4-24-2023

Operationalising Analytics for Action: A Conceptual Framework Linking Embedded Analytics with Decision-Making Agility

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OPERATIONALISING ANALYTICS FOR ACTION: A CONCEPTUAL FRAMEWORK LINKING EMBEDDED ANALYTICS WITH DECISION-MAKING AGILITY

Research in Progress

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Abstract

Organisations are increasingly practising Business analytics (BA) to make data-driven business decisions amidst environmental complexities and fierce global competition. However, organisations find it challenging to operationalise BA outputs (such as analytical models, reports, and visualization) primarily due to a lack of (a) integrated technology, (b) collaboration and (c) governance. These factors inhibit organisations' ability to make data-driven decisions in an agile manner. Embedded analytics, an emerging BA practice, has the potential to address these issues by integrating BA outputs into business applications and workflows, thereby promoting the culture of data-driven decision-making. In this research-in-progress paper, we integrate the diverse areas of literature on BA, embedded analytics, and dynamic capabilities theory and propose a research model that links embedded analytics to decision-making agility through the development of dynamic capabilities. The details of the framework highlight how organisations can get maximum value from data and analytics initiatives through operationalisation of BA outputs.

Keywords: Business Analytics, Embedded Analytics, Dynamic Capabilities, Decision-Making Agility.

1 Introduction

Rising uncertainty and hyper competition is driving organisations to leverage Business Analytics (BA) to make informed business decisions (Seddon et al., 2017). Since BA improves decision-making performance (Ghasemaghaei et al., 2018), organisations are increasingly investing in BA resources to develop systems, processes, and applications that help them turn data into insights and actions (Chen et al., 2012, Sharma et al., 2014, Elia et al., 2022).

Although BA has become an essential organisational practice, yet it is challenging for organisations to operationalise BA outputs (such as analytical models, reports, and visualisation) due to following three reasons. First, lack of integrated workflow and structured process for resource coordination across analytics function, IT, and the business users, coupled with analytical models' complexities, have limited the scalability (SAS, 2020). Consequently, less than half of the analytical outputs developed are being deployed (Ghasemaghaei et al., 2018). Second, highly trained individuals (e.g., data scientists, data engineers and data analysts) with necessary skills to perform and manage individual BA tasks (e.g., data integration, data engineering, data analytics and reporting) remain in short supply (Ghasemaghaei et al., 2018, Choi et al., 2022). Complicating this challenge is the lack of effective data governance that

reduces transparency and trust, which can be further exacerbated by rigid organisational culture, resisting change and lack of buy-in from stakeholders (SAS, 2020).

Embedded Analytics, an emerging BA practice, has the potential to address the aforementioned challenges by integrating diverse analytical outcomes inside the business applications (such as CRM and ERP) and workflows, allowing business users to consume BA outputs by combining insights and actions in the same business workflow (Attaran and Attaran, 2018, Eckerson, 2016). For instance, using embedded analytics, a single workflow can integrate an insurance fraud model that assesses, and scores claims in real-time to ascertain the probability of fraud and a dashboard that displays scores and interventions at the point of decision-making. Such actionable insights and integration avails managers a single view of accounts, values, and risks, allowing them to make agile decisions (Halper, 2016). Our aim in this study is to examine the link between embedded analytics and decision-making agility. We define decision-making agility as an organisation's capability to make informed data-driven business decisions consistently, efficiently and effectively (ZareRavasan, 2021, Levallet and Chan, 2022).

Prior studies have noted BA facilitates decision-making agility through the development of dynamic capabilities i.e., "ability to integrate, build, and reconfigure internal and external competencies to address rapidly-changing environments" (Teece et al., 1997) (p. 516). For instance, Park et al. (2017) noted that BA contributes to organisational agility by influencing sensing, decision making, and acting capabilities. Similarly, Levallet and Chan (2022) discussed how BA capability supports decision-making agility using a sense-respond and continuous learning process. However, since embedded analytics and decision-making agility represent relatively new and complex phenomenon, there is a lack of empirical studies using a theory-driven approach that examines how embedded analytics influences decision-making agility. This gap in the literature motivates our main research question: *How can organisations achieve decision-making agility using embedded analytics?*

To address this research question, we reviewed and integrated the literature on BA, embedded analytics, and dynamic capabilities theory. Subsequently, we developed a research model that explains the process through which embedded analytics leads to decision-making agility via the development of dynamic capabilities. Through our examination of the above relationships, we explain how organisations can get maximum value from data and analytics initiatives through operationalisation of BA outputs. From a practical point of view, our study provides practitioners the understanding of the various capabilities and factors that they need to consider when operationalising analytics across the enterprise.

The rest of the paper proceeds as follows: In Section 2, we review the existing literature on BA, embedded analytics and the link between BA and dynamic capabilities. In Section 3, we present and explain our research model. Then in Section 4, we discuss the planned research methodology. Finally, Section 5 concludes the paper by discussing our research contributions.

2 Literature Review

An integrative literature review was conducted to synthesise and analyse diverse areas of research on business analytics, embedded analytics, and decision-making agility. Dynamic capabilities view was used to synthesize the literature conceptually. The review was conducted following guidelines proposed by Snyder (2019), and Webster and Watson (2002) using combination of keywords including, "business analytics," "embedded analytics," "dynamic capabilities" and "decision-making agility."

First, we searched for articles, in English, discussing the link between BA, dynamic capabilities, and decision-making agility. This resulted in 281 publications. Further, after reviewing titles and abstracts, only 93 articles that reported on the business use of BA, using dynamic capabilities as the primary theoretical lens were selected. Finally, to ensure that our review reflects important prior empirical developments, specifically focusing on information systems domain, we only selected articles from key information systems journals. Through this, we identified 22 articles.

In contrary, since embedded analytics is an emerging concept, the search resulted in only 22 publications, all which were further refined by examining the titles, abstracts, and introductions, which filtered the list to 10 relevant articles. To expand further, we reviewed practitioners' literature by

organisations such as Gartner, Eckerson Group and The Data Warehouse Institute, thereby, increasing the number of relevant articles to 13. Overall, we identified 35 relevant articles for the review, which were classified into the research model (shown in Figure 1 below).

2.1 Business Analytics

Considering the complexities of the business environment, and latest developments in digital transformation, BA has been characterised as the next frontier for decision-making, innovation and productivity (Elia et al., 2022). Existing literature suggest that BA enables organisations to generate critical insights from large volumes of data, thereby improving their decision-making efficiency (swiftness) and effectiveness (quality) (Ghasemaghaei et al., 2018) and adapt their operations based on competitive environmental trends (Chen et al., 2012, Mikalef et al., 2019a). For instance, the New South Wales State Emergency Service (NSW-SES) operationalised BA by integrating multiple data sources from several agencies such as the Bureau of Meteorology and its own website, and social media channels. By combining them with historical information, NSW-SES enhanced the effectiveness and swiftness of responses to crises and disasters (Wamba et al., 2015).

While BA is valuable, organisations face challenges in operationalising BA outputs due to (a) complexity of models that limit scalability, (b) lack of integrated technology, (c) analysis paralysis (too much data and too little actionable insight), (d) stunted data to action timeframe, (e) poor governance and compliance, (f) lack of coordination across analytics, IT and the business users (SAS, 2020), and (g) short supply of specialised BA talent (Ghasemaghaei et al., 2018, Choi et al., 2022). This negates the goal of BA that aims to economically extract value from large volumes and variety of data and enable swift and effective decision-making (Mikalef et al., 2017, Naseer et al., 2016a). Therefore, we argue that organisations need to address these challenges to realise the full value of BA. To achieve this, organisations must prioritize integration of BA technology and systems, which would increase coordination among business analytics, IT, and business users. These measures can increase the scalability of models and democratisation of data, and minimize analysis paralysis, thus leading to more effective and efficient decision-making(Attaran and Attaran, 2018, Sharma et al., 2014, LaValle et al., 2010). Hence, in this research we investigate how embedded analytics may help organisations to overcome these challenges.

2.2 Embedded Analytics

Embedded analytics is an emerging BA practice that integrates diverse analytical content and recommendations in a single business workflow or application such as (CRM, ERP, marketing, or financial systems) that can be easily operationalised and shared with relevant business stakeholders to enhance data-driven decision-making. This makes users more productive without having to switch between multiple applications to derive insights and take actions (Griffith et al., 2019, Attaran and Attaran, 2018). Embedded analytics is not a new concept in the field of BA. The reason embedded analytics is gaining attention recently is because it makes BA outputs more consumable i.e., ease of access to data that can be utilised by the right people, at the right time and at the right point of need (Kandogan et al., 2013).

From the embedded analytics conceptualization perspective, three broad features can be drawn from its existing definitions in the literature (see Table 1), which are, (1) integrating analytical capabilities into applications and business workflows (Attaran and Attaran, 2018, Davenport et al., 2010), (2) enabling data-driven decision-making (Davenport, 2013, Griffith et al., 2019) and (3) addressing analytics latency i.e., data-to-action timeframe (Attaran and Attaran, 2018). Whilst embedded analytics has started to receive attention in recent times, mostly amongst practitioners, it is still an emerging BA practice, and lacks empirical studies that investigates its influence on decision-making agility.

Reference	Conceptualisation	Embedded Analytics Features		
		Integrate Analytical Capabilities	Enable Data-Driven Decision-Making	Address Analytics Latency
(Attaran and Attaran, 2018)	Embedded analytics inserts intelligence or a set of tightly integrated capabilities inside the everyday systems or applications (such as CRM, ERP, marketing, or financial systems) that employees or customers use to improve the analytics experience. This makes users more productive without having to switch between multiple applications to derive insights and take actions.	X	X	X
(Davenport, 2013)	Consistent with the increased speed of data processing and analysis, models in Analytics 3.0 are often embedded into operational and decision processes, dramatically increasing their speed and impact.		X	
(Davenport et al., 2010, Griffith et al., 2019, Leventhal and Langdell, 2013, Eckerson, 2006)	Embedding analytics is about integrating actionable insights into systems and business processes used to make decisions. The goal is to integrate analytics into operational systems so that users will be able to access historical data and perform analytics on those data while executing transactions and making decisions.	X	X	
(Shankararaman and Gottipati, 2015, Rayner, 2010)	Embedded analytics integrates analytics into the operational systems, for example, an ERP, that is part of organisation's business processes. Business users will be able to access historical data and perform analytics on this data while performing transactions. Thus, they can work more efficiently with the applications they use every day.	X		

Table 1. Concept Matrix: Embedded Analytics Definitions and Features

2.3 Linking Business Analytics with Dynamic Capabilities

The dynamic capabilities theory emphasizes two critical attributes. First, "dynamic" indicates organisation's ability to monitor, analyse and learn from events and trends in their changing environment to achieve congruence. Second, "capabilities" signify organisation's ability to 'adapt, integrate, and reconfigure internal and external organisational skills, resources, and functional competencies to match the requirements of a changing environment' (Teece et al., 1997) (p. 516). Prior studies have conceptualised BA as an enabler of dynamic capabilities (Conboy et al., 2020), indicating that BA is operationalised through the development of dynamic capabilities (Naseer et al., 2018). BA comprises of analytical systems, practices, applications and technologies, which help organisations to analyse and interpret data and generate insights to make data-driven decisions (Seddon et al., 2017). Development of BA enabled dynamic capabilities enable business users to learn new routines, allowing for timely and purposive reconfiguration of resources (Rialti et al., 2019, Naseer et al., 2016b). This, in turn, positively impacts organisational performance and agility (Mikalef et al., 2021, Seddon et al., 2017). Overall, organisations with BA enabled dynamic capabilities can better adapt to changing market environment and enable business managers to make business decision quickly (Kunc and O'brien, 2019).

2.4 Role of Data-Driven Culture

Data-driven culture has emerged as a pivotal aspect of modern organisation for its impact on improving decision-making and enhancing performance (Provost and Fawcett, 2013). We define data-driven organisational culture as a set of organisational norms, values, attitudes, and behaviour patterns and an orientation towards continuous learning (Mikalef et al., 2020) that encourages the enterprise-wide use of data to make informed business decision (Shamim et al., 2019). This approach has been linked to decision-making agility, as it enables organisations to rapidly adapt to changing business conditions, identify emerging trends, and capitalise on new opportunities (Davenport, 2014). Organisations recognise that a data-driven culture is critical to BA success and sustainability (Grover et al., 2018).

Several studies highlight the importance of data-driven culture in fostering collaboration, communication, and democratisation of data, which contribute to decision-making agility (Popovič et al., 2018). A strong data-driven culture supports the development of analytical capabilities, including data literacy and critical thinking skills, across all organisational levels (Ransbotham et al., 2016). Moreover, it promotes a mindset of continuous learning and experimentation, which is essential for agile decision-making (LaValle et al., 2010). However, despite much focus on understanding organisational culture as an antecedent to the BA-dynamic capabilities relationship, there is lack of literature that examines how does data-driven organisational culture impact the influence of embedded analytics on dynamic capabilities and its subsequent impact on decision-making agility.

2.4.1 Summary

Overall, our review of the existing literature outlines that organisations face challenges in operationalising BA due to various reasons such as lack of integrated technology, stunted data to action timeframe and poor culture and governance, among other factors. Embedded analytics can help organisations overcome these challenges by integrating analytical content and functionality into business workflows or applications to provide targeted insights at the point of need to facilitate data-driven decisions. Further it influences organisations dynamic capabilities by enabling business users to learn new routines, and timely and purposively reconfigure resources. However, these interactions need a strong data-driven organisational culture to thrive.

3 Research Model

Building on prior literature that proposes BA indirectly impacts organisational performance/competitive advantage through the development of dynamic capabilities (Božič and Dimovski, 2019, Conboy et al., 2020), we argue that embedded analytics also indirectly impacts decision-making agility through the development of dynamic capabilities. In addition, we also argue that data-driven culture moderates the process through which embedded analytics and dynamic capabilities impact decision-making agility. The concepts in the research model (Figure 1) together with their definitions are presented in Table 2.

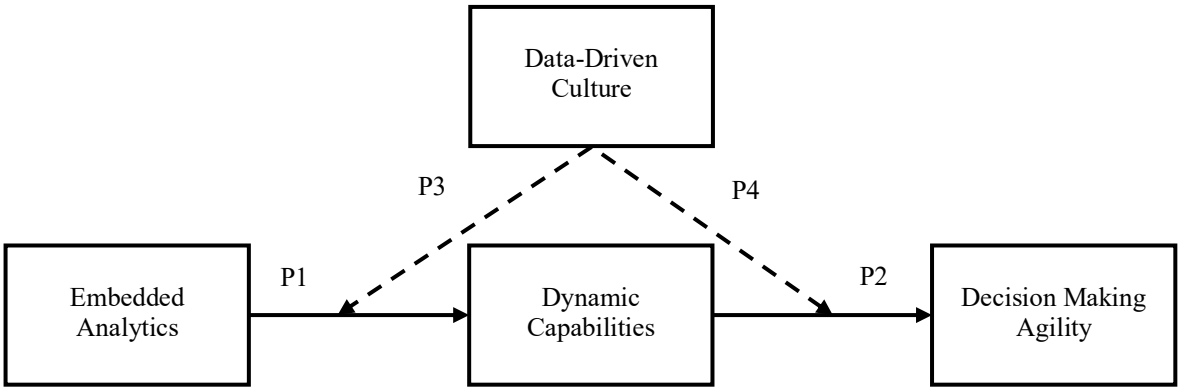

Figure 1. Research model.

Concepts	Definitions	References
Embedded Analytics	Ability to integrate diverse analytical content and recommendations in a single business workflow or application that can be easily operationalised and shared with relevant business stakeholders to enhance data-driven decision-making.	(Attaran and Attaran, 2018, Griffith et al., 2019)
Dynamic Capabilities	Ability to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments.	(Teece et al., 1997)
Decision-Making Agility	An organisation's ability to make informed data-driven business decisions consistently, efficiently, and effectively.	(ZareRavasan, 2021, Nafei, 2016)
Data-driven Culture	Set of organisational norms, values, attitudes, and behaviour patterns that encourages the enterprise-wide use of data to make informed business decision.	(Shamim et al., 2019)

Table 2. Concepts and Definitions of the Proposed Research Model

3.1 Building Dynamic Capabilities using Embedded Analytics

In fast-changing business environment, organisations need dynamic capabilities to develop new value creating strategies (Rialti et al., 2019, Teece et al., 2016). We argue that embedded analytics is the mechanism that enable organisations to develop such capabilities by rapidly building, integrating, and reconfiguring their analytical resources; making BA outputs available when and where needed. This increased agility can enable organisations to make better strategic decisions and pursue new opportunities (Kiron et al. 2018). For instance, analysis of customer interaction data on social media (using applications such as Hootsuite) allow organisations to understand their consumers' attitude and response to marketing efforts and compare relevant metrices against their competitors (Russom et al., 2014). This allows managers to respond to the ongoing campaign needs and subsequently, update their practices, routines and develop new strategies for future campaigns (Russom et al., 2014).

Prior studies indicate that BA can enhance organisations learning and adaptation capabilities, which are crucial for developing dynamic capabilities (Conboy et al., 2020, Popovič et al., 2018). By providing insights and feedback within the same workflow, embedded analytics can facilitate continuous learning and adaptation, leading to more efficient and effective decision-making. This can enable organisations to respond quickly to market changes and customer demands, thus enhancing their dynamic capabilities. Further, embedded analytics can help organisations to develop a data-driven culture and promote cross functional collaboration (Hyun and Kamioka, 2020, Attaran and Attaran, 2018). Therefore embedded analytics enables business managers to alter their workflows - acquire and shed analytical resources, integrate them together, and recombine them – to generate new value-creating strategies (Teece et al., 1997). Consequently, we propose that:

> *P1: Embedded analytics operationalises BA outputs at the point of need by altering, integrating, coordinating, and reconfiguring analytical resources to develop dynamic capabilities.*

3.2 From Dynamic Capabilities to Decision Making Agility

Continuous changes in business environment demand organisations to develop and apply dynamic capabilities to proactively adapt or create new capabilities to sustain competitive advantage (Pavlou and El Sawy, 2011, Park et al., 2017). This process is also known as building organisational agility, a manifested type of dynamic capability (Teece et al., 2016), which includes sensing agility, decision-making agility and acting agility (Park et al., 2017). A typical aspect of agility is the external pressure for an organisation to sense, interpret and respond within given timeframes or even continually. This distinguishes agility from other concepts such as flexibility or resilience (Salmela et al., 2022). To make business decisions within constrained timeframes, organisations need to operationalise analytics

efficiently and effectively. Park et al. (2017) noted that decision-making agility is enabled through BA, sensu, the latter operationalising analytical information to devise an action plan. This supports efficient decision-making to maximise profit, reduce risk, and gain a competitive edge.

Our literature review shows that embedded analytics enables rapid integration and synthesis of multiple sources and large volumes of data. This streamlines decision-making across multiple organisational units (executive, managerial and operational level) and relevant stakeholders, as analytical insights are shared and operationalised effectively, allowing business users to act swiftly without needing to leave the business workflow (Attaran and Attaran, 2018, Naseer et al., 2020). For instance, during a crisis, executives depend on middle managers and tactical units for analytical insights to make quick decisions. In such instances, embedded analytics can help organisations to develop high quality analytical insights, facilitate stakeholder collaboration, and reduce data-to-action timeline, using a single business workflow, thereby improving decision-making agility (Griffith et al., 2019). Therefore, we propose that:

> *P2: Embedded analytics-enabled dynamic capabilities help organisations achieve decision-making agility by empowering business users to take swift actions based on analytical insights using a single business workflow.*

3.3 The Moderating Role of Data-Driven Culture

Data-driven culture is crucial for the effective deployment of BA outputs (Mikalef et al., 2019b). Organisations with strong data-driven culture accelerate the application of BA and enable ease of data access, usage, governance, and transparency (Tallon et al., 2013, Vidgen et al., 2017). Organisational agility is impacted by data governance, competence, trust, and the ability to absorb new knowledge, which are dependent on organisational culture (Mishra et al., 2014, Yusuf et al., 2001). Therefore, lack of data-driven culture negatively impacts operationalisation of BA, which, in turn, affects decision-making agility i.e., data can become disparate and disconnected from essential business processes, making it difficult to operationalise timely (Kiron, 2017). Hence, we argue that organisations need to foster a data-driven culture to promote operationalisation of BA outputs (Grover et al., 2018). For instance, organisational culture that are non-supportive of BA, become less favourable to change, which hinders the development of dynamic capabilities (Shamim et al., 2019). Similarly, Karaboğa et al. (2019) note that organisational culture enables acquisition, exchange, and transformation of resources, leading to dynamic capabilities.

Organisational culture can moderate decision-making agility by influencing organisation's dynamic capabilities i.e., capacity for learning and adaptation. Crossan et al. (2013) highlighted that organisations that prioritize learning and experimentation are more agile in their decision making and are better equipped to adapt to changing circumstances. By contrast, organisations with a rigid culture may struggle to adapt to changing circumstances and may be slower to make decisions. Overall, leaders must be mindful of cultural factors that affect decision-making agility and work to create a culture that supports agile decision-making (Shamim et al., 2019). Based on the above argument, we propose that:

> *P3: Data-driven organisational culture moderates the impact of embedded analytics in building dynamic capabilities.*
>
> *P4: Data-driven organisational culture moderates the impact of dynamic capabilities in achieving decision-making agility.*

4 Planned Research Method

While the existing literature has examined the link between business analytics and dynamic capabilities, the relationship between embedded analytics, dynamic capabilities and decision-making agility has not been explored yet. We therefore adopt an inductive theory building approach using the multiple-case study design (Eisenhardt and Graebner, 2007), following guidelines specified in (Yin, 2018) and Gioia et al. (2013) to further develop/refine the proposed model.

This research will use purposeful sampling to select large Australian organisations that are mature in their implementation and use of BA solutions, including embedded analytics (Patton, 2015). As the

theory is simple but early, a high degree of certainty is needed to lay a solid foundation for further research (Yin, 2018). Therefore, to ensure literal replication from multiple case studies, we will recruit 5-7 organisations to collect empirical data (Yin, 2018). At each case organisation, we will conduct 60-minutes, semi-structured interviews with top-level executives (Chief Data Officer, Chief Information Officer, Director of Analytics etc.), middle and senior managers (Head of Analytics, Senior Manager Analytics etc.), and data analysts with a rich understanding and experience of using embedded analytics. Prior research suggest that the saturation occurs after 12 interviews, and reliability increases with 13-18 interviews (Alam, 2020, Guest et al., 2006). Thus, we plan to conduct 30–60 interviews. However, the exact number of interviews will depend on the difficulty of finding participants and the actual time when the saturation is achieved. After obtaining consent, the interviews will be recorded and transcribed.

Besides interviews, we will take notes and request background information from the organisations (such as annual reports, strategic reports and relevant departmental reports, and presentations) to supplement the primary data collected through interviews. Additionally, organisations' website and reports will be analysed to triangulate their business analytics strategies, policies, practices, and outcomes (Yin, 2018).

For qualitative data analysis, we will code the interview data following Braun and Clarke (2006) guidelines, which include (1) familiarisation with the data, (2) coding, (3) searching for themes, (4) reviewing themes, (5) defining and naming themes, and (6) writing up. Open coding, axial coding and selective coding will be used via the NVivo software to analyse the transcripts (Yin, 2018).

At the time of writing this article, ethics has been approved and we have recruited eleven participants. We have developed an interview guide on the concepts of BA, embedded analytics, decision-making agility, and corresponding literature on dynamic capabilities. Few example questions that we will ask during the interviews include: “How do you use embedded analytics to enable data-driven decision-making?”, “What are the major enablers and challenges in operationalising analytics? and “Can you share examples on how embedded analytics has influenced the speed and quality of analytics delivery?”

5 Conclusion, contributions, and limitations

BA helps organisations turn data into insights and actions. However, organisations struggle to operationalise BA outputs, which hinders data-driven decision-making. This research-in-progress paper describes how embedded analytics can improve organisational decision-making agility. We posit that embedded analytics empowers organisations to develop dynamic capabilities by rapidly building, integrating, and reconfiguring their analytical resources, making BA outputs available at the point of need. We propose a research model that highlights how embedded analytics-enabled dynamic capabilities aid decision-making agility. The model also explains how data-driven culture moderates the process through which embedded analytics and dynamic capabilities impact decision-making agility.

This study may contribute to literature in several ways. First, it extends BA and dynamic capabilities knowledge by conceptualising the relationships between embedded analytics, dynamic capabilities, and decision-making agility in data-driven decision-making. Second, the proposed conceptual model systematically explains the importance of operationalising BA outputs using embedded analytics.

This study has many practical applications. First, embedded analytics can make BA outputs more consumable, thereby increasing BA value. Second, embedded analytics quickly integrates multiple sources and large volumes of data into business workflows or applications, empowering organisations to make timely and effective business decisions and become more competitive.

Our study also has several limitations. First, this research employs dynamic capabilities theory to link embedded analytics with decision-making agility. Some other factors or theories that might explain this link can be considered in future research, such as business environment, leadership, organisational structure, and resource orchestration perspective. Second, this study focuses on organisations using embedded analytics to drive a data-driven culture. Caution should be taken when generalizing the results of this study in other organisational contexts. Third, the research method may bias interviewees. Fourth, future research can apply other research methods, such as survey research and action research, to empirically validate and further develop the proposed research model.

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