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Mediating Value Realisation in SME's with Big Data Analytics: A Literature Review of Empirical Studies Spanning From 2020-2021

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Abstract

This literature review sets out to find empirical evidence for realising value in an small to medium firm (SME) settings. It builds upon previous information systems research exploring the role big data analytics (BDA) dynamic capabilities play as a mediator of competitive advantages, and explores inertia inhibitors to BDA uptake among SME's. The review protocol follows a structured material collection, scoring of literature and a concept matrix extracted from the selected literature. Commentary explores the empirical evidence in the previous 18 months analysing if the call for more empirical research within BDA has been substantially met. A simple pathway to value realisation for SME's is suggested for consideration.

Keywords: SME; Big Data Analytics; Value Realisation

Introduction

Big Data Analytics and Value Creation

The call for more empirical investigation of applied big data analytics (BDA) theory into practice is echoed across information systems (IS), information technology (IT) organisational publications. Chiang et al. (2018, as cited in Tofangchi et al., 2021, p. 384) perhaps put it best, "analysis of data without generating value offers no contribution to an organisation, regardless of weather data are big or small". Theoretically generating value from BDA has been covered substantially across the literature, with well cited frameworks emerging that recent research has built upon (Provost & Fawcett, 2013; Wamba et al., 2015; Günther et al., 2017; Mikalef et al., 2017). Within BDA literature, generating value is often referred to as realising value, which is dually faceted. Economically and socio-economically (Günther et al. 2017). This paper will focus on the former. Realising economic value from commercial IT investments is arguably of most importance to small to medium size firms (SME), whose innovation investments can be coupled with substantial financial risk (Karhade & Dong, 2020), which is not always net positive. Therefore, as this paper mentions realising economic value it is referencing the creation of profit.

Dynamic Capabilities

Value realisation with BDA in its basic premise: A firm's ability to make dynamic, data-driven decisions empowering them to seize opportune marketplace advantages from harnessing streams of real time data. Colloquially known as 'dynamic capabilities' (DC). DC has deep roots in IS literature (Teece et al., 1997), with the framework being embraced by BDA scholars too (Davenport et al., 2012; Baker & Chasalow, 2015), the tributaries of the DC framework are prominent in research occurring in the last 18 months, this recognition in academia and interest by large IS publications potentially is a promising sign for a tried-and-true pathway to value realisation. For example, DC can directly contribute to a firms innovation strategies (Baker & Chasalow, 2015) to drive innovations in: market positioning, strategic marketing (Shine et al., 2020), productivity (Tofangchi et al., 2021), product development, customer experience and recognising hidden buying patterns (Zhang et al., 2021).

BDA Inertia

Integrating and developing dynamic capabilities that directly realise value for organisations is expected to come with challenges (Raguseo et al., 2021). The works of Mikalef et al. (2017; 2019; 2021) are well cited to observe these hinderances as spokes of organisational inertia, having diffused up from seminal works in organisational transformation (Besson & Rowe, 2012). Karhade & Dong (2020) implied a caution to executives from all industries to not overspend in IT investments as they do not always yield returns in favour of economic value, though they may still progress firm innovation. Feasibly explaining why economic inertia an important challenge is to overcome if BDA uptake across all sectors is to improve. Positively for SME's, the other remaining spokes of organisation inertia, besides the economic factor could be less difficult for them to overcome than larger multi-national firms with complex internal structures (Dong & Yang, 2020).

Competitive Landscape Shift

Countries across the globe are reacting to the landscape shift cloud computing has brought to hardware, software and storage accessibility (Hashem et al., 2015). For instance, the UK government has committed to investment across all sectors building towards an AI enabled economy, unbiased by firm size (Office for Artificial Intelligence, 2021). Social media, machine sensors, transaction data and the IoT are creating large amounts of varied data types (Zbakh et al., 2018), and the associated costs to access and process this data in volume, means SME's can compete in "the next frontier for innovation, productivity, science and competition." (Manyika et al., 2011).

Research Objective: The objective of this literature review (LR) is to help SME managers and executives overcome BDA inertia and advance their dynamic capabilities that in turn realise economic value. In turn, assist in the creation of profit. To meet this objective, a review of current IS literature is carried out, targeting empirical studies that present relevant results to the objective discussion. The frequent commentary in BDA LR's calls for the gap in empirical studies to be addressed. This review aims to demonstrate the areas that have been measured in the last 18-24 months and identify areas of future research relevant to the LR objective.

The remainder of this LR will be set out as followed, a description of the research selection and review protocols, a discussion of the findings, closing with a pertinent account of the professional, ethical and moral considerations present in BDA.

Literature Review Design Protocol

Structural Design Overview

In order to meet the objective of this LR, a structured material collection was curated from several sources. First, clarity of the LR objective is sharpened by asking questions to guide the selection from top down (Marying, 2008):

1. Which BDA techniques are being deployed in SME settings?
2. What mediators and, or moderators are observed between deployed BDA technique and realised value?
3. What, if any, completive gains are being made with DC as a result of the deployed BDA?

Keywords, Journals Exclusion Criteria

Primary keywords were selected based upon the LR objective, using a synonym expansion bucket, branching out from: big data analytics, value realisation, dynamic capabilities, organisational inertia and empirical studies. The results were then aggregated into a Boolean format as shown in Table 1.

Table 1 Electronic Journal and Database Boolean

Boolean
(("Empirical" OR "study" "Case*") AND ("Big Data Analytics" OR "Business Intelligence") AND ("dynamic*" OR "Competitive*") AND ("SME" OR "organisations"))

The basket of eight mainstream IS journals, selected by AIS senior scholars were preferred for the manual search. Two were omitted on University of Huddersfield institutional access rights but replaced with a high impact business intelligence journal. The Boolean was also searched in three bibliographic computing and business repositories. The results of these searches were counted (See Table 2) and then filtered through a set of delimiting criteria (Webster & Watson, 2002):

1. Is the study date relevant (2020-2021)?
2. Is this an empirical analysis or case study?
3. Does the title or abstract point to relevant features outlined in the research questions.

Table 2 Keyword Return Volume

	IS & BI Journals	Abbreviation	Keyword Return	Scope Delimited
1	Information Systems Journal	ISJ	3	1
2	Journal of Association of Information Systems	JAIS	3	0
3	Journal of Information Technology	JIT	1	0
4	Journal of Management Information Systems	JMIS	8	5
5	Journal of Strategic Information Systems	JSIS	4	3
6	MIS Quarterly	MISQ	7	4
7	*Journal of Intelligence Studies in Business*	JISIB	2	2
			28	15
	Computing Bibiliogrpahic Repositories			
	IEEE Xplore	-	57	7
	ScienceDirect	-	202	8
	Scopus		23	5
			282	20
			310	**35**

Scoring Selection

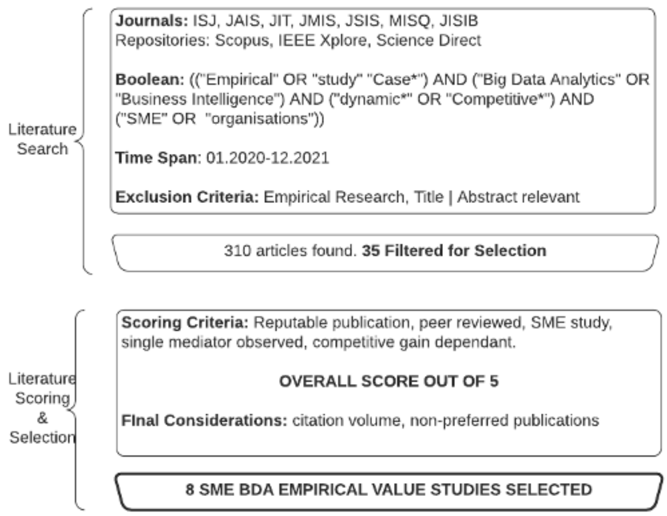
Following a popular LR in the BDA archive (Kitchenham et al., 2009) a scoring matrix was devised and adapted, differing in questions poised, but assuming a scoring procedure with three options. Five criterion were scored with a possible highest score of 5, and the lowest being 0, as shown in Table 3. The average score of the 35 was 3.54. The maximum was 5 and the lowest, 2. The average was used as a final filter, eliminating a further 18, leaving 17 for final review. The final review observed the papers first against the LR objective, the research questions, and the quality of publication. The citation quantity was initially ignored as the time span for these studies was restricted to 2020-2021. Resulting in 8 empirical observations and case studies for critical analysis aligned with the review objective. Figure 1. Demonstrates the protocol flow overview from initial search to final selection.

Table 3 Scoring Matrix

Publication	Publication Quality	Business Relation
1 = Journal, 0.5 = Conference, 0.25 = Management Report or Unknown	1 = Pref IS, 0.5 = Published & Peer Reviewed, 0.25 = Early Access. 0 = Not journal article	1 = SME's , 0.5 = Industry specific, 0.25 = Large, international, corporate, financial.

BDA Independants	Competitive Gains
1 = Reviewed a singular analytical method, 0.5 = Provided a framework of reccoemended analytics, 0.25 = Unknown	1 = Authors review of BDA focussed on improving a CG dimension, 0.5 = Indicates impications for CG, 0.25 = Less than above

Figure 1 Literature Selection Protocol



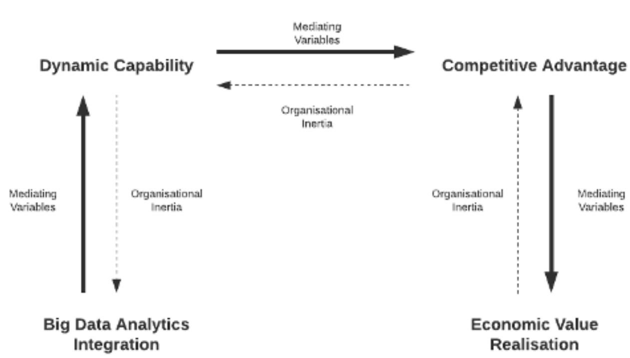
Analysis Design

Webster & Watson (2002) present a concept-centric matrix for structuring the critical discussion. For a crisper analysis, isolating common concepts is recommended and noting author commentaries within those variables. For this analysis, it was decided to identify the BDA technique or tool involved, the independent, and the competitive gain (CG) as the dependent. Mediators and moderators were also noted, so to was the mode of study. See Table 4 (Bottom of document). The methodologies, discussions and conclusions were thoroughly read for depth and credibility of analysis.

Critical Analysis

The diagram in Figure 2. establishes the lens in which the selected literature is examined in this LR. The framework flow has been guided by previous BDA LR's (Davenport et al., 2012; Baker & Chasalow, 2015; Wamba et al., 2015; Günther et al., 2017). From BDA integration to dynamic capabilities, then seizing a competitive advantage and eventuating in realised value. This framework builds the blueprint for the critique. Mediating variables are balanced with Mikalef et al. (2021) branches of organisational inertia identified in the papers.

Figure 2 Targeted Literature



BDA Integration Developing Dynamic Capabilities

Raguseo et al. (2021) surveyed large firms, n = 302, to measure the mediating effect of their readiness to integrate multiple streams of data, known as digital data stream readiness (DDSR) on competitive advantages that return a profit for these companies. Responses were from firms with an annual minimum revenue of one million US dollars. From this work it can be ascertained that the more prepared a firm is when integrating BDA technologies, both structurally and psychologically, the more likely they are to turn a profit from the competitive advantages available by utilising multiple streams of data effectively. The survey measured psychological and structural components as mindset, skillset, toolset and dataset. Where a company had developed in these areas, DC's were successfully leveraged, the authors particularly note that firms who focused on using BDA for product effectiveness had better results in favour of focusing on workflow efficiencies. For example, a company can achieve more out of their marketing analytics if their staff are well trained and have access to the correct tools to do the job. Similarly, Dong & Yang (2020) found that companies with access to more data, and the ability to utilise it – a spoke of technological inertia (Mikalef et al., 2021), compound their ability to create a return on their BDA investments. In this quantitative field experiment with SME's and large enterprises, n = 18,816, the authors showed SME's were more capable of realising value from their BDA efforts than larger companies, extrapolating that larger companies with complex internal structures may not benefit to the same degree as a smaller company able to streamline their inertia combating labours. Both Raguseo et al. (2021) and Dong & Yang (2021) found that access to multiple streams of data is generative of competitive gains that can create profit. The remaining papers in this LR do not particularly cover readiness to integrate multiple streams of data but this does seem to echo Günther et al. (2017)'s well cited LR synthesising organisational level, work practice developments must run parallel to the collecting and analysing of data to realise value.

Mediating Dynamic Capabilities Into Competitive Advantages (CA)

The following is not an exhaustive list of CA's firms have mediated from BDA integration but rather a reflection of what was observed in this LR. Cost reductions through workflow efficiencies achieved with machine learning (Tofangchi et al., 2021), marketing effectiveness provisioned by real time interface design modifications habituated by GPS data (Molitor et al., 2020). Additionally once more, marketing effectiveness. Observed by applying a machine learning artefact to successfully predict engagement outcomes of social media posts (Shin et al., 2020).

The empirical field experiment of (Molitor et al., 2020), n = 4,434, is of particular interest to the SME sector. Exhibiting how digital BDA can drive value for offline stores. Coupons were shown to users relative to their GPS location. The weight of this study did focus on the distribution design efficacy for coupon redemption but a higher level view can observe how real time streams of GPS data can secure offline modal stores a CA. Services such as Honey and Karma capture the same opportunity online, arguably more accurately as the coupon presentation is dependant on the consumer virtually browsing a store. Nonetheless, for offline SME's curious as to how cloud computing can drive their profits, the work of Molitor et al. (2020) demonstrates services available to offline stores making a measurable impact. The expansion of services equipping cloud computing to serve in the business and consumer markets aligns with previous LR's (Hashem et al., 2015; Zbakh et al., 2018).

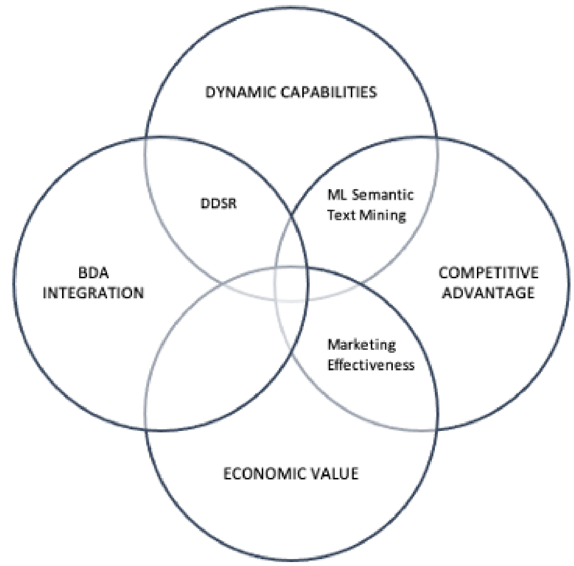
Implications for SME's DC and CA can be drawn indirectly from Tofangchi et al. (2021). The authors applied a machine learning artefact trading off autonomous vehicle efficiencies with passenger preferences. Concluding that BDA enabled both fuel economy, and rider preference. Researchers go on to highlight the potence of such technology in saturated, highly competitive markets, like ride sharing. On the other hand, similar methods were deployed in the on-demand movie domain with less positive outcomes. Zhang et al. (2021) looked at recommendation engines preferentially selecting high value movies in the most salient promotional locations. Conversely to Tofangchi et al. (2021) attempts to maximise profit and increase entertainment impeded user welfare. Welfare decline was reported as high as 28.7%. This work acts as a caution to executives and managers involved with BDA projects, machine learning enabled DC is a still an area under academic rigor. Zhang et al. (2021) suggests balance may be achieved with adjustments for the movie recommendation engine. Karhade & Dong (2020) in a newly published longitudinal study, n = 3,129 also bring attention to negative outcomes associated with dynamic adjustments of pricing. The time-span of their data however stretches from 1997-2004 and although recent, may not theoretically withstand the test of time.

Where predictive modelling was able to act as a DC leveraged for CG with marketing efficiencies (Shin et al., 2020), Wang et al. (2020) in a large quantitative case study, n = 40,010 showed that semantic text mining of credit applications, coupled with fixed inputs, increased the correct instances of predicting credit risk. Accurately interpreting meaning from soft factors, such as user input text with machine learning supports data-driven decision making, which has been shown to be a significant CG in realising value (Davenport et al., 2012; Provost & Fawcett, 2013; Wamba et al., 2015). Although determining credit risk may not be a pertinent issue for the restaurant and grocery store SME's discussed until now in this LR, being able to develop dynamic capabilities from semantic text mining with machine learning has been shown to increase marketing efficiency (Shin et al., 2020) and product effectiveness (Tofangchi et al., 2021) in recent quantitative studies. The value of Wang et al. (2020)'s work is indeed of use to the IS literature. Furthermore, the ability to quickly detect inaccuracies in easy to exploit user text inputs has the potential to reduce fake reviews and boost security, although both factors are outside the scope of this LR.

Conclusions Implications

This LR set out to reduce inertia in SME mangers and executives by shining a light on the recent empirical research that shows different ways SME's are preparing to on-board a BDA strategy. Furthermore, from the same body of literature it attempted to find successful application of dynamic capabilities deployed measured with a substantiated competitive gain, that helped a business return profit. The literature was carefully selected to reflect recent empirical studies, to make this knowledge useful to IS, IT and business professionals at all levels of an organisation. Due to the scope of this LR, many articles had to be omitted which could have otherwise served depth to the points made or revealed new knowledge. The research objective questions guided this LR. Throughout attention has been brought to areas requiring further investigation. To conclude this research and assimilate the findings to be of intended use, a proposed model with a pathway designed for SME professionals to consider when taking on the challenge of realising value from BDA is aggregated in figure. 3 below.

Figure 3 Targeted Literature



Big Data, Big Issues

This section paves a short backstory to how big data issues have become more present in the public domain, sequentially followed by a deeper analysis of professional, legal and ethical issues.

Zuboff (2019) paints a particularly bleak picture for the future of consumers in her international bestseller The Age of Surveillance Capitalism. Going under the hood of Google's mission statement, "To organise the world's information, making it universally accessible and useful.". She unveils many of the professional, legal and ethical modern challenges of data in a business setting. Continuing with Google as an example, Zuboff (2019) presents a typical data life cycle. User engages with a service, the service analyses interaction data, the processed data is used for service improvements, archived and eventually deleted. The challenges occur when user data is processed beyond its initial intended use, more on this shortly, and used to create predictions on how consumers behave online. The selling of said predictions to the highest bigger creates what she calls a 'market in future behaviour' or more aptly, 'surveillance capitalism'. Zuboff (2019) does a good job in her book of informally educating the public to issues tech companies have worked hard not bring to the public domain, and regulators have run into many obstacles to legislate with the pace that their technology evolves (Piltz, 2013).

Within the last decade the sentiment towards ones own data protection has been growing. A year that seismically shifted the data paradigm was 2018. Every business in Europe felt the pressure to bring their companies in line with the EU's legislation directive "GDPR". GDPR defined exactly what data companies could store from their customers, how they could use it and what determined an lawful breach (Freund & Schmidt, 2021). These definitions were definite, rocking the boat across all member states. In the same year, Google was handed a record breaking 4.34 billion euro fine from the EU executive commission in Brussels by leveraging an unfair competitive advantage through its own Android platform (NPR.org, 2021), an example of users data going beyond its 'intended use' (Zuboff, 2019). Google appealed from the initial European Commission's investigation (Kokkoris, 2017) and continues to do so presently (NPR.org, 2021). For good reasons, data handling has come to the forefront of regulatory concerns in recent years, helped by the aforementioned series of events.

Legal Issues

The General Data Protection Act (GDPR) was introduced to protect the data privacy of individual citizens who interact with commercial businesses (EU, General Data Protection Regulation, 2016). It puts the onus on every firm to safeguard customer data. Excellent literature surrounds the complex relationship of GDPR and BDA, for firms to adopt a framework that ensures compliance, particularly for the growing IoT (Pham, 2019; Rhala et al., 2021). BDA professionals involved with managing data projects should consider a 'privacy by design' approach in order to circumvent complacency (Dickie & Yule, 2017).

Professional Ethical Issues

Managing data privacy in compliance with GDPR is fundamental for the data professional. Companies often start strong and inadvertently let privacy standards slip the further down the timeline a project goes (Hurwitz, 2013). Agreeing with Dickie & Yule (2017), a proactive approach that considers the lifespan of data upfront is best practice. Lane (2014) introduces the idea of a walled garden, data is viewed only by team members when they need it, otherwise restrictions are enforced. BDA professionals must take care to gain knowledge of sensitive ethical issues to upkeep a professional integrity. Besides GDPR, avoiding biases is critical. This topic deserves more than an honourable mention but some examples include, under representing a population, misleading interpretations or graphical representations, cognitive and methodical biases, outlier bias and confirmation bias (Techtarget.com, Lawton, 2020). A professional can aggregate the biases into four important buckets to investigate further, sampling, measurement, demographics and aggregation (Griffin et al., 2020).

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Table 4 Electronic Journal and Database Boolean

	Authors	Study Type (N)	BDA Independents	Mediator	Moderator	CG Dependents
1	(Raguseo et al., 2021)	Empirical, Quantitative, survey (n = 302)	Digital Data Stream Readiness (DDSR)	DDSR development of mindset, skillset, dataset. Individual & organisational level	-	Product quality & innovations, lowered cost, efficiency of proccesses, accelerated time to market.
2	(Molitor et al., 2020)	Empirical, Quantitative field experiment, (n = 4,434)	GPS data of users	Interface Design of Coupons	Provision of user location data	User reedeming coupon
3	(Tofangchi et al., 2021)	Empirial, Quantitive applied IS artifact (n = 37,987)	Autonomous vehicle driving patterns trading off between efficiency & passenger preference	Trained ML models on manual user inputs with NN time series data	-	Leveraged consumer insights, efficiency of vehicle use lowers operational costs
4	(Wang et al., 2020)	Empirical, Qunatitative (n = 40,010)	Semantic Data Mining	Reducing exploitation factors of descriptive inputs by borrowers	-	Reduced lending risk
5	(Zhang et al., 2021)	Empirical, Quantitative (n = 4,680)	Reccomendation engines	-	Price elasticity for on-demand services with selective placement	Mitigating damage to consumer welfare, profit maximisation
6	(Shin et al., 2020)	2 Empirical Case Studies	CNN Deep Learning & Text mining	Quality of Analytics		Faster data-driven decisisons of unstructured data to drive engagement in adverstisements.
7	(Dong & Yang, 2020)	Empirical Suvery (n = 18,816)	Diverse data from multiple social media channels		Complexity of integration, firm size dependant	Revenue
8	(Karhade & Dong, 2020)	German firm survey data 1997-2004 (n = 3129)	Dynamic adjustment costs	-	-	IT commercial Investment Performance