Using Analytical Information for Digital Business Transformation through DataOps: A Review and Conceptual Framework

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Abstract

Organisations are increasingly practising business analytics to generate actionable insights that can guide their digital business transformation. Transforming business digitally using business analytics is an ongoing process that requires an integrated and disciplined approach to leveraging analytics and promoting collaboration. An emerging business analytics practice, Data Operations (DataOps), provides a disciplined approach for organisations to collaborate using analytical information for digital business transformation. We propose a conceptual framework by reviewing the literature on business analytics, DataOps and organisational information processing theory (OIPT). This conceptual framework explains how organisations can employ DataOps as an integrated and disciplined approach for developing the analytical information processing capability and facilitating boundary-spanning activities required for digital business transformation. This research (a) extends current knowledge on digital transformation by linking it with business analytics from the perspective of OIPT and boundary-spanning activities, and (b) presents DataOps as a novel approach for using analytical information for digital business transformation.

Keywords: Digital business transformation, Business analytics, Analytical information processing capability, Boundary spanning, DataOps.

1 Introduction

Digital business transformation is a strategic imperative for many organisations. Gartner (2021) reports that 58% of boards flagged digital tech initiatives as the single biggest strategic business priority. Organisations invest in digital technologies such as the Internet of Things (IoT), Cloud Computing, Big Data Analytics, and Artificial Intelligence to transform their business and thereby improve customers' experience, achieve operational efficiency, deliver new products or services, and innovate with new business models (Bonnet & Westerman, 2021; Dwivedi et al., 2021). While these disruptive digital technologies are valuable to organisations, Warner and Wäger (2019) suggest that they may also create uncertainties in the business environment. Hence, organisations need to adjust their business strategies to thrive in the dynamic digital environment (Sia et al., 2016).

Digital business transformation refers to how organisations can alter their value creation and change the scope of their business by using digital technologies (Hess et al., 2016). In this digital age, the ability to manage and exploit data for value creation and business transformation is becoming a vital competency in organisations' transformation journeys (Dremel et al., 2017). Hence, organisations are increasingly practising business analytics to generate actionable insights that can guide their digital transformation initiatives (Pappas et al., 2018; Sebastian et al., 2017). Business analytics is defined as the extensive use of data, statistical and quantitative analysis, and explanatory or predictive models to drive decisions and actions (Davenport & Harris, 2017). Through business analytics, organisations generate analytical information that refers to the insights (quantitative or qualitative) used by business executives in their analysis and decision-making (Naseer et al., 2021). For instance, predicted ATM usage and customer withdrawal patterns can be identified by analysing transactional data, which a bank could then use to optimise its business (Sia et al., 2016). The capacity to generate analytical information for business transformation in organisations that have high volumes and wide varieties of data requires a mature business analytics capability (Vidgen et al., 2017).

Although existing research has explored how organisations could gain value from business analytics (e.g., Wixom et al., 2013; Vidgen et al., 2017;Grover et al., 2018; and Wee et al., 2022), there is a scarcity of research that links the value of business analytics with digital business transformation. In the context of digital business transformation, business analytics needs to not only support decision-making, but more importantly, it needs to support organisations to drive change in the business and generate a transformative impact on the business across the whole organisation. Using business analytics for digital business transformation requires organisations to develop enterprise-wide analytical capabilities and promote collaboration activities (Karippur & Balaramachandran, 2022; Setia et al., 2014).

DataOps is a business analytics practice that aims to better manage data, provide high-quality insights, and promote collaboration through analytics in a dynamic business environment (Ereth, 2018; Heudecker et al., 2020). The majority of digital transformation literature focuses on digital transformation strategy (e.g., Hess et al., 2016; Ismail et al., 2017; and the organisational and societal impact of digital technologies (e.g., Nambisan et al., 2019). However, digital business transformation is an ongoing, long-term process (Davenport & Westerman, 2018), and organisations need a disciplined approach to using analytical information for their transformation. Although DataOps has the potential to be such an approach, there is little research linking DataOps with digital business transformation. Therefore, we employ organisational information processing theory (OIPT) (Galbraith, 1974; Premkumar et al., 2005; Tushman & Nadler, 1978) and a boundary spanning activities perspective (Aldrich & Herker, 1977; Ancona & Caldwell, 1990; Someh & Shanks, 2013) to link DataOps with digital business transformation. Subsequently, this research aims to answer the following research question:

How do organisations use analytical information for digital business transformation through DataOps?

To address this research question, we propose a conceptual framework by reviewing the diverse areas of literature on business analytics, DataOps, and digital business transformation through the lens of OIPT. The details of the framework explain how organisations can employ DataOps to develop an analytical information processing capability and facilitate boundary spanning activities for digital business transformation.

In the next section, we provide the theoretical background and present the research method for our literature review. Then we synthesize the business analytics, DataOps, OIPT and digital business transformation literature to develop the conceptual framework. We also develop a set of propositions that explain the utility of our framework. Finally, we conclude the paper by describing the contributions and limitations of our work.

2 Theoretical Background

In this section, we review the literature around the intersection of business analytics, DataOps, OIPT, and digital business transformation. In addition, we also link the key concepts in our study (i.e., analytical information, analytical information processing capability, boundary spanning activities, and DataOps) to the context of digital business transformation.

2.1 Using Analytical Information for Digital Business Transformation

Existing research views digital transformation as the evolution of digitization and digitalization (Verhoef et al., 2021). Digitization refers to the encoding of analogue information into digital format (Yoo, 2010). Digitalization is about how IT or digital technologies can be used to alter existing business processes for not only cost savings but also process improvements (Verhoef et al., 2021). Compared with digitization and digitalization, digital transformation is a broader concept. It refers to an enterprise-wide phenomenon with broad organisational implications in which, most notably, the core business model of the firm is subject to change by using digital technologies (Hess et al., 2016; Verhoef et al., 2021). Digitization, digitalization, and digital transformation can be viewed as three phases of the transformation journey, in which organisations "may start with minor changes (e.g., digitization or digitalization) to gradually transform their traditional business into a digital one" (Verhoef et al., 2021, p. 892). This research focuses on how organisations transform their business in the digital era using analytical information.

An organisation can be viewed as an information processing system facing complexity and uncertainty (Tushman & Nadler, 1978). In OIPT, uncertainty refers to the absence of information (Daft & Lengel, 1986). When organisations first start their transformation journeys, they are very likely to encounter a high degree of uncertainty (Matt et al., 2015; Vial, 2019). For instance, given the changing diffusion of technologies and customers' expectations, organisations may lack information that can guide them regarding how to transform their products or services using disruptive technologies to improve customer satisfaction (Ismail et al., 2017; Matt et al., 2015). Organisations may need rich analytical information about their current operations assessment to identify bottlenecks that need to be transformed by digital technologies (Sia et al., 2016). Analytical information about customers' demands is also needed to sense an opportunity for new business models (Loebbecke & Picot, 2015; Setia et al., 2014).

Indeed, digitization and digitalization have fostered the generation of big data, which emphasizes the volume, velocity, variety, veracity, variability, and value of data (Conboy et al., 2020). Big data provides huge opportunities for organisations to get rich analytical information (Dwivedi et al., 2021; Grover et al., 2018; Ranjan & Foropon, 2021). By applying statistical and quantitative analysis, and explanatory and predictive models to analyse big data, organisations can get useful analytical information that affords them opportunities for their transformations (e.g., improving the current business models or creating new business models) (Bonnet & Westerman, 2021). Table 1 lists examples of how analytical information is obtained from big data and used for digital business transformation in different industries.

Industry	Data	Analytical Information	Digital Business Transformation	Reference
Manufacturing	Product-related data from embedded sensors	Patterns of product usage extracted from product usage	Segment the market and identify opportunities for new product development and new services	(Frank et al., 2019)
Telecommunications	Data generated by interactions with users on social media	Best practices and methods for marketing approaches by applying social media analytics	Improve customers satisfaction and position itself as the largest service provider in the market	(Conboy et al., 2020)
Technology provider	Customers' service requests and feedback	Real-time patterns and trends of customers' needs by monitoring the feedback of thousands of customers with text analytics	Achieve efficiency gains and improve customer service	(Muller et al., 2016)
Retailer	Business data such as orders and delivery schedule	Predictive information (e.g., future sales) and prescriptive information (e.g., price recommendations	Transforming the supply chain management by proactively preparing for emergency situations and preventing and mitigating risks	(Papanagnou et al., 2022)
Entertainment	User behavioural data, public feedback, and comments	Insights (e.g., fail rate and user's preference) that help to optimize the game design and maximize user experience	Shifting towards a new business model	(Tim et al., 2020)
Electronic	Sensors' data and satellite images	Predictive demand of electricity to match the supply and demand	Revolutionising the operational processes through which electricity is generated, transported, distributed, and sold.	(Neirotti et al., 2021)

Table 1. Examples of Using Analytical Information for Digital Business Transformation in Different Industries

2.2 The Need for Analytical Information Processing Capability and Boundary Spanning Activities for Digital Business Transformation

Modern digital technologies provide two notable business value drivers: the expansive role of data, and digital ecosystems (Subramaniam, 2021). We argue that analytical information processing capability and boundary spanning activities are needed to realize these business value drivers. Analytical information processing capability enables organisations to transform expansive data into useful analytical information that solves uncertainties in the transformation journey (Cao et al., 2019). Boundary spanning activities enable organisations to share their analytical information (Karippur & Balaramachandran, 2022; Someh & Shanks, 2013) and foster the digital ecosystem for digital business transformation (Tan et al., 2020). Below, we explain why these two aspects are necessary for organisations' transformation journeys.

Based on Galbraith (1974, p. 28), "the greater the uncertainty is, the greater the amount of information is needed to be processed among decision-makers to achieve a given level of performance." To get the needed information, organisations need to develop the information processing capability: the ability to gather, transform, interpret, synthesize, analyse, store, and communicate data, information, and knowledge to cope with the variety, uncertainty and unclear environment (Naseer et al., 2021; Premkumar et al., 2005; Tushman & Nadler, 1978). According to Li et al. (2021), the information processing capability enabled by digital technologies can positively impact business transformation by enhancing market agility. We argue that analytical information processing capability, a specialised form of information processing capability enabled by business analytics, is needed to generate analytical information for digital business transformation. Analytical information processing capability is the ability to use business analytics technologies or applications that analyse critical business data to better understand business and market and make timely business decisions (Anand et al., 2020; Cao et al., 2019; Naseer et al., 2021; Saldanha et al., 2017).

From the boundary spanning perspective, a digital business transformation has a boundary-spanning nature. Boundary spanning refers to the activities or practices that transcend functional division and increase communication and coordination between different stakeholders (Schotter et al., 2017). From the internal boundary perspective, digital business transformation needs cross-functional efforts and requires alignment between different functions (Matt et al., 2015). For example, Dremel et al. (2017) emphasize the important role of collaboration among the sales and marketing departments, digital innovation hub, and IT department in leveraging business analytics to transform their business. Treating digital business transformation in functional silos would not maximise cross-fertilization opportunities (Verhoef et al., 2021). From the external boundary perspective, the digital business transformation will impact the interactions that take place across firm borders with their clients, competitors, partners, and suppliers (Hess et al., 2016). Sia et al. (2016) give an example of how an organisation collaborated with an external research institute to develop its analytics capabilities to better understand its customers and thus provide more personalized interactions. Pappas et al. (2018) also propose a big data and business analytics ecosystem where data, information and knowledge are shared and transferred among stakeholders, enabling collaboration among multiple actors, including private and public organisations, academia, and individuals/entrepreneurs. This results in new business opportunities, the development of digital data-based designs, and the transformation of current business models (Pappas et al., 2018). The blurring boundaries of entities resulting from digital business transformation exemplify the need for boundary spanning activities to enable organisations to use analytical information effectively.

Existing research has identified a wide range of boundary spanning activities such as buffering and representing activities, coordination of task performance, information searching, and guarding (Ancona & Caldwell, 1990; Marrone, 2010). In our research, we focus more on the activities that enable organisations to share and exchange information (Fleischer & Carstens, 2021), bridge the knowledge gap (Someh & Shanks, 2013), and facilitate communication, interactions and cooperation (Schotter et al., 2017) across different domains (e.g., business departments, suppliers, partners, and customers) involved in the transformation journey. Table 2 summarizes boundary spanning activities that seamlessly enable a team/organisation to interact with its external actors and meet the overall goals of digital business transformation. These boundary spanning activities can complement analytical information processing capability by disseminating the information delivered by the analytics process, thus facilitating the cross-boundary collaboration required for digital business transformation.

Activity Types	Explanation	Examples	Reference
Organisational structure design	Arranging business functions and resources to promote the cross-boundary collaboration	Decentralized governance architecture; having cross-functional work groups	(Singh et al., 2020)
Task coordinating	Interactions with interdependent entities to solve coordinating issues, synchronize work efforts, exchange, and combine work outcomes in the transformation journey,	Formal or informal meetings to discuss data ownership problems, obtain feedback, coordinate, and negotiate with outsiders.	(Ancona & Caldwell, 1990; Dremel et al., 2017; Levina & Vaast, 2014; Marrone, 2010)
Scouting	Searching and accessing information or expertise from different domains; learning different organisational systems, and developing a shared language to interact with them	Sensing and exploiting new opportunities to implement analytics-enabled transformation initiatives in other functional areas	(Someh & Shanks, 2013; Yang et al., 2021)
Embedding	Developing social ties and establishing relationships with another based on familiarity, trust, and commitment to connect resources, collaborate, share knowledge	Creating a data-driven culture and embedding analytics in the organisation's process and routines.	(Someh & Shanks, 2013)
Influencing	Influencing or forcing other functional areas or organisations to conform to values, norms or traditions, and social expectations in an institutional environment	The successful adoption of analytical initiatives in one functional area may influence other functional areas to change their values and norms	(Someh & Shanks, 2013)
Adopting boundary spanning objects	Adopting and having entities that enhance the capacity of an idea, theory, or practice to translate across culturally defined boundaries, for example, between communities of knowledge or practice.	Developing protocols, repositories, standardized documentation, models, information systems and collaboration tools to facilitate the shared understanding and collaboration work of different actors	(Beckett, 2021; Fox, 2011; Vilvovsky, 2009)

Table 2. Types of Boundary Spanning Activities

Digital business transformation is a long-term process and journey. As emphasized by Warner and Wäger (2019, p. 327), “the genuine digital transformations are an ongoing process of using digital technologies in everyday organisational life”. The long-term nature of digital business transformation requires not only extensive investment and time but also a holistic and integrated approach to make steady progress toward the right end state (Davenport & Westerman, 2018; Sia et al., 2016). According to OIPT, organisations should develop their information processing capabilities to fulfil their information needs (Flynn & Flynn, 1999; Galbraith, 1974; Premkumar et al., 2005). This means that there should be a disciplined approach that supports organisations (a) to develop their analytical information processing capability to constantly fulfil their analytical information needs, and (b) to facilitate boundary spanning activities to better share analytical information throughout the transformation journey. We argue DataOps as such a disciplined approach and explain its potential role in the digital business transformation below.

2.3 Linking DataOps with Digital Business Transformation

With the high volume and wide variety of data being generated each day, getting and using analytical information from analytical information processing capability and boundary spanning activities is challenging. Wells (2019) and Zahid et al. (2018) identify several challenges, including rapidly increasing data volumes, more sources of data, more data use cases, more stakeholders in modern data ecosystems, and poor data management. These challenges increase the risk of conflicting and erroneous data, the establishment of data silos, and delays in getting needed information, which subsequently inhibits organisations from extracting analytical information as required for digital business transformation. DataOps, as an emerging business analytics practice, aims to overcome such challenges in modern analytical ecosystems.

Popularised by Palmer (2015), DataOps acknowledges the interconnected nature of data engineering, integration, quality, security and privacy to help organisations accelerate analytics and enable previously impossible analytics tasks. DataOps applies to analytics the best principles and practices from diverse methods (i.e., Agile, DevOps, Lean, and Total Quality Management) used in the software engineering and manufacturing areas. It enables organisations to streamline the process of analytics, maximize the business value of data as well as improve business analytics user satisfaction (Eckerson, 2019a; Ereth & Eckerson, 2018).

Since DataOps was coined, it has been most closely associated with the quality and efficiency in the delivery of analytical information (Aslett, 2020; Capizzi et al., 2020). From the perspective of quality, DataOps helps to promote communication between, and integration of, formerly siloed data, teams, and systems (Thusoo & Sarma, 2017), which reduces the risks of conflicting and erroneous results from analytics and thus ensures the quality of analytical information. From the perspective of efficiency, DataOps represents a culture change that focuses on improving collaboration and accelerating analytical delivery by adopting lean or iterative practices where appropriate (Heudecker et al., 2020). Moreover, teamwork and collaboration are the key themes in DataOps (Atwal, 2020). Transforming data into insights usually requires collaboration between different stakeholders such as data architects, engineers, analysts, and scientists, as well as IT operations and business users (Ereth & Eckerson, 2018). The goal of DataOps is to foster greater collaboration and trust among development, test, operations, and business teams and thus improve both the speed and quality of analytical information delivery (Ereth & Eckerson, 2018).

Therefore, in our research, DataOps is viewed as a disciplined approach to improving collaboration and building analytical capabilities in a way that continuously accelerates output and enhances the quality of analytical information (Ereth & Eckerson, 2018; Naseer et al., 2020). Given the potential of DataOps, organisations can adopt DataOps to develop their analytical information processing capability and facilitate the boundary spanning activities to get their required analytical information that will improve the likelihood of optimising digital business transformation.

3 Research Method

We conducted an integrative literature review to combine the diverse literature on digital business transformation, business analytics, and DataOps, following the guidelines outlined in Snyder (2019). The aim of the integrative literature review is to assess, critique, and synthesize this diverse literature in a way that "enables new theoretical frameworks and perspectives to emerge" (Snyder, 2019, p. 335). Accordingly, the aim of our integrative literature review is to build a novel conceptualisation linking DataOps with digital business transformation through the lens of OIPT (Snyder, 2019).

3.1 Data Collection

The purpose of our data collection is to combine perspectives from different fields rather than cover all published articles on a topic, which helps expand on the theoretical foundation of a specific topic (Snyder, 2019). We first searched literature from popular literature databases, including Science Direct, AIS Electronic Library, Scopus, and Google Scholar by using a combination of key words such as digital business transformation, analytical information processing capability, and DataOps. Our search terms are listed in Appendix A. We selected a timeframe to include literature published between 2015 and 2023, with 2015 being used as the earliest date, given that the DataOps term was only popularised by Palmer (2015) in that year. The search results for the different search terms across the databases are listed in Appendix B.

As the aim of this integrative review is not to comprehensively cover as many publications as possible, we sorted the search results by relevance and went through the first 200 results for each search to focus on the most relevant works in the field (vom Brocke et al., 2015). We examined the title and abstract of the articles to exclude papers that were duplicates or deemed not relevant to our research question (i.e., *How do organisations use analytical information for digital business transformation through DataOps?*). We also excluded papers published in journals that are not ranked in either Australian Business Deans Council Journal quality list or Scimago. This screening process resulted in the selection of 301 articles from the literature databases for the full-text eligibility assessment. Notably, as DataOps emerged from practice, we also searched 178 articles from practitioner research and advisory firms such as Gartner, DataKitchen and The Eckerson Group to identify articles that provided us with insights into how DataOps is used in practice in the context of using analytical information for digital business transformation. In an effort to broaden the search, we noted cited works of potential interest in the articles reviewed and identified 30 articles as per Webster and Watson (2002) for eligibility assessment. As a result, there were 509 articles in total for full-text eligibility assessment.

In the eligibility assessment stage, we read the full text of each article and omitted articles for the following reasons: a) papers focused on the technical side of analytics and DataOps rather than the usage of analytical information for digital business transformation; b) papers that mentioned digital transformation in passing, such as growing trend type papers; c) papers in which data operation(s) refer to the general operation of data rather than the DataOps method that learns from DevOps, Agile, Total Quality Management, and Lean method. The eligibility assessment resulted in a total of 87 articles for in-depth review. The data collection process and the exclusion criteria for the screening and eligibility process (in the dashed boxes) are shown in Figure 1.

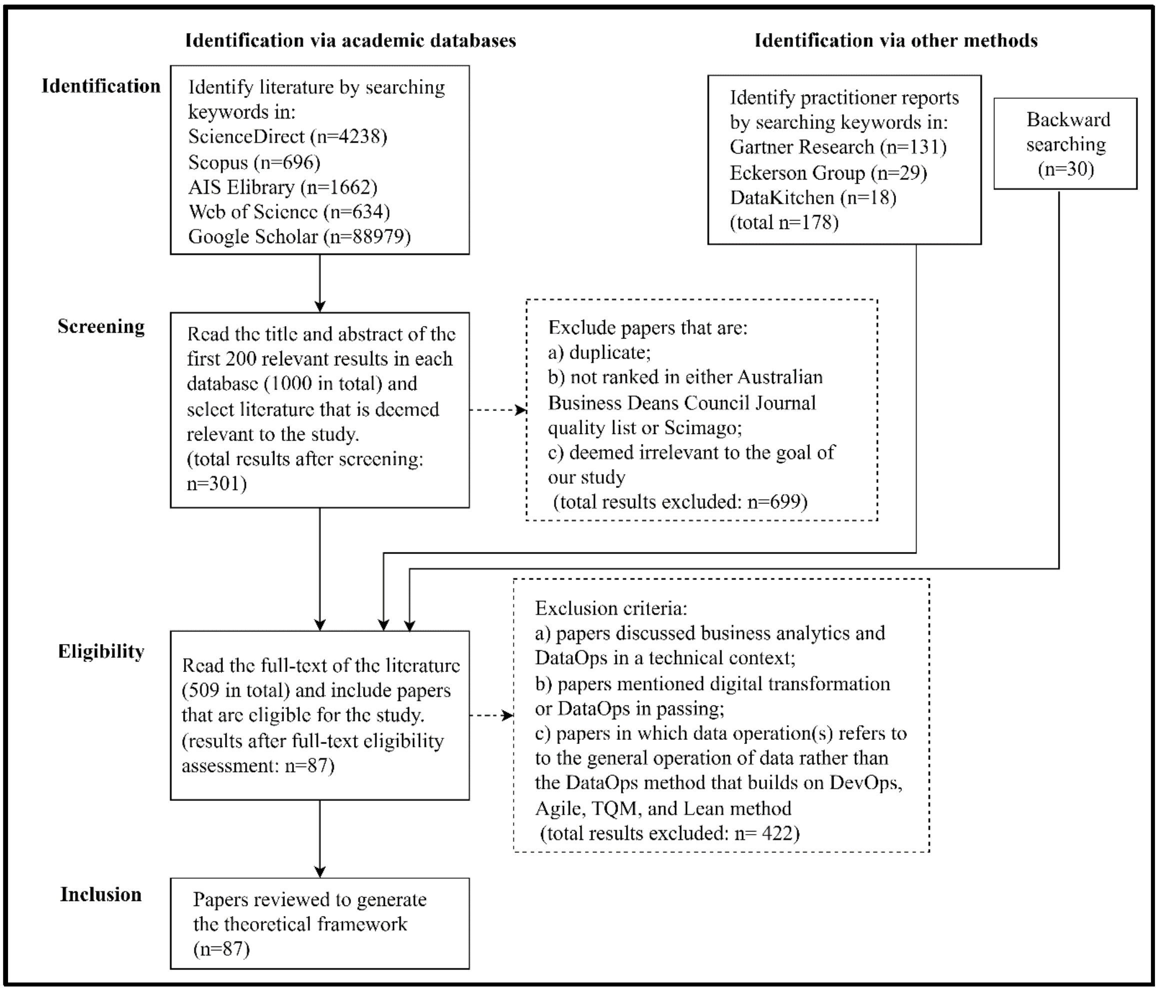

Figure 1. Data Collection (Literature Search) Process – Adapted from Page et al. (2021)

3.2 Data Analysis

We synthesized, analysed and integrated the literature using OIPT by following Watson and Webster (2020)'s concept-centric approach. Specifically, we first reviewed the literature to get an in-depth understanding of the key concepts (e.g., DataOps, analytical information processing capability, boundary spanning, and digital business transformation) included in the study to lay the foundation of the framework building.

Next, guided by OIPT, we analysed the literature to identify the relationship between these concepts. We first identified the uncertainties in digital transformation and what analytical information can be provided by analytical information processing capabilities for digital business transformation. Then we focused on the boundary spanning activities needed in digital business transformation. We linked DataOps research with digital transformation by focusing on the principles and practices from DataOps that can help in using the analytical information processing capability and facilitate the boundary spanning activities for digital business transformation. We classified the literature and integrated the review into the paths shown in Figure 2. The list of 87 articles that were reviewed for this study is provided in Appendix D.

4 Digital Business Transformation through DataOps: A Conceptual Framework

Based on our synthesis, analysis, and integration of the literature, we develop a conceptual framework that links digital business transformation and DataOps through the lens of OIPT (see Figure 2). The dynamic digital environment brings uncertainties to organisations' digital business transformations. DataOps provides organisations with an integrated and disciplined approach to developing their analytical information processing capabilities and facilitating boundary spanning activities to address the uncertainties in digital business transformation. Boundary spanning activities mediate the relationship between analytical information processing capability and digital business transformation by enabling the analytical information to be shared and exchanged across the whole enterprise for digital business transformation. Table 3 gives definitions of the concepts in this framework. Below, we explain the framework by deriving propositions about how analytical information can be leveraged for digital business transformation using DataOps.

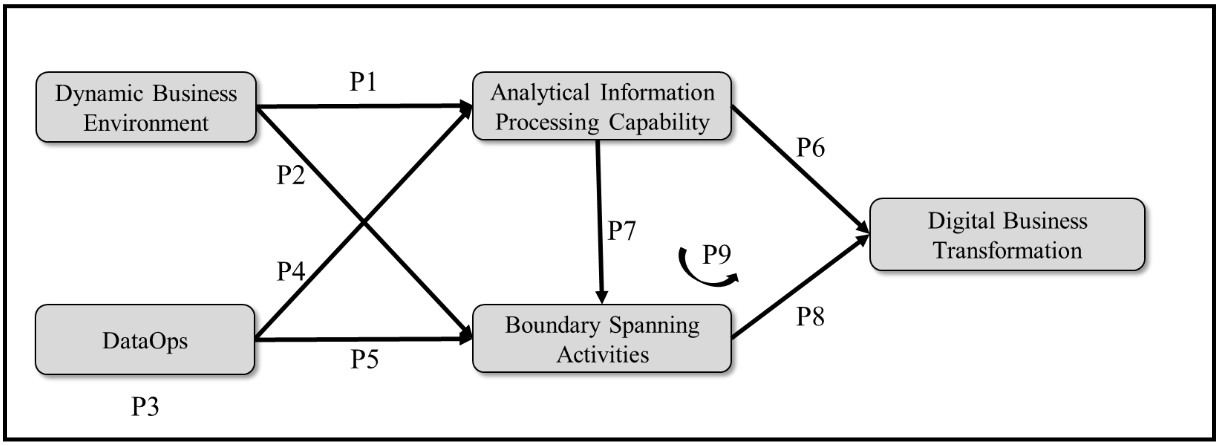

Figure 2. Using Analytical Information for Digital Business Transformation through DataOps

Concept	**Definition**	**Exemplar References**
Dynamic Business Environment	A dynamic environment consisting of disruptive digital technologies, new competitors, and changing customers' expectations.	(Vial, 2019; Warner & Wäger, 2019)
DataOps	An integrated and disciplined approach to developing analytical information processing capability and facilitating boundary spanning activities for digital business transformation.	(Heudecker et al., 2020; Naseer et al., 2020)
Analytical Information Processing Capability	The ability to use business analytics technologies or applications that analyse critical business data to better understand business and market and make timely business decisions.	(Cao et al., 2019; Saldanha et al., 2017)
Boundary Spanning Activities	The activities or practices to increase the communication and coordination between different stakeholders involved in digital business transformation.	(Schotter et al., 2017)
Digital Business Transformation	An ongoing process where an organisation strategically transforms its business dimensions (e.g., value propositions, critical business operations, organisational routines and structures, and management) to radically improve the business enabled by digital technologies.	(Vial, 2019; Warner & Wäger, 2019)

Table 3. Definitions of Key Concepts in the Proposed Conceptual Framework

4.1 Dynamic Business Environment

The business environment in this digital age is becoming more dynamic than before. Table 4 summarizes the dynamics of the business environment. Organisations operate in a dynamic digital environment with opportunities and uncertainties. On the one hand, opportunities to transform a business exist within the digital environment, given the rapidly evolving nature of digital technologies. Artificial Intelligence is one example where organisations can use it to engage customers and employees and deliver new products and services (Borges et al., 2021). 3D printing is another example of where customized products can be produced and manufacturing a range of goods using the same resources can be made possible (Frank et al., 2019). On the other hand, the environmental dynamism is intensified given the advancement and disruption of novel digital technologies (Gupta & Bose, 2022), thereby increasing uncertainty, characterized by the entrance of new competitors and changing expectations of customers (Warner & Wäger, 2019).

Taking a market competition perspective, disruptive technologies impact the existing market by creating a new market in which entrants would always win because of the established firms' delay in making the strategic commitment to enter the emerging market (Christensen, 2013). Facing the threat of new competitors, organisations have an imperative to start their digital business transformation journeys to better compete in the market. Further, disruptive digital technologies such as smartphones also play decisive roles in shaping and mediating all dimensions of people's lived experiences (Yoo, 2010), creating change in customers' expectations and requirements (Schallmo et al., 2017; Vial, 2019). Facing uncertainties, organisations require analytical information to understand the market and their competitors as well as customers (Sia et al., 2016). According to OIPT (Daft & Lengel, 1986; Flynn & Flynn, 1999), organisations should develop their analytical information processing capability to match their information needs for digital business transformation. Thus, we propose the following:

P1: *A dynamic and uncertain business environment triggers the need to develop analytical information processing capability.*

Dynamics of the business environment	Description	Exemplar References
Disruptive digital technologies	Disruptive digital technologies are creating far-reaching effects on business	(Ashrafi et al., 2019; Matt et al., 2015; Verhoef et al., 2021; Vial, 2019; Warner & Wäger, 2019)
Changing customers' requirements and expectations	Digital technologies (e.g., mobile, and social media) have a profound impact on customers' behaviour and thus influence their expectations and requirements of services and products	(Ashrafi et al., 2019; Ismail et al., 2017; Schallmo et al., 2017; Sia et al., 2016; Vial, 2019; Warner & Wäger, 2019)
Competitive Landscape	Digital technologies facilitate the generation of new forms of digital offerings and new disruptive competitors, which moves the competition from a physical plane to a virtual plane	(Ismail et al., 2017; Sia et al., 2016; Verhoef et al., 2021; Vial, 2019; Warner & Wäger, 2019)

Table 4. Dynamics of the Business Environment

The uncertain environment encourages team members to broaden their attempts to collect information from outside of the team and so turn their focus externally, scanning for information (Ancona & Caldwell, 1990; Gupta & Bose, 2022). Boundary spanning activities allow boundary spanners to search, acquire, and convey relevant information about the environment to the internal organisation to reduce uncertainty (Xue et al., 2022). According to Leifer and Delbecq (1978), when the perceived environmental uncertainty is high and the information need is unanticipated and irregular, the boundary spanning actives will be nonregulated and nonroutine. Therefore, with the increasing uncertainties in the dynamic business environment, organisations need to have more nonregulated and nonroutine boundary spanning activities as an important mechanism to cope with the complexity of the dynamic business environment (Ancona & Caldwell, 1990). Accordingly, the following proposition is developed:

P2: *A dynamic and uncertain digital business environment triggers the need to have boundary spanning activities.*

4.2 Employing DataOps for Digital Business Transformation

Organisations can leverage analytical information for digital business transformation, however, unpacking the value of such information requires an integrated approach. DataOps can provide this to help organisations unite stakeholders, govern the flow of data, and ensure that the insights from analytics can satisfy the digital business transformation needs in time. Just as DevOps contributes to building collaboration between software development and IT operations (Munappy, Mattos, et al., 2020), DataOps unites data stakeholders such as data engineers, data analysts, IT operations, and business users, around business requirements to achieve digital business transformation (Ereth & Eckerson, 2018; Munappy, Bosch, et al., 2020). DataOps verifies that results at each intermediate step in the production of analytics match business requirements, borrowing the process from Total Quality Management in using statistical measurement to monitor and control manufacturing processes (Bergh et al., 2019). To identify waste and manage the flow of data, lean thinking can be used to deliver analytical solutions as quickly as possible (Atwal, 2020). Moreover, DataOps can discover common ground where various stakeholders and technologies can act in concert (e.g., orchestration tools that enable automatic combinations of various technologies) (Ereth & Eckerson, 2018; Richardson, 2020). Last but not least, Guinan et al. (2019)'s research showed that organisations navigated digital business transformation through the Agile method to improve the speed of adapting and responding to the dynamic business environment. By adopting Agile and welcoming changing requirements, DataOps embraces changes and enables organisations to cope with the dynamic digital environment when using analytics (Atwal, 2020). Overall, learning from these mature methods of software engineering and manufacturing, DataOps makes it possible for organisations to sense internal and external changes, improve decision-making effectiveness, and reorganise the resources to remain competitive (Ereth, 2018; Gur et al., 2022). DataOps is not only a method for analytical product development but also a discipline that integrates people, processes, technology, and data for digital business transformation. Therefore, we propose:

P3: *DataOps provides an integrated and disciplined approach for organisations to leverage analytical information for digital business transformation.*

The analytical information processing capability in our framework refers to the ability to use analytical practices and applications to process data – that is, to capture, store, transform, analyse, and visualise it, and generate insights for digital business transformation (Cao et al., 2019; Saldanha et al., 2017). OIPT posits that organisations should design their structures, mechanisms, and business processes in such a manner that facilitates information processing and thereby enables informed decision-making and improved organisational performance (Flynn & Flynn, 1999; Galbraith, 1974; Premkumar et al., 2005). Therefore, to build analytical information processing capability, organisations need to leverage tools, techniques, people, and processes in analytics to meet the above goal (Srinivasan & Swink, 2018). During the literature review process, we identified the relevant DataOps principles and practices that enable the development of analytical information processing capabilities by integrating the analytical resources such as people, processes, tools, and techniques (Aslett, 2020; Ereth, 2018; Naseer et al., 2020).

From a people's perspective, DataOps champions the business value mindset that data is not an end in itself but should deliver insights that add value to the business (Atwal, 2020; Bahaa et al., 2023; Ereth & Eckerson, 2018). By applying this mindset, each stakeholder involved views data quality as a top priority to deliver analytical insights that satisfy the needs of digital business information. Moreover, teams in DataOps are expected to self-organized to meet goals (Atwal, 2020). Self-organized teams can help to create self-contained tasks which help to reduce the amount of analytical information processed and thereby reduce the uncertainty (Galbraith, 1974).

From a processes' perspective, emphasizing the importance of testing and monitoring at every stage in data processing is key to performing DataOps, which ensures that the analytical information delivered satisfies the needs of digital business transformation. Issues can be identified quickly through testing before they are delivered to the business and become hard to fix (Mainali et al., 2021). Monitoring the performance of data movement processes is also important as it can detect unexpected patterns and problems (Ereth & Eckerson, 2018; Sahoo & Premchand, 2019). Moreover, a key pillar in DataOps is to continuously improve (Eckerson, 2019a), where teams learn from their mistakes and review processes continuously to adapt to the changing environment (Heudecker et al., 2020; Rodriguez et al., 2020). Such an iterative process with incremental improvements ensures that the analytical information that organisations extract is high-quality, thus promoting digital business transformation in a sustainable manner.

From a tools and technologies perspective, wherever possible, DataOps uses technologies to automate (Ereth, 2018), which can improve the reliability of the analytical information processing capability easing reliance on human intervention and thus reducing the time required for data processing. With appropriate levels of governance and metadata, the automated analytical information delivery also helps to improve the use and value of analytical information in a dynamic environment (Heudecker et al., 2020).

Overall, DataOps can be a catalyst for organisational and cultural shifts (Wells, 2019), as it emphasizes the notion that processing data is about more than simply the technologies. Instead, all resources, including people, technologies, and processes, need to be combined and orchestrated (Friedman & Heudecker, 2019; Wells, 2019) for data processing capabilities and delivering the needed analytical information for digital business transformation. Accordingly, we propose:

P4: *DataOps enables the integration of analytical resources such as people, processes, tools, and technologies needed to develop the analytical information processing capability.*

DataOps also helps facilitate the boundary spanning activities when organisations leverage business analytics for digital business transformation in the following ways:

Leveraging boundary spanning objects: DataOps provides boundary spanning objects, such as version control systems and code repositories, fostering parallel development and code reuse for analytics (Ereth & Eckerson, 2018). Like the Agile method, DataOps is a highly iterative approach in which prototypes of analytics products/solutions (as boundary spanning objects) are provided to gather feedback across different domains (Ereth & Eckerson, 2018). The adoption and usage of these boundary spanning tools enables stakeholders to better align and integrate their knowledge domains (Beckett, 2021; Pershina et al., 2019).

Promoting cross-functional coordination: Based on Beckett (2021), a multidisciplinary agile team with a clear collaboration and knowledge-sharing mindset facilitates boundary spanning. Learning from the Agile and DevOps method, DataOps requires a cross-functional team consisting of people from the IT team, data team, and business team (Ereth & Eckerson, 2018; Walsh, 2023). Also, DataOps values cross-functional ownership over siloed responsibility (Bergh et al., 2019). Teams in DataOps should be organized around shared data-centric goals to eliminate barriers (Atwal, 2020). Rearranging business functions by creating such a cross-functional team with shared goals brings everyone involved together, helping stakeholders to interact and coordinate more efficiently (Eckerson, 2019b), thereby promoting boundary spanning across different domains.

Enriching communication and collaboration mechanisms: DataOps provides both informal and formal mechanisms for cross-functional teams' communications and collaboration. For example, communities of interest can be established to share knowledge, tools, and practices (Atwal, 2020). Teams can also be linked by a formal hub and spoke model through a central team responsible for harmonizing best practices and consistency across other teams (Atwal, 2020). These formal and informal mechanisms enable knowledge sharing and improve communications within and between teams (Ereth & Eckerson, 2018), which facilitates both the scouting and task coordinating boundary spanning activities.

Encouraging continuous learning: DataOps encourages continuous learning through iterations (Heudecker et al., 2020). Each iteration generates feedback, which better informs the next iteration, creating a loop that is critical to improving results. It also helps to publicize the early benefits of adopting DataOps and thus creates curiosity and excitement among other teams (Atwal, 2020). In this sense, the adoption of DataOps in one team can influence other business teams to learn and change their ways of using business analytics for digital business transformation, thereby creating a standardized ways of using business analytics for digital business transformation across an organisation. Therefore, we propose:

P5: *DataOps enables boundary spanning activities for digital business transformation by leveraging boundary spanning activities, promoting cross functional coordination, enriching communication, and collaboration mechanisms, and encouraging continuous learning.*

4.3 Analytical Information Processing Capability, Boundary Spanning Activities, and their Interaction for Digital Business Transformation

The existing literature conceptualised, explained, or gave examples of the analytical information processing capability, analytical information, and boundary spanning activities in the context of digital business transformation differently (summarised in Appendix C). Below, we explain in detail how analytical information processing capability and boundary spanning activities play a role in digital business transformation by synthesizing and analysing the literature.

In a dynamic business environment, organisations may lack information for digital business transformation. For example, since the diffusion of digital technologies can change swiftly, organisations may not have enough information to make reliable assumptions within their organisational digital business transformation strategies (Matt et al., 2015). Further, it can be challenging to obtain sufficient information to predict how the market will change in line with customers' varying expectations and requirements, especially given the rate at which born-digital firms enter the market (Ismail et al., 2017). Moreover, many complexities exist in internal operations, such as the tension between exploiting the existing business while also exploring new digital initiatives that are compatible with the pact dependencies of the past (Warner & Wäger, 2019). It is within these types of complexities that organisations may not have adequate information to cope effectively, impacting the digital business transformation process.

From a OIPT perspective, when the information process capability satisfies the information needs, it brings the effectiveness in the tasks for organisations (Tushman & Nadler, 1978). Facing uncertainties in digital business transformation requires extensive useful information, including market trends, customers' expectations, the performance of business operations, and stakeholders' sentiments on the cultural shift towards digital business transformation (Ismail et al., 2017; Loebbecke & Picot, 2015). To significantly improve the amount and richness of information used in digital business transformation, analytical information processing capabilities can be utilised to generate actionable insights to satisfy the analytical information needs (Ashrafi et al., 2019; Dremel et al., 2017; Vidgen et al., 2017; Wee et al., 2022). For example, organisations can get analytical information about new customer-centric trends that are hard for strategic planners to predict (Warner & Wäger, 2019). Conboy et al. (2020) and Sebastian et al. (2017) also found that organisations can extract rich analytical information, such as the sentiment of customers and staff and predicted defect rates, to understand customers and competitors and identify internal inefficiencies that need to be addressed through transformation.

Hence, the following proposition is derived:

P6: *Analytical information processing capability provides the analytical information needed to address uncertainties and guide digital business transformation.*

Analytical information processing capabilities also play a role in facilitating boundary spanning activities. First, analytical information processing capabilities help to measure and monitor boundary spanning activities. For instance, in Schwade (2021)'s research, a dashboard monitoring a boundary spanning network is developed to facilitate and interpret boundary spanning activities. Second, given the explosive growth in data generated in this digital age, organisations may face information overload when managing, exploiting, and disseminating information across organisational boundaries (Aldrich & Herker, 1977; Fleischer & Carstens, 2021). Analytical information processing capabilities can help to reduce information overload for boundary spanning, as evidenced in Song et al. (2021)'s research on the usage of analytics-embedded digital platforms to analyse relevant data, which enabled decision makers to find the targeted information, make targeted decisions, and effectively organize business activities. Third, analytical information processing capabilities may reshape the organisational boundaries. Internally, the existing boundary setting will be reshaped based on data and analytics accessibility (Jonsson et al., 2009). Externally, analytical information processing capabilities deliver analytical information that alters organisations' understanding of its external environment, which facilitates new boundary spanning forms that can interact with the environment (Conboy et al., 2020). For instance, supported by analytics-enabled capabilities to monitor and analyse internal and external data, a firm can sense threats and trends in the environment and adapt as necessary. Further, the organisation can provide aggregated information to their customers and other companies under an alliance, which creates new boundary spanning forms in which the organisation interacts with their external stakeholders (Conboy et al., 2020). Taken together, the following proposition is developed:

P7: *Analytical information processing capabilities facilitate boundary spanning activities by monitoring the boundary spanning network, reducing information overload, and reshaping boundaries.*

As a strategic imperative for organisations, digital business transformation requires boundary spanning activities to extend the benefits beyond the focal team itself to the performance of other parties and to the achievement of higher-order organisational and cross-organisational goals (Marrone, 2010). Boundary spanning activities improve coordination effectiveness, scale analytics applications across the organisation, promote innovation, and foster a digital ecosystem for digital business transformation. Below, we explain how boundary spanning activities play a key role in digital business transformation.

Improve coordination effectiveness: Increased collaboration, both internally and externally, is integral to organisations' digital business transformation (Dremel et al., 2017). According to Azzouz and Papadonikolaki (2020), boundary spanning activities at all frequencies (e.g., project, iteration, and ad-hoc), their associated boundary spanning artefacts, and a coordinator role increase explicit coordination effectiveness. For example, Singh et al. (2020) explain the importance of the Chief Digital Officer (CDO) and its coordinator role in spanning the vertical boundary and horizontal boundary through formal (e.g., board meetings) and informal coordination mechanisms (e.g., webinars). These mechanisms performed by CDO facilitate effective cross-unit relationship-building and achieve efficient coordination across an organisation. Dremel et al. (2017) explained that solving the data ownership issues and data transparency issues (as a task coordinating activity) helps to embrace operational transparency and grant access to the data, which fosters a data sharing culture and improves the coordination of business functions across the firm when leveraging operational data for digital business transformation.

Scale analytics applications across the organisation: Someh and Shanks (2013) explain how the success of analytics initiatives in one functional area of an organisation may influence other functional areas to change their values and norms and therefore adopt analytics. This assists with scaling analytics-enabled digital transformation initiatives across the entire organisation. Lighthouse projects and proof-of-concept are valid devices for familiarizing the business with the opportunities arising from digitization and operational business data (Dremel et al., 2017). Moreover, the embeddedness as a boundary spanning activity helps to establish social ties across the organisation based on the analytics-driven culture (Someh & Shanks, 2013). Dremel et al. (2017) exemplify how embedding analytics as an internal competence, cutting across individual IT units and other organisational entities, enables the firm to leverage analytics as a service and evidence-based decision-making, thus assisting digital business transformation.

Promote innovation: Most research on digital business transformation acknowledges the need for firms to engage with other parties to generate digital innovation (Vial, 2019), which always occurs in the context of a community of cooperatives (Harter & Krone, 2001). According to Glaser et al. (2015), a potential key driver of exploratory innovation is boundary spanning, with activities such as scouting helping to reduce knowledge gaps and promote digital innovation for digital business transformation. Searching for new knowledge across organisational and technical boundaries brings in novel and heterogeneous knowledge to accelerate technological advancements (Yang et al., 2021). By creatively combining a diverse set of knowledge, digital business transformation occurs by prompting the emergence of novel ideas, services and products (Pershina et al., 2019).

Foster a digital ecosystem: The collaboration and interaction of a firm with its stakeholders (e.g., customers, suppliers, and partners) in the digital transformation journey result in a digital ecosystem (Pappas et al., 2018). Such ecosystems provide opportunities for organisations to transform their business and create value by engaging with their customers and partners (Suseno et al., 2018). The analytics embeddedness boundary spanning activity can help to establish a digital ecosystem necessary for digital business transformation. For example, by embedding analytics into operations, a firm can better interact with its customers and co-create value with customers (Gupta et al., 2020).

Accordingly, we formulate the following proposition:

P8: *Boundary spanning activities enable digital business transformation by improving coordination effectiveness, scaling the analytics across the whole organisation, promoting innovation, and fostering a digital ecosystem.*

Although analytical information processing capability generates the needed analytical information that supports organisations' digital business transformations, boundary spanning activities elevate the analytical information usage and enable organisations to integrate, exchange, and share the analytical information for digital business transformation. By integrating, exchanging, and sharing the analytical information across the internal and external organisational boundaries, a network effect can be created to improve communication and coordination in the transformation (Khuntia et al., 2022; Papanagnou et al., 2022). Based on Aldrich and Herker (1977), information needs to be summarized and directed to the organisational unit that needs it. It is important for boundary spanning roles to summarize and interpret information and mediate the flow of information between relevant actors in a focal organisational unit and its task environment (Aldrich & Herker, 1977), making each relevant unit get its needed analytical information. According to Beckett (2021), boundary spanning activities facilitate the flow of information across different kinds of boundaries, including geographical, cultural, and organisational. By having boundary spanning activities such as embedding analytical experts into a hybrid team and making analytics reports available to all employees, stakeholders across boundaries can better share and exchange their knowledge and analytical information. This enables the entire organisation to embrace analytics as the key driver for the transformation (Tim et al., 2020). Therefore, we propose:

P9: *Boundary spanning activities foster analytical information usage and sharing and thereby mediate the relationship between analytical information processing capability and digital business transformation.*

5 Discussion

The purpose of this study is to answer the following research question: *How do organisations use analytical information for digital business transformation through DataOps?* By analysing and synthesizing the literature through the lens of OIPT, we develop a conceptual framework that explains how DataOps helps to enable the analytical information processing capability and facilitate boundary spanning activities required for digital business transformation. Below, we discuss the implications of our study for research and practice.

5.1 Implications for research

By integrating the diverse literature on digital business transformation, DataOps and Business analytics through OIPT, our study formulates a new topic of investigation (Cronin & George, 2023; Torraco, 2016), that is, using analytical information for digital business transformation through DataOps, and thereby contributes to research on data-driven digital business transformation. Our framework links business analytics and DataOps with digital business transformation, which extends the current knowledge on digital business transformation by arguing DataOps as a disciplined approach to enabling organisations to use analytical information to achieve such transformation. Organisations need to develop their capabilities to realize the benefit of business analytics on digital business transformation (Setia et al., 2014). Our research contributes to this by proposing analytical information processing capability as the requirement and introducing DataOps as the discipline to build the analytical information processing capability. According to Ranjan and Foropon (2021), business analytics is considered a vital information processing mechanism to reduce uncertainty and equivocality in decision-making processes. Other analytical information processing capabilities have been identified by Anand et al. (2020), such as Online Analytic Processing (OLAP), automated and ad-hoc reporting, social media analytics, and sentiment analytics. Our research extends these studies by explaining the importance of analytical information processing capabilities for digital business transformation and proposes a disciplined approach to develop such capabilities.

One of the key features of digital business transformation is its broader scope. Digital business transformation needs to include various business functions and customers across all value-added chain segments (Schallmo et al., 2017), and as such, digital transformation can be significant and have implications beyond the organisation's immediate value network (Vial, 2019). Our research extends these studies by emphasizing the importance of boundary spanning activities in digital business transformation. Our study explains what boundary spanning activities are needed and how these boundary spanning activities contribute to digital business transformation. Boundary spanning activities such as task coordinating, scouting, embedding, and influencing help to improve coordination effectiveness, scale analytics applications, promote innovations, and foster a digital ecosystem for digital business transformation. Further, boundary spanning activities allow the analytical information to be shared and exchanged across the organisation, enhancing the value of business analytics for digital business transformation.

This paper also contributes to research on DataOps by linking it with digital business transformation through OIPT and boundary spanning activities perspective. Based on Heudecker et al. (2020), the real benefit of DataOps is as a lever for organisational change. Our research aligns with this view of DataOps and indicates that DataOps enables organisations to develop their analytical information processing capabilities for digital business transformation. The principles and practices of DataOps, such as testing and monitoring, automation, continuous improvement, and business value mindset, help to align analytical people, processes, and technologies to generate high-quality analytical information needed in the digital business transformation. DataOps also helps to foster boundary spanning activities for digital business transformation by providing the boundary spanning objects (e.g., code repositories) and communication and collaboration mechanisms (e.g., communities of interests). DataOps is not strictly a technical competency (Heudecker et al., 2020). Instead, DataOps is a discipline that helps organisations leverage business analytics and maximizes the value of business analytics for digital business transformation.

5.2 Implications for practice

First, this research highlights the important role of analytical information in digital business transformation. By using analytics practices and applications, the numerous data generated in the digital world can be transformed into useful analytical information, solving the uncertainties in digital business transformation. Therefore, organisations need to realize the importance and necessity of analytical information and use it throughout their digital business transformation journey. More importantly, rather than viewing analytics simply as a technology, organisations need to build analytical information processing capability that aligns people, processes, and technologies for digital business transformation.

Second, this research provides organisations with ways to manage external and internal boundaries (e.g., the boundary of different business functions) and improve collaboration for digital business transformation. For example, using DataOps, a cross-functional team across the business, IT, and analytics can be established. People in this cross-functional team can act as boundary spanners who connect their original teams with other teams across the organisation. As the joint use of assets or combining resources in a company is value-enhancing (Cao et al., 2019), organisations can adopt the practices from DataOps to foster the joint use of analytical resources across the organisation to drive digital business transformation.

Third, given the potential role of DataOps in fostering the boundary spanning activities for digital business transformation, business analytics vendors need to consider the different needs of users and develop DataOps tools accordingly. In other words, DataOps tools or platforms need to provide a common language that can be understood by people from different backgrounds. DataOps tools should allow different users to work collaboratively to improve the efficiency of teamwork in digital business transformation with business analytics.

6 Conclusions, Limitations, and Future Research

An increasing number of organisations are embarking on their digital business transformation journeys. However, transforming a business digitally and getting value from it is challenging (Davenport & Westerman, 2018). In this study, we develop a conceptual framework that explains how organisations can transform their business by leveraging analytical information through DataOps. Specifically, DataOps provides principles and practices that help organisations develop their analytical information processing capabilities and facilitate boundary spanning activities to share and exchange analytical information for digital business transformation.

Although our research extends the current knowledge on digital transformation by bringing in business analytics and DataOps for digital business transformation through the lens of OIPT, this research has a few limitations that offer opportunities for future research. First, we did not explore the specific analytical information processing capabilities needed for digital business transformation. Future research can explore the role of different types of analytical information processing capabilities, such as descriptive, diagnostic, predictive, and prescriptive analytics (Lepenioti et al., 2020). Second, boundary spanning activities usually include both the activities that enable cross-boundary collaboration and activities that guard the boundary to control the release of information (Ancona & Caldwell, 1990). Our framework focuses on the boundary spanning activities that enable cross-functional collaboration and encourage the sharing and exchanging the analytical information across the organisation. Future research can explore the boundary spanning activities that protect the key analytical information to keep a firm competitive in the market. Third, our framework does not include details on the implementation of DataOps for digital business transformation. Future research can explore the aspects (e.g., technologies, processes, and people) needed to implement DataOps for digital business transformation. In addition, in this study, we only discuss the relevant DataOps principles and practices that play an integral role in the development of analytical information processing capabilities. Future research can focus on building a comprehensive list of DataOps principles and practices in the context of digital business transformation. Finally, we propose a conceptual framework using an integrative literature review. Future research can further develop, refine, and test the proposed framework through in-depth case studies and validate it by conducting a large-scale survey.

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Appendices

Appendix A

Search Terms

No.	Search Terms
1	(“DataOps” OR “Data Operations” OR “Data Operation”) AND (“analytics” OR “analytical information” OR “analytical information processing capability”) AND “boundary spanning” AND “digital transformation”
2	(“analytics” OR “analytical information” OR “analytical information processing capability”) AND “boundary spanning” AND “digital transformation”
3	(“analytics” OR “analytical information” OR “analytical information processing capability”) AND “digital transformation”
4	(“DataOps” OR “Data Operations” OR “Data Operation”) AND (“analytics” OR “analytical information” OR “analytical information processing capability”)
5	(“DataOps” OR “Data Operations” OR “Data Operation”) AND “boundary spanning”
6	(“DataOps” OR “Data Operations” OR “Data Operation”) AND “digital transformation”
7	“Boundary spanning” AND “Digital transformation”

Appendix B

Search Results

	Science Direct	Scopus	AIS E-Library	Web of Science	Google Scholar
Search terms 1	0	0	0	0	1
Search terms 2	50	2	36	2	625
Search terms 3	3611	652	1495	603	28000
Search terms 4	479	28	46	22	61200
Search terms 5	1	0	9	0	22
Search terms 6	30	2	9	0	841
Search terms 7	67	12	67	7	1290

Appendix C

The conceptualisations, explanations, or examples of analytical information processing capability, analytical information, and boundary spanning activities in the context of digital business transformation

Note: This appendix shows all the articles that discussed more than one of these concepts. Articles that only discuss one of the concepts are not included in the table.

Reference	Analytical Information Processing Capability	Analytical Information	Boundary Spanning Activities	Digital Business Transformation
(Conboy et al., 2020)	People, process, technology, and organisational structure that support the usage business analytics techniques	Detailed insights such as stakeholders' sentiment and needs, inefficiencies, customers segmentation that help to improve the business	Forming alliances and joint ventures. Having boundary spanning tools (e.g., interactive dashboards) to share information	Improving operational efficiency, developing new business models and services; and improving firms' competitiveness in the market
(Dremel et al., 2017)	The collection of organisational governance instruments needed to implement big data analytics	Data based insights (e.g., patterns, predictive orders amount, and demographic distribution of customers) that improve information availability and evidence-based decision making	Fostering new ways of intra-organisational collaboration between existing departments and the integration of new departments. (e.g., establishing an innovation hub)	Changing the nature of the company's offerings and value propositions
(Gupta et al., 2020)	Digital analytics capability which consists of firm-related capabilities, consumer-related capabilities, and macro-level capabilities	Superior insights (e.g., new customers insights) for decision makers	Embedding analytics in business processes; interacting with customers and thereby creating more value.	Marketing productivity, operational excellence, customer value growth
(Papanagnou et al., 2022)	Orchestration and management of the data-related resources by the firm	Predictive information (e.g., future sales) and prescriptive information (e.g., price recommendations	Sharing information and knowledge. Coordinating upstream suppliers and downstream customers	Transforming the supply chain management by proactively preparing for emergency situations and preventing and mitigating risks
(Sia et al., 2016)	Analytical systems (e.g., a cognitive cloud-based data analytics solution)	Insights that help managers unpack the complexity of the market and predict customer patterns and needs	Cultivating leadership and investing collaborative technology to facilitate enterprise coordination	Providing new digital customer experiences

(Sebastian et al., 2017)	An operational backbone with a single source of truth for critical data. A digital services platform with analytics engines to covert data into insights	Customer demands; optimized suggestions for operations	Creating cross functional teams	Delivering new digital services; improve customer engagement; and achieve operational excellence
(Tim et al., 2020)	-	Insights (e.g., fail rate and user preference) that help to optimize the game design and maximize user experience.	Broadening use of analytics by embedding analytical experts into a hybrid team and making analytics reports available to all employees	Shifting towards a new business model
(Vial, 2019)	-	Insights that help firms better answer the needs of customers or perform processes more efficiently	Leaders to act as boundary spanners to implement digital business strategy and foster close collaboration between internal business and IT functions and external parties	Providing new services, redefining value networks, and better adapting to the changes in the environment
(Ismail et al., 2017)	-	Insights that support real-time and right decisions	Customer collaboration, cross-channel integration, and information sharing	Transforming the customer experience
(Warner & Wäger, 2019)	-	New customer-centric trends	Fostering a wider internal and external collaboration activities (e.g., knowledge sharing and establishing a digital joint venture)	Renewing of the business model, the collaboration, and the culture of the organisations
(Schallmo et al., 2017)	The usage prediction data-based routing systems	Warning alerts as well as maintenance guidance and recommendatio ns	-	Digitally transforming their business model by developing an innovative maintenance management system
(Cao et al., 2019)	The ability to use analytical practices	-	-	Increasing customer loyalty

	and applications to process data			and empowering employee to act quickly enabled by effective and fast decision making
(Beckett, 2021)	-	-	Representing the views/requiremen ts of the parties involved. Coordinating task requirements. Searching information; Utilising boundary spanning tools	Proactively responding and coping with changes in client expectations and/or accessible technology
(Pershina et al., 2019)	-	-	Adopting digital and non-digital boundary spanning tools to facilitate collaborative work among specialists with different background	Gradually transforming analogue expertise into a novel digital format and creating digital games as digital innovation
(Matt et al., 2015)	-	-	Formulating a digital transformation strategy to integrate the entire coordination	Exploring new digital technologies to transform key business operations and affects products and processes, as well as organisational structures and management concepts.
(Loebbecke & Picot, 2015)	Using big data analytics to analyse and interpret any kind of digital information	Insights that allowed the organisation to adjust their operations proactively	-	Reshaping business models and increasing productivity
(Ashrafi et al., 2019)	A technologically enabled ability that can helps process large volumes of high–velocity data, and several varieties of data insights	New knowledge and actionable insights that help firms react properly to a changing environment	-	Gaining competitive advantage and improving firm performance
(Fleischer & Carstens, 2021)	-	-	Transferring of information and knowledge,	Designing the digital solutions for pre-selected,

			including generic insights into the digitalization of the public sector; Requiring the engagement of various external actors	prioritized services across a wide range of policy areas
(Azzouz & Papadonikolaki, 2020)	-	-	Boundary spanners promote information exchange, knowledge sharing, collaboration, and innovation adoption through boundary spanning objects	Adopting novel digital innovations to digitise processes
(Singh et al., 2020)	-	-	Chief Digital Officer (CDO) acting as coordinator to span the vertical boundary and horizontal boundary through formal (e.g., board meetings) and informal coordination mechanisms (e.g., webinars)	Strategic change of the business
(Harter & Krone, 2001)	-	-	Providing networks of learning. promoting the legitimacy of cooperative forms of organizing, and protecting cooperatives' interests	Embracing innovation and change
(Pappas et al., 2018)	The combination of analytical resources, including big data, technology, technical and managerial skills, data driven culture and organisational learning	-	Data actors (e.g., academia, private and public organisations) in the big data and business analytics ecosystem need to cooperate, coordinate, and collaborate to enable the use of big data towards the achievement	Value creation, business change, and societal change

			of digital transformation and the creation of sustainable societies	
(Suseno et al., 2018)	-	-	Organisations' activities and interactions with stakeholders can create value for digital innovation	Scaling the innovation through data-driven operation, instant release, and swift transformation
(Khuntia et al., 2022)	-	-	Integrating information within and across partner firms. Improved communication and coordination of services,	Being flexible to address changing business environments and customer expectations

Appendix D

A complete list of the 87 reviewed articles

This table below shows the 87 reviewed articles. We cited these articles in Section 2 (Theoretical Background) and Section 4 (Digital Business Transformation through DataOps, A Conceptual Framework).

#	Papers
Academic Articles	
1	Anand, A., Sharma, R., & Kohli, R. (2020). The Effects of Operational and Financial Performance Failure on BI&A-Enabled Search Behaviors: A Theory of Performance-Driven Search. *Information Systems Research*, *31*(4), 1144-1163. https://doi.org/10.1287/isre.2020.0936
2	Ashrafi, A., Zare Ravasan, A., Trkman, P., & Afshari, S. (2019). The Role of Business Analytics Capabilities in Bolstering Firms' Agility and Performance. *International Journal of Information Management*, *47*, 1-15. https://doi.org/10.1016/j.ijinfomgt.2018.12.005
3	Azzouz, A., & Papadonikolaki, E. (2020). Boundary-Spanning for Managing Digital Innovation in the AEC Sector. *Architectural Engineering and Design Management*, *16*(5), 356-373. https://doi.org/10.1080/17452007.2020.1735293
4	Beckett, R. C. (2021). Agile Coping in a Digital World: An Expanding Need for Boundary Spanning. In *Agile Coping in the Digital Workplace* (pp. 119-145). https://doi.org/10.1007/978-3-030-70228-1_7
5	Borges, A. F. S., Laurindo, F. J. B., Spínola, M. M., Gonçalves, R. F., & Mattos, C. A. (2021). The Strategic Use of Artificial Intelligence in the Digital Era: Systematic Literature Review and Future Research Directions. *International Journal of Information Management*, *57*, 1-16. https://doi.org/10.1016/j.ijinfomgt.2020.102225
6	Cao, G., Duan, Y., & Cadden, T. (2019). The Link between Information Processing Capability and Competitive Advantage Mediated through Decision-Making Effectiveness. *International Journal of Information Management*, *44*, 121-131. https://doi.org/10.1016/j.ijinfomgt.2018.10.003
7	Capizzi, A., Distefano, S., & Mazzara, M. (2020). From DevOps to DevDataOps: Data Management in DevOps Processes. In *Software Engineering Aspects of Continuous Development and New Paradigms of Software Production and Deployment: Second International Workshop, DevOps 2019* (Vol. 12055). Springer, Cham. https://doi.org/10.1007/978-3-030-39306-9_4

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