.1016/j.bushor.2018.01.011
Kogut, B., & Zander, U. (1992). Knowledge of the Firm, Combinative Capabilities, and the Replication of Technology. *Organization Science, 3*(3), 383–397. https://doi.org/10.1287/orsc.3.3.383
Lee, Y. Y., & Falahat, M. (2019). The Impact of Digitalization and Resources on Gaining Competitive Advantage in International Markets: Mediating Role of Marketing, Innovation and Learning Capabilities. *Technology Innovation Management Review, 9*(11), 26–38.
Leiponen, A. (2006). Managing Knowledge for Innovation: The Case of Business-to-Business Services. *Journal of Product Innovation Management, 23*(3), 238–258. https://doi.org/10.1111/j.1540-5885.2006.00196.x
Lindell, M. K., & Whitney, D. J. (2001). Accounting for common method variance in cross-sectional research designs. *Journal of Applied Psychology, 86*(1), 114–121. https://doi.org/10.1037//0021-9010.86.1.114
Leiponen, A., & Helfat, C. E. (2010). Innovation objectives, knowledge sources, and the benefits of breadth. *Strategic Management Journal (John Wiley & Sons, Inc.), 31*(2), 224–236. https://doi.org/10.1002/smj.807
Lokshina, I., Lanting, C., & Durkin, B. (2018). IoT- and Big Data-Driven Data Analysis Services for Third Parties, Strategic Implications and Business Opportunities. *International Journal of Social Ecology and Sustainable Development, 9*(3), 34–52. https://doi.org/10.4018/IJSESD.2018070103
Lumpkin, G. T., & Dess, G. G. (1996). Clarifying the Entrepreneurial Orientation Construct and Linking It To Performance. *Academy of Management Review, 21*(1), 135–172.
Maheshwari, S., Gautam, P., & Jaggi, C. K. (2021). Role of Big Data Analytics in supply chain management: Current trends and future perspectives. *International Journal of Production Research, 59*(6), 1875–1900. https://doi.org/10.1080/00207543.2020.1793011
Maroufkhani, P., Tseng, M.-L., Iranmanesh, M., Ismail, W. K. W., & Khalid, H. (2020). Big data analytics adoption: Determinants and performances among small to medium-sized enterprises. *International Journal of Information Management, 54*, Article 102190. https://doi.org/10.1016/j.ijinfomgt.2020.102190
Matarazzo, M., et al. (2021). Digital transformation and customer value creation in Made in Italy SMEs: A dynamic capabilities perspective. *Journal of Business Research, 123*, 642–656. https://doi.org/10.1016/j.jbusres.2020.10.033
Menon, T. and Pfeffer, J. (2003) Valuing Internal vs. External Knowledge: Explaining the Preference for Outsiders. SSRN Electronic Journal . Doi: 10.2139/ssrn.369480.
Mikalef, P., & Pateli, A. (2017). Information technology-enabled dynamic capabilities and their indirect effect on competitive performance: Findings from PLS-SEM and fsQCA. *Journal of Business Research, 70*, 1–16. https://doi.org/10.1016/j.jbusres.2016.09.004
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. (2019). Exploring the relationship between big data analytics capability and competitive performance: The mediating roles of dynamic and operational capabilities. *Information & Management, [online], 57*(2). https://doi.org/10.1016/j.im.2019.05.004
Mikalef, P., et al. (2023). All eyes on me: Predicting consumer intentions on social commerce platforms using eye-tracking data and ensemble learning. *Decision Support Systems [Preprint]*.. https://doi.org/10.1016/j.dss.2023.114039
Miller, D. (1983). The Correlates of Entrepreneurship in Three Types of Firms. *Management Science, 29*(7), 770–791. https://doi.org/10.1287/mnsc.29.7.770
Miller, K., et al. (2021). Business models big and small: Review of conceptualisations and constructs and future directions for SME business model research. *Journal of Business Research, 131*, 619–626. https://doi.org/10.1016/j.jbusres.2020.12.036
Miroshnychenko, I., Strobl, A., Matzler, K., & De Massis, A. (2020). Absorptive capacity, strategic flexibility, and business model innovation: Empirical evidence from Italian SMEs. *Journal of Business Research*. https://doi.org/10.1016/j.jbusres.2020.02.015
Mitchell, A. P., Trivedi, N. U., Gennarelli, R. L., Chimonas, S., Tabatabai, S. M., Goldberg, J., et al. (2021). Are Financial Payments From the Pharmaceutical Industry Associated With Physician Prescribing? *: A Systematic Review. Annals of Internal Medicine, [online], 174*(3), 353–361. https://doi.org/10.7326/M20-5665
Narayanan, V. K., Yang, Y., & Zahra, S. A. (2009). Corporate venturing and value creation: A review and proposed framework. *Research Policy, 38*(1), 58–76. https://doi.org/10.1016/j.respol.2008.08.015
Nonaka, I., & Takeuchi, H. (1995). *The Knowledge-Creating Company - How Japanese Companies Foster Creativity and Innovation for Competitive Advantage*. New York: Oxford University Press.
Nwankpa, J. K., & Datta, P. (2017). Balancing exploration and exploitation of IT resources: The influence of Digital Business Intensity on perceived organizational performance. *European Journal of Information Systems, 26*(5), 469–488. https://doi.org/10.1057/s41303-017-0049-y
Okhuysen, G. A., & Eisenhardt, K. M. (2002). Integrating Knowledge in Groups: How Formal Interventions Enable Flexibility. *Organization Science, 13*(4), 370–386. https://doi.org/10.1287/orsc.13.4.370.2947
O'Dell, C., & Davenport, T. (2019). *Application of AI for knowledge management*. Fort Lauderdale: CIO Review. Available at https://knowledgemanagement.cioreview.com/cxoinsight/application-of-ai-for-knowledge-management-nid-30328-cid-132.html.
Ozer, M., & Dayan, M. (2015). Strategic, organizational and operational challenges of product innovation in emerging economies. *Journal of Global Scholars of Marketing Science, 25*(1), 5–16. https://doi.org/10.1080/21639159.2014.980040

Parkhe, A. (1993). Strategic Alliance Structuring: A Game Theoretic and Transaction Cost Examination of Interfirm Cooperation. *Academy of Management Journal, 36*(4), 794–829. https://doi.org/10.5465/256759

Pavlou, P. A., Liang, H., & Xue, Y. (2007). Understanding and Mitigating Uncertainty in Online Exchange Relationships: A Principal-Agent Perspective. *MIS Quarterly, 31*(1), 105. https://doi.org/10.2307/25148783

Pérez-Luño, A., Wiklund, J., & Cabrera, R. V. (2011). The dual nature of innovative activity: How entrepreneurial orientation influences innovation generation and adoption. *Journal of Business Venturing, 26*(5), 555–571. https://doi.org/10.1016/j.jbusvent.2010.03.001

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, [online], 88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Powell, W. W., Koput, K. W., & SmithDoerr, L. (1996). Interorganizational Collaboration and the Locus of Innovation: Networks of Learning in Biotechnology. *Administrative Science Quarterly, [online], 41*(1), 116–145. https://doi.org/10.2307/2393988

Preacher, K. J., & Hayes, A. F. (2004). SPSS and SAS procedures for estimating indirect effects in simple mediation models. *Behavior Research Methods, Instruments, & Computers, 36*(4), 717–731.

Rai, A., & Tang, X. (2010). Leveraging IT Capabilities and Competitive Process Capabilities for the Management of Interorganizational Relationship Portfolios. *Information Systems Research, 21*(3), 516–542. https://doi.org/10.1287/isre.1100.0299

Rajagopalan, N., Rasheed, A. M. A., & Datta, D. K. (1993). Strategic Decision Processes: Critical Review and Future Directions. *Journal of Management, 19*(2), 349–384. https://doi.org/10.1177/014920639301900207

Rojo, E., et al. (2018). Soft tissue volume gain around dental implants using autogenous subepithelial connective tissue grafts harvested from the lateral palate or tuberosity area. A randomized controlled clinical study. *Journal of Clinical Periodontology, 45* (4), 495–503. https://doi.org/10.1111/jcpe.12869

Rosenbusch, N., Brinckmann, J., & Bausch, A. (2011). Is innovation always beneficial? A meta-analysis of the relationship between innovation and performance in SMEs. *JOURNAL OF BUSINESS VENTURING, 26*(4), 441–457. https://doi.org/10.1016/j.jbusvent.2009.12.002

Salunke, S., Weerawardena, J., & McColl-Kennedy, J. R. (2011). Towards a model of dynamic capabilities in innovation-based competitive strategy: Insights from project-oriented service firms. *Industrial Marketing Management, 40*(8), 1251–1263. https://doi.org/10.1016/j.indmarman.2011.10.009

Salunke, S., Weerawardena, J., & McColl-Kennedy, J. R. (2019). The central role of knowledge integration capability in service innovation-based competitive strategy. *Industrial Marketing Management, 76*, 144–156. https://doi.org/10.1016/j.indmarman.2018.07.004

Sanders, N. (2014). *The definitive guide to manufacturing and service operations master the strategies and tactics for planning, organizing, and managing how products and services are produced.* Nj Pearson Education: Upper Saddle River.

Shepherd, N. G., & Rudd, J. M. (2013). The influence of context on the strategic decision-making process: A Review of the Literature. *International Journal of Management Reviews, 16*(3), 340–364. https://doi.org/10.1111/ijmr.12023

Srinivasan, R., & Swink, M. (2018). An Investigation of Visibility and Flexibility as Complements to Supply Chain Analytics: An Organizational Information Processing Theory Perspective. *Production and Operations Management, 27*(10), 1849–1867. https://doi.org/10.1111/poms.12746

Swink, M., & Song, M. (2007). Effects of Marketing-Manufacturing Integration on New Product Development Time and Competitive Advantage. *Journal of Operations Management, 25*(1), 203–217.

Talwar, S., et al. (2021). Big Data in operations and supply chain management: A systematic literature review and future research agenda. *International Journal of Production Research, 59*(11), 3509–3534. https://doi.org/10.1080/00207543.2020.1868599

Teece, D. J. (2004). Knowledge and Competence as Strategic Assets. *Handbook on Knowledge Management, 1*, 129–152. https://doi.org/10.1007/978-3-540-24746-3_7

Teece, D.J. (2007) 'Explicating dynamic capabilities: the nature and microfoundations of (sustainable) enterprise performance', Strategic Management Journal (John Wiley & Sons, Inc.) - 1980 to 2009, 28(13), pp. 1319–1350. doi:10.1002/smj.640.

Teece, D. J. (2012). Dynamic Capabilities: Routines versus Entrepreneurial Action. *Journal of Management Studies, 49*(8), 1395–1401. https://doi.org/10.1111/j.1467-6486.2012.01080.x

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%3C509::AID-SMJ882%3E3.0.CO;2-Z

Tehseen, S., Ramayah, T., & Sajilan, S. (2017). Testing and Controlling for Common Method Variance: A Review of Available Methods. *Journal of Management Sciences, 4* (2), 142–168. https://doi.org/10.20547/jms.2014.1704202

The World Bank. (2022) Small and Medium Enterprises (SMEs) Finance - Improving SMEs' access to finance and finding innovative solutions to unlock sources of capital. Washington, DC: World Bank. Available from: https://www.worldbank.org/en/topic/smefinance#:~:text=SMEs%20account%20for%20the%20majority,(GDP)%20in%20emerging%20economies.

Thrassou, A., Vrontis, D., Weber, Y., Shams, S.M.R. and Tsoukatos, E., eds. (2020) The Changing Role of SMEs in Global Business. Cham: Springer International Publishing. Doi: 10.1007/978-3-030-45831-7.

Trabucchi, D., & Buganza, T. (2019). Data-driven innovation: Switching the perspective on Big Data. *European Journal of Innovation Management, 22*(1), 23–40. https://doi.org/10.1108/ejim-01-2018-0017

Verona, G. (1999). A Resource-Based View of Product Development. *The Academy of Management Review, 24*(1), 132. https://doi.org/10.2307/259041

Wamba, S. F., & Akter, S. (2019). Understanding supply chain analytics capabilities and agility for data-rich environments. *International Journal of Operations & Production Management, 39*(6/7/8), 887–912. https://doi.org/10.1108/ijopm-01-2019-0025

Wamba, S. F., et al. (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, H., & Li, J. (2008). Untangling the effects of overexploration and overexploitation on organizational performance: The moderating role of environmental dynamism. *Journal of Management, 34*(5), 925–951. https://doi.org/10.1177/0149206308321547

Wang, Z., & Wang, N. (2012). Knowledge sharing, innovation and firm performance. *Expert Systems with Applications, 39*(10), 8899–8908. https://doi.org/10.1016/j.eswa.2012.02.017

Weerawardena, J. (2003). Exploring the role of market learning capability in competitive strategy. *European Journal of Marketing, 37*(3/4), 407–429. https://doi.org/10.1108/03090560310459023

Weerawardena, J., Mort, G. S., Salunke, S., Knight, G., & Liesch, P. W. (2015). The role of the market sub-system and the socio-technical sub-system in innovation and firm performance: A dynamic capabilities approach. *Journal of the Academy of Marketing Science, 43*(2), 221–239. https://doi.org/10.1007/s11747-014-0382-9

Weerawardena, J., et al. (2020). The learning subsystem interplay in service innovation in born global service firm internationalization. *Industrial Marketing Management, 89*, 181–195. https://doi.org/10.1016/j.indmarman.2019.05.012

Wetzels, M., Odekerken-Schröder, G., & van Oppen, C. (2009). Using Pls Path Modeling for Assessing Hierarchical Construct Models: Guidelines and Empirical Illustration. *MIS Quarterly, 33*(1), 177–195. https://doi.org/10.2307/20650284

Wiklund, J., & Shepherd, D. (2005). Entrepreneurial orientation and small business performance: A configurational approach. *Journal of Business Venturing, 20*(1), 71–91. https://doi.org/10.1016/j.jbusvent.2004.01.001

Wilden, R., & Gudergan, S. P. (2014). The impact of dynamic capabilities on operational marketing and technological capabilities: Investigating the role of environmental turbulence. *Journal of the Academy of Marketing Science, 43*, 181–199. https://doi.org/10.1007/s11747-014-0380-y

Wilhelm, H., Schlömer, M., & Maurer, I. (2015). How dynamic capabilities affect the effectiveness and efficiency of operating routines under high and low levels of environmental dynamism. *British Journal of Management, 26*(2), 327–345. https://doi.org/10.1111/1467-8551.12085

Xu, Z., Frankwick, G. L., & Ramirez, E. (2016). Effects of big data analytics and traditional marketing analytics on new product success: A knowledge fusion perspective. *Journal of Business Research, 69*(5), 1562–1566. https://doi.org/10.1016/j.jbusres.2015.10.017

Yang, J. (2005). Knowledge integration and innovation: Securing new product advantage in high technology industry. *Journal of High Technology Management Research, 16*(1), 121–135. https://doi.org/10.1016/j.hitech.2005.06.007

Zhou, K. Z., & Li, C. B. (2012). How knowledge affects radical innovation: Knowledge base, market knowledge acquisition, and internal knowledge sharing. *Strategic Management Journal, 33*(9), 1090–1102. https://doi.org/10.1002/smj.1959

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