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Developing an effective data-led strategy: managing the enablers

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Abstract

Purpose – Despite that a transformational shift has occurred in many organisations towards data-driven management, many organisations struggle to harness and translate new technology, such as "big data" into a competitive advantage. This study aims to undertake an empirical investigation into the enabling factors which lead to the practice of formulating an effective data-led strategy (EDLS). Leveraging the theoretical lenses of the resource-based view, absorptive capacity and attention-focus view, a range of various factors are hypothesised to influence EDLS.

Design/methodology/approach – The study takes place in South Africa and is based on primary survey data focused on the Fin-tech industry sector where the need to formulate and implement an EDLS has become urgent considering the move to technology enabled banking solutions. Partial Least Squares Structural Equation Modelling (PLS-SEM) is used to test the hypotheses.

Findings – Results highlight that several factors are related to EDLS as significant predictors, which include the data platform, technical skills, knowledge management, transformation and focus-alignment. This latter factor has the largest influence on EDLS, which suggests that the alignment of focus across multiple firm divisions both vertically and horizontally significantly enables an EDLS.

Practical implications – Managers need to appreciate the intricacy of the range of factors involved in enabling an EDLS. Managers are advised to grow their organisational knowledge regarding which enablers offer the best pathway towards the development of a more robust framework when putting an EDLS into practice.

Originality/value – The article offers new insights into better understanding the relevant antecedents which enable the successful practice of an EDLS from an African emerging market perspective.

Keywords Effective data-led strategy, Resources, Attention-focus, Absorptive capacity, Management, Emerging market

Paper type Research paper

Introduction

In an era of constant disruption and digital transformation, the challenge for most organisations is to continuously manage and translate modern technology developments into a competitive advantage (Behl, 2022; Dana *et al.*, 2022; Wrede *et al.*, 2020). Several scholars and practitioners argue that a transformational shift has occurred in organisations towards data-driven insights, which now drives their strategy formulation and implementation initiatives across different domains (Grover *et al.*, 2018; Shan *et al.*, 2019; Wang *et al.*, 2018). Recognising such developments, it has been noted that research requires a "re-orientation" to achieve future understanding of data-driven decision making, containing emerging topics on information technologies such as artificial intelligence (AI), blockchain technology, big data (BD) and big data analytics capabilities (BDAC) (Elgendy *et al.*, 2022; Lv *et al.*, 2023; Ulrich *et al.*, 2023). For instance, increasing research shows that the coexistence of AI supported systems with human decision makers invariably leads to more "intelligent" data analysis, which supports and enhances decision making (Elgendy *et al.*, 2022; Grover *et al.*, 2018; Lenart-Gansiniec *et al.*, 2023; Lv *et al.*, 2023). Furthermore, focussing on future data-driven decision making not only advances theory, but is also highly relevant for management

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strategy and practice. In this regard, studies reveal that data-driven organisations have a higher potential to attract new customers, are more likely to generate higher profits, and obtain superior value creation as a result of adopting an effective data-led strategy (EDLS) (Dubey *et al.*, 2019; Ghasemaghaei, 2019; Hausberg *et al.*, 2019). Consequently, we build on in this research direction by empirically examining the relevance of key enablers as determinants of an EDLS (Mikalef *et al.*, 2019).

The management literature demonstrates that digital transformation necessitates a change in the management decision-making context (Truant *et al.*, 2021; Wamba *et al.*, 2017), which requires developing resources and capabilities, while using data as an effective decision enabler (Wrede *et al.*, 2020). Prior studies suggest that the enablement of an EDLS is dependent on key enablers such as the firm's resources and specialised skills (Mikalef *et al.*, 2019), where each of these resources and capabilities require varying degrees of transformation to drive any intended strategic change in the organisation (Frisk and Bannister, 2017). However, several studies indicate that there are several challenges when employing an EDLS, including a lack of relevant resources, capabilities and technical knowledge, as well as operational concerns such as adaptive learning and quantifying all the required activities (Hamilton and Sodeman, 2020; Mikalef *et al.*, 2019; Palmié *et al.*, 2016). Moreover, research reveals that given the newness of resources and capabilities associated with BD, the requisite levels of capacity and skills are often missing when developing an EDLS, as many organisations remain stuck in a loop of underinvestment in terms of developing requisite enablers for an EDLS (Wamba *et al.*, 2017; Wang *et al.*, 2018).

Despite the hype surrounding BD, the issue of examining whether, and under what conditions, BD investments produce value, remains underexplored, severely hampering their strategic potential (Iranmanesh *et al.*, 2023; Palmié *et al.*, 2016). We see this research gap as an opportunity to provide a deeper empirical understanding of the relevant antecedents influencing an EDLS. While prior studies have focused on the wider spectrum of elements critical to the success of BD, they do not include specific organisational resources and capabilities that are required to transform BD into an EDLS (Mikalef *et al.*, 2019; Singh and Del Giudice, 2019). Subsequently, in order to contribute to this promising stream of literature, while prompting broader discussions for practical management purposes, we formulate the study research question as: To what degree do organisational resources and capabilities, absorptive capacity and attention-focus capabilities influence an EDLS?

In terms of a theoretical contribution, the article adds to the emerging stream of research on the concept of BDAC which has gained much traction over recent years due to its promise of enabling organisational transformation (Mikalef *et al.*, 2019; Xie *et al.*, 2018). While scholars have formulated conceptual links between BDAC and provided links with innovations and firm performance (Wamba *et al.*, 2017), we focus instead on previously unrelated phenomena to obtain a more nuanced understanding of EDLS. In order to achieve this, we build on existing theoretical foundations where different dimensions of resources and dynamic capabilities have been shown to effect competitive advantage, in direct and indirect ways (Behl, 2022; Singh and Del Giudice, 2019).

Acknowledging the future context of data-driven decision making we employ the resource-resource-based view (RBV) of the firm insofar dynamic capabilities enable firms to develop and reconfigure their resources and capabilities in the face of changing conditions (Barney, 1991; Teece *et al.*, 2016). As such, in recognising that dynamic capabilities in relation to the RBV can be leveraged by means of BD (Gaglio *et al.*, 2022; Hausberg *et al.*, 2019), our article makes an original contribution to the management literature by empirically testing links between previously unrelated theories and EDLS. These theories include examining enablers of an EDLS through the perspectives of the absorptive capacity theory (ACAPT) (Xie *et al.*, 2018), and the attention-based view (ABV) (Palmié *et al.*, 2016). Furthermore, we connect these phenomena with practical management issues and anticipate a novel, well-rounded and more holistic understanding of antecedents influencing EDLS.

Our study also provides methodological contributions, insofar EDLS is proposed as a multidimensional third-order latent construct, affected through influences of the latent second order constructs of (1) resources, (2) absorptive capacity and (3) attention focus (Hausberg *et al.*, 2019). These constructs are modelled as independent precursors influencing EDLS. This framework is further conceptualised through eleven first order sub-dimensions with respective measurement items which are empirically tested using partial least squares structural equation modelling (PLS-SEM) (Hair *et al.*, 2017). In terms of practical implications, the finalised structural model provides management practitioners with a set of reliable and valid predicters, which lays the tracks for the successful practice of an EDLS.

A further contribution of the study is that it takes place in an emerging market context, South Africa which is one of Africa's most sophisticated economies (Urban, 2020). Nonetheless, South Africa "also has one of the highest inequality rates in the world" and a crucial priority is to foster technological development to improve the country's competitiveness and socio-economic development (Dana *et al.*, 2022; Urban, 2020). Focussing research on practical problems in the African context provides an important contrition to the research stream of management decision-making, since organisations in these countries often lack digital resources and capabilities (Urban, 2020).

The article starts with a brief review of the relevant theoretical foundations upon which hypotheses are formulated. Methods are then described, and data is analysed and discussed. The article ends with insights made in terms of conclusions and managerial implications.

Literature review

Theoretical background on EDLS enablers

The relevant theoretical underpinning, which serves as foundational assumptions for the study hypotheses, is the RBV of strategy, where ultimately, strategic management is about creating value and maintaining "sustained competitive advantage" (SCA) (Barney, 1991; Hausberg *et al.*, 2019). Across the management literature studies view RBV as the "firm's ability to utilise and leverage its internal organisational resources such as assets, capabilities, processes, managerial attributes, information and knowledge to create a competitive advantage and ensure superior financial performance" (Barney, 1991). Resources and capabilities are the core components of RBV, and have received a great deal of attention in past studies (e.g. Mikalef *et al.*, 2019). Deriving from the Schumpeterian reasoning of creative destruction, dynamic capabilities enable firms to "integrate, build and reconfigure their resources and capabilities in the face of changing conditions" (Teece *et al.*, 2016). The theoretical and empirical literature associated with the microfoundations of dynamic capabilities has developed rapidly according to Chen *et al.* (2023), who highlight that research on culture and leadership, combined with data-driven topics are valuable for our understanding of the microfoundations of dynamics capabilities. Indeed, the conversion of resources into potentially strategic assets via the development of firm-specific capabilities has proven that insofar capability-building is concerned with the orchestration and management of these resources into strategically useful assets, managers can effectively deal with changes not the least of which is technological knowledge, capabilities and expertise (Bharadwaj, 2000; Teece *et al.*, 2016). As such, the dynamic capabilities view is matched in relation to the RBV by explaining the rent-yielding properties of organisational capabilities that can be leveraged by means of BD (Gaglio *et al.*, 2022; Hausberg *et al.*, 2019).

Past studies on information technology (IT) have focused on capabilities to refer to the broader context of the firm's ability in leveraging and mobilising the different resources and capabilities (Bharadwaj, 2000). More recently studies emphasise that new digital technologies, such as BD, must be developed through digital capabilities in order to succeed and boost their performance (Behl, 2022; Gaglio *et al.*, 2022). The notion of BD capability incorporates all related organisational resources that are important in leveraging BD to their full strategic potential (Mikalef *et al.*, 2019; Xie *et al.*, 2018). Furthermore, BDAC are a critical part of decision-making processes due to advanced modelling (Wamba *et al.*, 2017), where research shows that rather than simply seeking greater "volume, variety, or velocity with BD investments, decisions by learning organizations are based on the principles that greater data flows will translate to increased veracity, variability, viability, visualization, and value of data stocks" (Jha *et al.*, 2020; Mazzei and Noble, 2019). Sabharwal and Miah (2021) provide a model showing links between BDAC and organisational development theory and illustrates how it affects organisational development in terms of organisational capacity, culture and climate, and their future resources. Relatedly, Huang *et al.* (2022) formulate a theoretical framework from the perspective of RBV and in their framework BDAC is the antecedent variable and has two forms BD management capability and BD technology capability. Findings emanating from their study show that BD technology capability only has a direct effect on resource bricolage, while BD management capability has a stronger effect on resource optimisation than that on resource bricolage. Investigating BD-assisted decision-making technology and BD intelligent decision-making technology, Liu *et al.* (2023b) demonstrate how these technologies improve supply chain resilience.

Nonetheless, research relating to specific antecedents and consequences of managing BD as an EDLS is limited (Gupta *et al.*, 2022) and despite the enormous influence of BD transformation on firms, literature remains negligible on these developments (Wrede *et al.*, 2020). Explanations for this deficiency of research suggest that BD is a somewhat contemporary phenomenon and such fast-paced transformation often obstructs the proper study of EDLS (Hausberg *et al.*, 2019). To overcome such obstruction, we attempt to close the research gap on EDLS, in the context of model testing where a valid empirical model which identifies relevant resources and capabilities required for an EDLS to succeed would be valuable (Mikalef *et al.*, 2019). To achieve this our model is structured on solid theoretical foundations upon which all relevant resources and capabilities can be identified and valued, as we examine specific enablers through the lens of the RBV, the ACAPT and the ABV. In this regard we argue that firm-specific and idiosyncratic resources underpinning an effective EDLS means firms need to recognise the value of developing enablers in the form of resources and capabilities to effectively manage an EDLS (Ghasemaghaei, 2019; Grover *et al.*, 2018).

Furthermore, based on the different theoretical perspectives which we have identified, which serve as key enablers underpinning the formulation of an effective EDLS strategy (Palmié *et al.*, 2016; Zahra and George, 2002), we acknowledge that the actual process of how an EDLS is shaped is multifaceted. As such, it is argued that no single BD application can singularly deliver an effective EDLS. Rather, what is important is to infuse key enablers into the organisational fabric, in our case this encompasses the ACAPT and ABV. In this sense we anticipate that by focussing on specific resources and capabilities as potential antecedents to developing an EDLS, new research avenues will emerge for the development of more complex conceptual frameworks and models applicable to scholars and practitioners. These key EDLS enablers, as informed by theory, are now discussed in relation to how they inform each of the study hypotheses.

Resources as an EDLS enabler

In the context of BDAC, factors such as BD as an asset, data infrastructure, technical skills of employees and data culture, can be considered relevant resources from the RBV perspective (Dubey *et al.*, 2019; Ghasemaghaei, 2019; Wamba *et al.*, 2017). Research highlights that technology, specifically in the form of data infrastructure, is a critical resource that requires integration with the organisation's IT landscape, to manage data assets and facilitate value creation and enable an EDLS (Grover *et al.*, 2018). Similarly, BD analytics capabilities have been reported to have a positive and significant impact on firm performance and competitive advantage (Behl, 2022). Indeed, BD is often considered a fundamental resource and asset, required for enabling a data-led strategy (Ghasemaghaei, 2019).

Furthermore, to enable an EDLS, technically skilled personnel such as data analysts, data scientists and data engineers, are critical components when developing a BDAC, even though they are often considered to be rare firm resources (Ghasemaghaei, 2019). At a technical level, IT skills are required to manage the vast, complex, structured and unstructured nature of data, in order to generate insights for a successful EDLS (Liu *et al.*, 2023a; Wang *et al.*, 2018). Such a focus on skills and capabilities require a close integration with legacy IT infrastructure and systems to interact with EDLS platforms and systems (Hausberg *et al.*, 2019).

Moreover, challenges that often arise in relation to EDLS implementation are leadership based, which are critical in driving organisational transformation towards a change in culture and norms to build data capabilities (Wang *et al.*, 2018; Wrede *et al.*, 2020). Studies indicate that the ability to drive an EDLS requires an appropriate organisational culture (Frisk and Bannister, 2017), where the firms' employees need to appreciate the simultaneity of exploratory and exploitative learning as key capabilities (Urban and Townsend, 2021). Appreciating that in the context of BDAC, from a RBV perspective, firm-specific and distinctive resources are necessary for an EDLS, it is hypothesised that:

H1. Firm resources positively influence an EDLS

Absorptive capacity as an EDLS enabler

Cohen and Levinthal's (1990) ground-breaking work on ACAPT proposes that an organisations' value creation depends on their ability to absorb added information and effectively build a capability in this respect. Studies suggest that ACAPT is best positioned as an enabler to EDLS insofar "knowledge acquisition and assimilation, transformation, exploration and exploitation" have all emerged as relevant factors when aligning ACAPT with BD (Xie *et al.*, 2018). Firms which embrace a learning perspective in terms of knowledge management view BD not only as an available resource to be exploited for improving their competitive position, but also anticipate any opportunities related to such use of data (Solís-Molina *et al.*, 2018).

In the context of EDLS, knowledge acquisition is concerned with using new information to drive or enable strategy execution, where organisational ACAPT is influenced by the direction, speed and intensity of these efforts (Xie *et al.*, 2018). Prior studies indicate that ACAPT, as a measure of the ability to recognise, obtain and understand the value of external knowledge, is often beset with challenges. Such challenges emerge when using business analytics and the firm has to deal with issues related to adaptability of employees, the reliability and validity of market segmentation, and information systems issues (Hamilton and Sodeman, 2020; Liu *et al.*, 2023a). To counteract some of these challenges the most effective approach to building an EDLS usually starts, not with the data, but with identifying an opportunity through a robust organisational ACAPT and determining how the EDLS model can improve performance. Such hypothesis-led modelling generates faster outcomes and establishes the EDLS model in practical data relationships that are better understood by managers (Jha *et al.*, 2020; Mazzei and Noble, 2019). Firms need to be adept at not only consuming external data assets but also obtain external knowledge through the process of deep understanding, thereby leveraging this knowledge to enhance their organisational competitive advantage (Xie *et al.*, 2018). This involves knowledge transformation which is associated with the ability to transform knowledge and relies on the organisations capacity to add new, remove old or combine new and old knowledge, which in turn creates capacity for organisations to absorb new knowledge (Xie *et al.*, 2018).

Consequently, in recognising that the ability for organisations to absorb added information and leverage it via assimilation, transformation, exploration and exploitation, in other words develop organisational ACAPT which leads to the development of an EDLS, it is proposed that:

H2. Absorptive capacity positively influence an EDLS

Attention-focus capabilities as an EDLS enabler

The ABV in organisational studies is focused on the cognitive process of choosing to focus on certain information while considering the trade-off in what information to ignore (Ocasio *et al.*, 2018). Attention is finite in nature hence the choice of where to focus is crucial to drive the allocation of organisational resources (Ocasio *et al.*, 2018). Prior studies show that organisations manage attention through three related concepts namely of how attention is focused, the situation surrounding it and how structure influences the distribution thereof. Often within organisations, the focus of decision-makers is directed towards the areas they want to influence and the spaces in which they execute their decision-making (Ocasio *et al.*, 2018).

However, given the limited capacity that decision-makers have in an era of digitalisation and the plethora of areas that require attention, the decision of where to focus attention needs to be affiliated with the strategic direction of the firm. The basic premise of the ABV is that situational factors of the decision-makers drive the focus of attention and that these situational factors are a result of organisational structural and operational choices in relation to the positioning of decision-makers (Ocasio *et al.*, 2018; Palmié *et al.*, 2016).

In the context of an EDLS, Liu *et al.* (2022) examine the effective use of industrial BD in the process of digital transformation by focussing on the "technology affordance–actualization process". Such research reveals the importance of ABV from the perspective of increasing the transient advantage of the firm. This notion can be interpreted in the sense that the concentration of attention can change given the need for adapting to different situational environments, where such varying situations alter the focus of decision-makers, thus leading to a focus of attention given to a particular context (Palmié *et al.*, 2016). Furthermore, organisational structures and channels have been proposed to impact the distribution of attention as they relate to issues of coordination and collaboration. In this regard, the channels for communication prevalent in an organisation can promote or inhibit the focus of attention (Ocasio *et al.*, 2018). Consequently, in relation to an EDLS the ability to react to dynamic markets requires organisations to be innovative and formulate the practice of acquiring new knowledge and develop an ability to leverage it, in order to exploit opportunities (Wrede *et al.*, 2020). Based on these findings and different streams of research which highlight how the ABV can be aligned with an EDLS, the last hypotheses is formulated as:

H3. Attention-focus positively influence an EDLS

Research design

A quantitative, cross-sectional, survey-based research design was used to gather specific data based on the hypothesised relationships. This approach allowed for statistical testing of the hypotheses. More specifically we tested the theoretical model by collecting survey data from top and senior management located at firms in South Africa in the financial-technology (Fin-tech) sector. Digitisation is disrupting the traditional financial services sector, particularly as Fin-Tech firms need to improve their data efficiencies as well as be more innovative in offering new products, services and methods of delivery (Urban and Townsend, 2021). Hence, the rationale for focussing on the Fin-tech industry sector is that the need to formulate and implement an EDLS has become urgent particularly with the move to technology enabled banking solutions (Kyari *et al.*, 2021).

Sampling

We randomly selected firms from relevant Fin-tech sampling frames and databases such as the "South African Chamber of Commerce and Industry, and the Johannesburg Chamber of Commerce and Industry," all of which are available to the public and which provided convenience for our centralised survey. The sampling selection criteria included (a) employees that are decision-makers within the organisation regarding data strategy, allowing us to get a sense of how their resource and capabilities are utilised and how their attentions are focused (Ocasio *et al.*, 2018) and (b) who are collaborators to an EDLS (Mikalef *et al.*, 2019; Palmié *et al.*, 2016).

Ethical concerns were addressed by "safeguarding the respondents' privacy, where confidentiality was respected at all times." To ensure that the instrument has satisfactory face and content validity, a preliminary analysis via a pilot study was undertaken where contact was made via email and telephone to arrange survey completion with six top and senior managers of different firms. This procedure ensured that the respondents had no difficulties in answering the questions and there was no problem in recording the data.

The minimum sample size was calculated based on the requirement suggested by the proposed multivariate statistical technique of PLS-SEM (Hair *et al.*, 2017). Imputation was used where possible based on industry averages and responses with less than a 50% completion rate were discarded. Of the 440 questionnaires that were disseminated, 192 were returned, of which 107 were valid, with no missing information. Sample characteristics reveal that in terms of firm size (number of full-time employees) the majority (76% of sample) had between 201–500 employees, while in terms of firm's age from the number of years since its founding, the majority (83% of sample) were established 6–10 years ago. This was not surprising considering the relative maturity associated with BDAC in these industries (Mikalef *et al.*, 2019). In terms of non-response bias, a comparison of participating and nonparticipating firms in relation to their size and age indicated no significant differences. There was also no "statistically significant difference" in model variables between early and late respondents.

Measures

Existing measurement scales were used to collect responses and have been adapted for relevance to the EDLS context. A "Likert 5-point scale ranging from 1 = strongly disagree to 5 = strongly agree" was used and we asked each respondent to evaluate his or her firm's levels of resources, absorptive capacity and attention-focus capabilities in terms of different dimensions related to each of the study construct and in line with each of the hypothesis. Refer to Table 2 for a list of the reflective constructs.

Firm resources were operationalised in terms of four dimensions relating to (1) Data infrastructure (4 items); (2) Technical skills (4 items); (3) Big Data platform (4 items) and (4) Data culture (4 items) (Ghasemaghaei, 2019; Wamba *et al.*, 2017).

Absorptive capacity was operationalised in terms of four dimensions relating to (1) Knowledge acquisition (4 items); (2) Knowledge assimilation (3 items); (3) Knowledge transformation (4 items) and (4) Knowledge exploitation (3 items) (Xie *et al.*, 2018).

Attention-focus was operationalised in terms of three dimensions relating to (1) Focus alignment (4 items); (2) Situation (4 items); (3) Structure and channels (4 items) (Palmié *et al.*, 2016).

In terms EDLS this construct was operationalised as a multidimensional third-order latent construct, influenced by the latent second order constructs of resources, absorptive capacity and attention-focus. This framework was further operationalised in terms of the abovementioned eleven first order sub-dimensions.

Only relevant profiling data was collected, such as firm size and firm age, as prior studies indicate that firm size and age to be relevant to a firm's strategic and operational outcomes, as larger firms may have more capacities to engage in BD activities (Hausberg *et al.*, 2019).

Data analysis techniques

Based on the operationalisation of the study measures, a finalised structural model was confirmed and the significance of the path model assessed. Path linkages between the selected first and second order constructs were tested against the EDLS. Both the outer (measurement) and inner (structural) models were subjected to reliability, validity and collinearity testing, respectively (Hair *et al.*, 2017). This model was then subjected to an overall model fit analysis, verifying the accuracy of the factors. Smart PLS 3.0 was adopted to assess the research model, which has been utilised in previous research within the BD domain (Wrede *et al.*, 2020).

Results

Reliability and validity testing

Scale development for EDLS was undertaken using principal component analysis (PCA) to understand the prominent factors from the data, in comparison to the proposed factors derived from the literature, as detailed in Table 1. The "Kaiser Meyer Olkin (KMO) values and the Bartlett's test for sphericity" were also calculated as prerequisites for running a factor analysis. To determine the factors that should be retained, any factor with "Kaiser's Eigenvalue" less than one was be discarded and the Varimax rotational method was adopted to improve the validation and interpretability of the PCA analysis (Hair *et al.*, 2017). See Table 1 for the PCA results which show KMO measures for all second order constructs all over the 0.5, threshold indicating sampling adequacy of the composed measured variables. Bartlett's test also proved significant with $p < 0.05$ for all second orders constructs allowing for a PCA. The factor compositions for the final research model were modified based on the PCA results and the composition of measured variables was reduced accordingly.

The PLS-SEM outer model was first assessed for internal reliability through "Cronbach's Alpha (CA) as well as the Composite Reliability (CR)" method considering some of the shortcomings presented on Alpha values when utilising PLS-SEM (Hair *et al.*, 2017). A lower

Construct	Resources	Absorptive capacity	Attention
Sample size	54	54	54
Number of items	14	14	6
KMO	0.81	0.86	0.64
Bartlett's test	0.00	0.00	0.00
% Variance extracted	67.17	70.97	62.20
Number of factors extracted	3	2	2

Source(s): Table by authors

Table 1.
PCA analysis results

bound score of 0.7 (on a scale from 0 to 1) was required to ascertain acceptable levels of reliability of a composite variable (Hair *et al.*, 2017). The results are summarised in Table 2. While CR is the preferred mechanism, the table compares the results to CA, to illustrate the differences. All items with an overall loading of less than 0.7 were removed from each relative first order construct due to poor reliability of the measurement items. The first order constructs of "knowledge acquisition and knowledge assimilation," merged in one construct named as knowledge management. In summary seven constructs were retained that constitute the first order hypothesised model were data culture, BD platform, technical skill, knowledge management, knowledge transformation, focus alignment, structure and channels.

"Convergent and discriminant validity of the PLS-SEM model was assessed using methods" described by Hair *et al.* (2017). For convergent validity to be achieved the "measured variables factor loadings, on its respective latent variables, needed to exceed 0.708. In addition, the Average Variance Extracted (AVE), which is the square root of the standardised indicator loading, had to be greater than 0.5 for convergent validity". The results are presented in Table 2 where the elimination of specific items was made due to poor loadings on the extracted components. The overall model had a first order dimension reduction to seven, first order constructs, detailed by the number of factors extracted, as illustrated in Table 2. The AVE for all the first order latent constructs ranged between 0.58 and 0.82, which exceeded the minimum thresholds of 0.5. All measured variable factor loadings exceeded the limit of 0.7 and an overall average of 0.81 confirmed that the hypothesised model demonstrates convergence in measuring the EDLS construct.

Reflective constructs	Items	Loadings	CA	CR	AVE
Data Culture	DC1	0.85	0.79	0.88	0.7
	DC2	0.87			
	DC4	0.79			
Big Data Platform	BDA2	0.76	0.84	0.88	0.6
	BDA3	0.79			
	DI1	0.80			
	DI4	0.77			
	TS4	0.76			
Technical Skill	TS1	0.92	0.89	0.93	0.82
	TS2	0.90			
	TS3	0.88			
Knowledge Management	A4	0.78	0.86	0.89	0.58
	AK1	0.75			
	AK3	0.74			
	E1	0.75			
	E4	0.78			
	T1	0.79			
Transformation	E3	0.83	0.84	0.89	0.68
	T2	0.85			
	T3	0.80			
	T4	0.82			
Focus Alignment	SC1	0.86	0.71	0.87	0.77
	SC2	0.90			
Collaboration and Coordination	SC3	0.90	0.74	0.88	0.79
	SC4	0.99			
	Average	0.83	0.81	0.88	0.71

Source(s): Table by authors

Table 2.
Reliability and validity measurement overview

The Heterotrait-Monotrait (HTMT) criterion measures the degree of difference between a hypothesised construct and others in a research model (Henseler *et al.*, 2015). Thus, the HTMT criterion was used to ensure that no discriminant validity issues were present in the research model. If correlations between constructs are less than 0.9, it implies that the specific construct is relatively unique from the others in the model and captures its hypothesised essence (Hair *et al.*, 2017). See Table 3 where the interpretation of the discriminant validity tests (HTMT) output indicated that no correlations exceeded 0.9 as per the recommended threshold (Henseler *et al.*, 2015). The highest correlation was the relationship between focus alignment and collaboration and coordination at 0.85, which is indicative of the initial grouping of these observed variables.

Based on these satisfactory results both the convergent and discriminant validity for the outer model was established. In this regard, our study makes a solid contribution to the management literature insofar that although the original scales had primarily been used primarily in developed economies; they have now been validated in an African market context allowing researchers to conduct replication studies in other similar emerging market contexts.

Model assessment

For the hypothesis testing, the structural model was evaluated to determine the links between the study constructs. As the PLS-SEM technique is rooted in ordinary least square prediction and the maximisation of dependent variable variance, levels of collinearity need to be assessed (Hair *et al.*, 2017). High levels of collinearity can lead to predictor variable bias and create unstable path linkages. Henseler *et al.* (2015) recommend the assessment of the variation inflation factor (VIF) which is interpreted as the inverse of tolerance. The inner model was assessed for collinearity through the assessment of the VIF with obtained values ranging between 1.42 and 3.50, well below the threshold of 5.0. Hence, the model shows no evidence of collinearity issues.

Given confirmation on the outer model and the constructs with associated measured variables, "descriptive statistics" were calculated where the highest mean score was 2.89 and the lowest was 2.24, with relatively low standard deviation of below 1.00 across constructs (not shown). This suggests that both the first and second order constructs were clustered around the mean of the scales adopted and there were no significant outliers noted with a standard deviation within the bounds of ± 3 (Hair *et al.*, 2017). Once the outer and inner models were evaluated as acceptable, the path models were assessed for significance. The significance of each path weighting was assessed with the bootstrap method at a chosen significance level of 99%.

Model fit for the research model was verified by assessing the standard root mean square (SRMR), coefficient of determination (R^2) and Stone-Geissers Q^2. SRMR is an evaluation between the discrepancies of the observed and expected relationships where an upper limit of 0.10 is recommended for a good model fit (Hair *et al.*, 2017). The Stone-Geissers indicator evaluates the relative predictive relevance, especially suited for a reflective model (Henseler *et al.*, 2015). The Stone-Geissers value ranges from 0 to 1, whereby values greater than 0.35 is classified as a large effect, between 0.15 and 0.02 is medium and less than 0.02 is weak (Hair *et al.*, 2017). See Table 4. In this regard, the overall model fit was adequate, as suggested by the SRMR value of 0.10.

Based on the combined outputs from the PCA and validity evaluation, the refined structural model is presented in Figure 1 which was used to prove or disprove the research hypotheses. While the first order constructs were refined, no new measurement items were introduced into the refined model. This refined model was assessed to determine the overall model fit and predictive determination. In Table 4 and it is notable that the model provides

Table 3.
HTMT results for the measured variables

Reflective constructs	Data culture	Big data platform	Technical skill	Knowledge management	Transformation	Focus alignment	Collaboration and coordination
	HTMT results						
Data Culture	–						
Big Data Platform	0.75	–					
Technical Skill	0.6	0.78	–				
Knowledge Management	0.55	0.68	0.49	–			
Transformation	0.51	0.52	0.51	0.84	–		
Focus Alignment	0.43	0.54	0.42	0.67	0.62	–	
Collaboration and Coordination	0.36	0.49	0.27	0.46	0.56	0.85	–

Source(s): Table by authors

Construct	Stone-Geiser's	Coefficient of determination (R^2)	Beta	Std. Dev	*t*-value	*p*-value	Hypotheses supported/not supported
Data Culture	0.41	0.62	0.788	0.055	14.248	0.00*	supported
Big Data Platform	0.46	0.87	0.935	0.013	70.069	0.00*	supported
Technical Skills	0.54	0.70	0.841	0.039	21.528	0.00*	supported
Knowledge Management	0.48	0.90	0.949	0.011	83.162	0.00*	supported
Transformation	0.52	0.81	0.901	0.028	32.077	0.00*	supported
Focus Alignment	0.60	0.81	0.905	0.023	38.389	0.00*	supported
Coordination and Collaboration	0.61	0.80	0.900	0.023	39.733	0.00*	supported
Resources	0.38	0.83	0.910	0.018	51.352	0.00*	supported
Absorptive Capacity	0.33	0.67	0.818	0.037	21.818	0.00*	supported
Attention	0.25	0.44	0.660	0.073	9.088	0.00*	supported

Note(s): *$p < 0.01$
Source(s): Table by authors

Table 4. Structural model assessment summary

many highly significant positive effects in terms of beta values: data culture ($\beta = 0.78$, $p < 0.01$), BD platform ($\beta = 0.93$, $p < 0.01$), technical skills ($\beta = 0.84$, $p < 0.01$), knowledge management ($\beta = 0.46$, $p < 0.01$), transformation ($\beta = 0.94$, $p < 0.01$), focus alignment ($\beta = 0.90$, $p < 0.01$), coordination and collaboration ($\beta = 0.90$, $p < 0.01$), resources ($\beta = 0.91$, $p < 0.01$), absorptive capacity ($\beta = 0.81$, $p < 0.01$), attention ($\beta = 0.66$, $p < 0.01$). In addition, the results in Table 4 show that all the t-values were higher than 1.96. Based on the *p* values, significant influences from all constructs were observed, and the study hypotheses supported, see Table 4. The Q^2 value for most first order and second order constructs is shown to be greater than 0.35, therefore indicating a large effect size with a medium effect from “attention”, however there is predictive relevance with all constructs in the model. Further to this, the R^2 values all show a relevant variance in the related constructs with “knowledge management” creating the largest variance as a second order construct “absorptive capacity” with an R^2 of 0.90, while “resources” shows the largest variance in EDLS with a R^2 of 0.83.

From the structural model, all path loadings show a positive relationship with related constructs, including for “data culture to firm resources,” and between “knowledge management to absorptive capacity,” and “focus alignment to attention-focus,” thus indicating strong relationships and providing partial support for H1, H2 and H3.

The structural model that shows that the most significant variance in “resources, absorptive capacity and attention-focus” is a result of “big data platform, knowledge management and focus alignment” respectively, based on the associated R^2. These very same first order constructs also had the most significant influence on their related second order constructs, based on respective path coefficients. Further to this, the largest variance in EDLS is because of ‘firm resources.

Discussion

The findings in relation to each study hypothesis are discussed and interwoven with the various theoretical perspectives, as examined through the lens of the RBV, ACAPT, ABV, to highlight how distinct enablers act as important determinants for an EDLS.

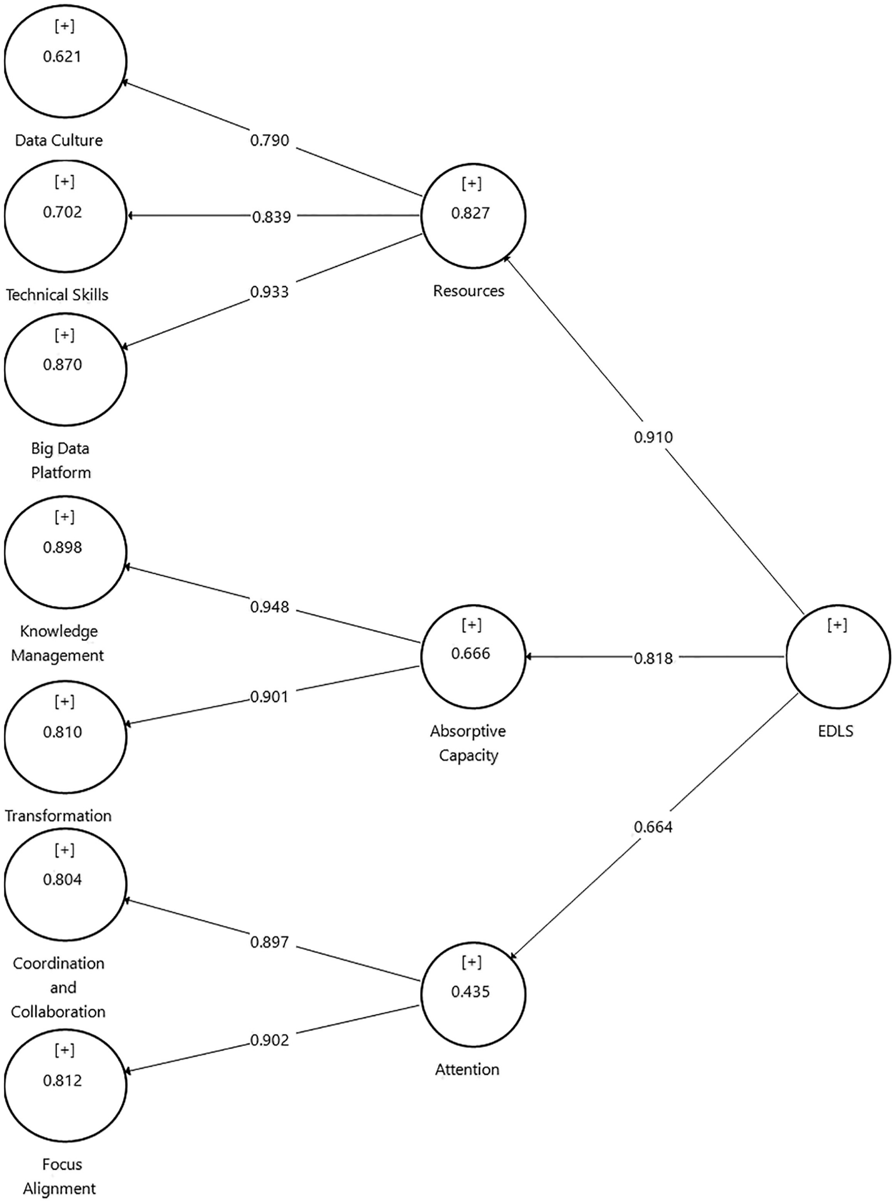

Figure 1.
EDLS structural model

Source(s): Figure by authors

In terms of H1, resources as enablers of an EDLS were examined through the RBV lens, which posits that a firm's ability to utilise and leverage off of its internal organisational resources such as assets, capabilities, processes, managerial attributes, information and knowledge can create a SCA (Barney, 1991). Our findings show that four first order constructs were significant predictors of an EDLS, namely BD, data infrastructure, technical skills and data culture (Dubey *et al.*, 2019; Wamba *et al.*, 2017). However, through more complex structural model testing, it was concluded that only data culture and technical skills remain as significant positive enablers to EDLS, providing partial support for H1. However, in the structural model the combination of BD and data infrastructure lead to the formation of BD platform as a singular construct. Furthermore, this construct of BD platform had the most considerable influence on EDLS, furthering the reach of the RBV insofar it is the combination of both data infrastructure together with the BD asset which provides an overall strategic resource that enables EDLS. These findings are generally congruent with the RBV where the ability to drive an EDLS requires relevant technical skills, and a supportive organisational culture founded on integrating the simultaneity of exploratory and exploitative learning and capability (Frisk and Bannister, 2017). Similar to other studies in the BD domain, our findings show that skills and IT infrastructure are required to manage EDLS, as well as the importance of integration with legacy IT infrastructure and systems to enable successful interactions with EDLS platforms (Wang *et al.*, 2018).

With respect to H2, findings reveal that EDLS is facilitated by the organisation's absorptive capacity. Hence H2 is supported. Based on the ACAPT, researchers such as Xie *et al.* (2018) note that the ability to "acquire, assimilate, transform and exploit knowledge", are necessary first order constructs in relation to relying on absorptive capacity to foster an EDLS. Accordingly, based on our positive and significant findings, theory is advanced in terms of the study model, insofar the construct of transformation showed a linkage to absorptive capacity, and knowledge management in relation to BD. This finding resonates with prior research which emphasises how knowledge transformation is associated with the capabilities within an organisation that develop or create a new process to combine new knowledge for strategic change (Xie *et al.*, 2018). An important contribution to ACAPT is that the knowledge management construct in the study model showed the most significant influence on absorptive capacity, based on the path coefficient and coefficient of determination, suggesting that knowledge management, is required to impact absorptive capacity in relation to EDLS.

The results for attention-focus, as a means of driving EDLS (H3), is aligned with theory where prior research (Palmié *et al.*, 2016) indicates that attention-focus alignment, situational as well as structures and channels, are relevant constructs for data strategy. However, our refined model findings did not entirely align with all of these constructs. Through the structural model analysis, the situational construct was removed from the model and the structures and channels construct were refined to form two first order constructs of focus-alignment as well as collaboration and coordination. This finding is insightful as it reveals that focus alignment has the largest influence on EDLS, which suggests that effective governing structures within an organisation enable the alignment of focus across multiple divisions both vertically and horizontally thus enabling EDLS. These results provide support for the H3 which offer evidence of a positive and significant influence on the higher order constructs of EDLS. Overall, our findings are aligned with ABV theory which confirms that varying situations alter the focus of decision-makers, thus leading to a focus of attention suited to a particular context (Ocasio *et al.*, 2018). Many implementations of BD and analytics fail as they are not aligned with the firm's operational day-to-day processes and decision-making norms. In this regard, EDLS designers need to understand the types of judgements and decisions that managers make must align with broader governing structures inherent at the firm to complement existing decision processes effectively (Mazzei and Noble, 2019).

In summary, considering the positive results for the hypotheses, theory is advanced insofar effective EDLS enablers are examined through the lens of the RBV, ACAPT and ABV. The results highlight the relevance and reach of these theories in developing enablers in the form of resources and capabilities to effectively manage an EDLS. The article has expanded on the dynamic capabilities view by showing how in relation to the RBV enablers for an EDLS can be further leveraged by means of ACAPT and the ABV. Considering the future context of data-driven decision making, the RBV, ACAPT and the ABV are useful perspectives enabling firms to develop and reconfigure their resources and capabilities for an effective EDLS in the face of changing conditions.

The results of the study are valuable to explain not only how theory is advanced, but also inform management practices, as managers who struggle to build a practice for a successful EDLS, can now benefit from using a data-driven decision-making empirical tested EDLS model. Additionality, an effective EDLS holds the promise of playing a significant role in the development of new strategic approaches to firm performance (Urban and Townsend, 2021; Wu *et al.*, 2022). It is recommended that management practitioners need to nurture various resources and capabilities in terms of the enablers identified and tested so as extract value from their EDLS investment (Liu *et al.*, 2022).

Study implications

The study holds several implications for management who can now better understand which enablers are useful to manage, that lead to the successful implementation of an EDLS. Managers are advised to grow their organisational knowledge regarding which enablers, as delineated in this article, offer the best pathway towards the development of a more robust framework when putting EDLS into practice. Furthermore, BD designers and managers can now better understand which factors and capabilities lead to towards the formulation and practice of an EDLS. Firms will need to upgrade their analytical skills and competencies to ensure that BD analytics are "part of the fabric of daily operations" (Mazzei and Noble, 2019). As a means of driving EDLS managers will need to implement different interventions which includes training, role modelling and formulating performance indicators in terms skills, ACAPT and attention-focus behaviours.

Since conventional management theories mostly indicate the North American and European contexts, findings are not always valid to African emerging market environments, without revisions (Dana *et al.*, 2022; Urban, 2020). This study has addressed this deficit to some extent insofar the findings have relevance in terms of the study setting, where over the past few decades many countries in Africa are focussing on adopting technology innovativeness as part of their strategy. Since conventional management theories mostly indicate the North American and European contexts, findings are not always valid to African emerging market environments, without revisions (Dana *et al.*, 2022; Urban, 2020). South African firms can obtain strategic benefits by leveraging their organisational competencies to achieve an EDLS, particularly as the antecedents of technology adoption are not yet altogether comprehended in emerging market contexts (Urban and Townsend, 2021). Moreover, implementing an effective EDLS can foster international competitiveness for firms in emerging markets as it is increasingly accepted that the significances of emerging technologies influence the opportunities of doing business globally. For instance, international markets and digital technologies are positively associated with business innovation in emerging markets (Dana *et al.*, 2022). The amplified use of technologies in many emerging markets has converted these economies from a predominantly manufacturing economies to digital economies focused on technology products and services. Indeed, through the adoption of technological advances, the socio-economic progress of countries such as China, India, Indonesia, Malaysia, the Philippines and Thailand has improved significantly (Dana *et al.*, 2022; Urban, 2020). Similarly in Africa, many firms are heading towards adopting technology strategically, especially as over the past few decades many countries in "Africa are becoming less reliant on raw material mineral extraction and agriculture" and aim to use technology to generate new foundations for Africa's economic and social development

(Urban, 2020). Developing a robust and relevant EDLS is crucial for South African firms, as their business ecosystem is somewhat unique in comparison to other developed countries.

Conclusion

Our findings provide important theoretical and practical contributions to the management literature. Results have verified that enablers such as strategic management of data infrastructure, technical skills, transformation, knowledge management and alignment are critical to leverage and to enable usefulness from BD assets in the form of EDLS. These study findings resonate with and extend the management literature insofar specific factors relating to RBV, ACAPT and ABV are now confirmed as effective enablers in achieving an EDLS. We make a novel contribution to the emerging stream of literature on BD by highlighting that EDLS necessitates a change in the management decision-making context, which requires firms' to develop specific resource and capability enablers.

Study limitations incorporate the "cross-sectional nature of the design which prevents causation to be credited to the factors under investigation." Future research may benefit by employing a longitudinal research design and relying on observation and interviews that could contribute to providing a richer understanding of relevant factors related to EDLS. Moreover, supplementing the measures and information obtained in the present study with additional macro-level variables can also add value and help explain the results. In this regard future research could potentially leverage institutional theory to see if the regulatory environment unlocks the promises of date-led firms in emerging markets. Here the focus of future research would be on the moderating influence of contextual surroundings which fluctuate extensively from one industry to another and from country to country.

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