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Business Analytics Revisited: A gap analysis of research and practice

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Completed research paper

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Abstract:

With the growing use of business analytics (BA), organisations have benefited from new ways to extract value from data and drive strategic, evidence-based decision making. However, much less thought about *how* Business Analytics contributes to business value in practice has been given. We have conducted an in-depth qualitative paper of fourteen semi-structured interviews of positions integral to BA within organisations using five value drivers and inhibiting factors that surround value generation. This paper takes a retrospective look at what has been done, and how well it compares to the practice of business analytics. This paper seeks to bridge the current knowledge gap through providing a holistic view of all five value factors and how they affect value generation. In order to answer the research question of "How does Business Analytics contribute to business value in organisations?". The results of this research can be utilised by managers of firms creating value through data-driven decisions, as well as by others in the ecosystem for analysing business analytic solutions. As well as identifying in what ways business analytics contributes to value by bridging the gap between research and practice.

Keywords Business Analytics, Business Intelligence, Competitive advantage, Business Value of Information Technology

1 Introduction

Business analytics (BA) and business intelligence (BI) are both longstanding IS areas which are experiencing a reprisal (Roy et al. 2020), having been a topic of importance for both researchers and practitioners of IS (Chen et al. 2012). With the quick development of artificial intelligence as well as developing concepts such as ‘big data’, business analytics and business intelligence have also gained increasing scholarly attention in the domain of the 4th industrial revolution and the future of work. BA can be defined as “the use of data to make sounder, more evidence-based business decisions” (Holsapple et al. 2014, p. 133). In a survey conducted by IBM Institute for Business Value and MIT Sloan Management Review, it was pointed out that increasingly firms are reporting a growth in competitive advantage through the use of analytics (Kiron and Shockley 2011). Inside this report, 58% of more than 4500 respondents reported competitive value gains from analytics (Božič and Dimovski 2019; Kiron and Shockley 2011). As the definition suggests, the use of BA and BI tools by managers primarily aims at taking advantage of the numerous sources of available data and information to enhance decision making within organisations (Caya and Bourdon 2016). In a survey of nearly 3,000 executives, managers and analysts working across more than 30 industries and 100 countries, top-performing organisations were found to be use analytics five times more than lower performers. These top-performing organisations also have substantial experience in harnessing BA and BA to create value (LaValle et al. 2011) With growing interest in this field, as well as the ever-growing need and the uptake of business analytics, comparatively little research has been undertaken to find out how BA creates value and competitive advantage within organisations (Grover et al. 2018; Seddon et al. 2017).

This paper addresses such a research gap. More specifically, it poses the following research question “How does Business Analytics contribute to business value in organisations?” as well as looking into what ways can BA create value and develop an understanding as to what factors influence this? Prior studies have explored the compelling pathways which link value generation from business analytics, through insights and decisions, to increased organizational benefits (Seddon et al. 2017; Sharma et al. 2017). Meanwhile, the elements of a successful business analytics implementation have been recognized for reshaping operational capabilities and generating economic value, including BA infrastructure and functionalities, e.g. (Cao and Duan 2014; Trkman et al. 2010; Wang et al. 2019; Wixom et al. 2013), analytical people (Tamm et al. 2013), data governance (LaValle et al. 2011; Tamm et al. 2013), information quality (Côrte-Real et al. 2019), data-driven decision-marking culture (Cao and Duan 2014; Kiron and Shockley 2011). This paper revisits the extant literature listed above with an empirical study that benchmarks best practices (Sharma et al., 2013) from industry on deriving value from business analytics.

The remainder of the paper is organised as follows. The next section provides a brief account of fundamental concepts from the extant literature of BA for business value. Section 3 describes the case analysis method and its significant findings. The paper concludes with a statement of theoretical and practical implications.

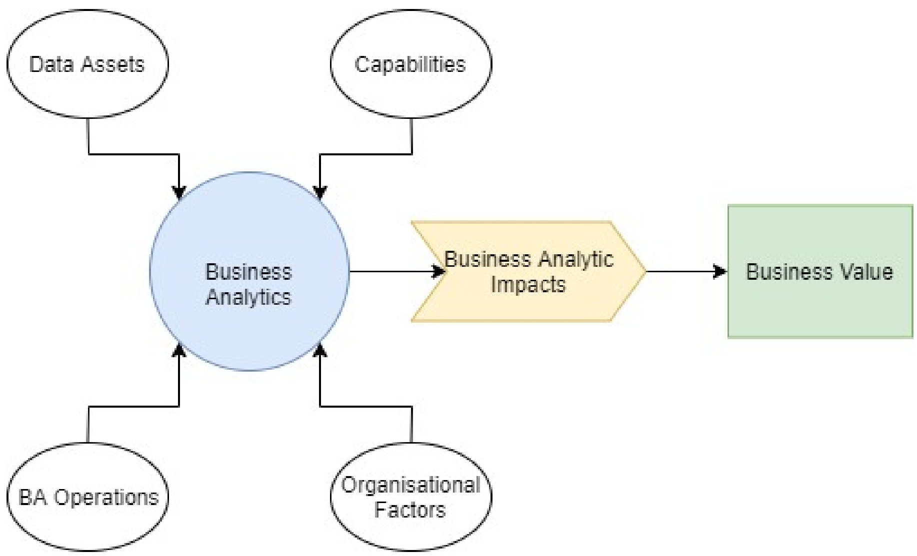
2 Background

Although data has been hailed as the oil that power the 4th industrial revolution (Schwab 2016), what makes data a valuable asset is the useful information hidden inside, which contains insight. Insight generation often requires different analytical techniques to find, which is either categorised as Data or Business Analytics. Data analytics is the all-encompassing term for any analysis on any type of data. As such, data analytics can be widely applied to almost any area; it has abundant applications in business, with benefits stemming from recognising patterning in a dataset and making accurate predictions based on events. The notion of creating and capturing value through the orchestration of resources such as assets and capabilities is central to business performance (Soh and Marcus, 1995; Sharma et al., 2007). Distinct from this, business analytics focuses on identifying trends in an organisation that can be optimised to improve overall business planning and performance. Which in turn supports continuous improvement in technology and processes which seeks to arrive at a single source of truth (Duan and Xiong 2015).

Analysis focused on summarising and analysing existing theories as to how business analytics can contribute to business/organisational value. This section focused on highlighting prevailing debates related to this topic while identifying supporting evidence and gaps in the literature (Jones & Gatrell, 2014; Templier & Paré, 2015). Through reviewing these papers, key themes were found as to how organisations realise value from business analytics.

Synthesising the scholarly literature on business analytics value realisation is fought with difficulty (Sharma and Djiaw, 2011). The focus of BI and BA in IS research has been primarily technical, with the inclusion of specific domains such as supply chain efficiency (Krishnamoorthi and Mathew, 2015). This literature review has highlighted that there is currently a lack of research pertaining to business value, adoption and business process management. A more systematic and structured review (Beckwith 2020) reveals key factors that support business analytics value creation, including factors such as BA assets, BA impacts, BA operations and organisational factors. Having analysed a substantial body of literature, Larson and Chang (2016) suggest that BA is currently gaining traction globally, and of great interest to the business community. However, there is such a vast number of different viewpoints and factors that it must be hard for managers, executives and organisations to decide what they need to do to realise value from BA (Seddon et al., 2017). For example, theoretically 'value' has been acknowledged as a key construct of IS Success (Delone & Mclean, 2004). Thus, there remains a need for a more in-depth analysis of the processes and factors that organisations require to receive value from BA, to allow for more efficient and effective uptake. Figure 1 is a preliminary research model adopted for empirical investigation (These value factors are detailed in the analysis and discussion section).

Figure 1: Business Analytics Value Factors



2.1 Research Model

Orchestrating resources is critical to developing and implementing a range of firm strategies. As such, in this section, we address the breadth of resource orchestration by examining its impact on and implications for corporate strategies, business strategies, and the competitive dynamics in industries (Sirmon et al., 2010). 'Resource orchestration' comprises of three stages: structuring, bundling and leveraging. The key insight that stems from resource orchestration is that organisations often differ systematically in the extent to which their process for transforming inputs into outputs lead to business value, with 'value' being defined in a resource orchestration context, as the amount that consumers are willing to pay for the organisations good or service and the organisations cost to produce and deliver that product (Yi Liu, 2019). This model formed conceptual scaffolding which was also tied with two pieces or prior research by (Seddon et al., 2017) and (Božič & Dimovski, 2019).

Seddon et al. (2017) looked into developing a business analytics success model (BASM). This comprised of five factors from Davenports DELTA model of business analytics success factors (Davenport, Harris, & Morison, 2010), six from Watson & Wixom and three from Seddon's model of organisational benefits. A preliminary assessment of the model was conducted using data from 100 customers success stories from prominent BA vendors such as IBM and SAP. This research was completed to provide managers with a clearer understanding of how an organisations BA capability can influence organisational performance. This paper was concluded with the "hope that other researchers will be able to take and extend our ideas and conduct further tests of the BASM or similar models." (Seddon et al., 2017, p. 266).

Following this research focus, Božič & Dimovski (2019) looked into business intelligence and analytics for value creation. In this paper, fourteen in-depth, semi-structured interviews over a sample of informants such in CEO, IT managers, Heads of R&D, as well as Market managers across nine medium to large firms, were conducted. The studies suggest that it might be insufficient to focus on improved decision making that stems from BA, without considering how knowledge creation occurred in the first place. With the findings also shedding light on how knowledge is created from BA and BI triggered insights.

Through synthesising the findings from these two researchers in conjunction with the research orchestration model form a lens in which will be used to form the basis and empirical context for which will be used to explain theoretical conclusions from our research. The present paper probes deeper into the orchestration of assets and capabilities in order to answer the question of how value is derived from analytics. In the empirical part of the paper this theoretical research model served two purposes in developing a structural interview template (SIT).

1. It addressed the key question of how Business analytics impacts Business Value?
2. It further delved into the structuring, bundling and leveraging aspect of the BA value chain.

2.2 Research Design and Method

(Sharma et al., 2017) provides a recent, definitive account of the organisational impact of BA. Drawing on this we may conclude that the area of data and business analytics within the IS field is new, broad and sophisticated, making it challenging to identify casual relations. Taking into account that the relevant literature on business analytics value realisation is scarce for this research, we built upon the research of (Božič & Dimovski, 2019) and (Seddon et al., 2017). In order to answer the research question, this paper was designed using an exploratory qualitative approach. We apply abductive scientific reasoning as we draw probable conclusions based on our extensive literature review and in-depth interviews with practitioners (Baker & Edwards, 2012; Basit, 2003) where initial inductive insights from empirical data are engaged with existing theoretical knowledge to explain empirical findings. We assume the semi-structured interview to be the most effective method of gathering information for our research since is suitable when the interviewer needs a deeper understanding of a problem, as it allows for the opportunity to identify details, which in this case is favourable to grasp the complexity of the problem area (St. Pierre & Jackson, 2014; Weston et al., 2001). Furthermore, due to the aim of this research, the collection of in-depth insights from various perspectives was needed, thereby a qualitative paper was applied. Based on the goal to gain multiple perspectives, 14 practitioners of BA (across the value chain) were selected. Of the 16 who consented to the research, this was for both convenience of face to face interviews (pre-Covid-19) as well as adequate coverage of perspectives (lead users, analysts, managers and strategic management). This was in order to gain a deeper understanding of the business analytics perspectives by examining different companies, their solutions and implementations and further providing the opportunity to contrast the interviews, to explore potential similarities and differences (Weston et al., 2001).

2.3 Interview Protocols

There are various ways in which data can be collected for qualitative research, including observations, focus groups and in-depth interviews (Bell et al., 2018; Braun & Clarke, 2006). The use of a survey instrument for the purpose of statistical analysis, a longstanding practice in IS research (Sharma and Conrath 1992), would not have served the research objective of in-depth analysis and theory exploration. Hence, the data was collected primarily using semi-structured interviews, with an interview template as a basis. Besides the flexibility of applying semi-structured interviews, it was also used due to the nature of the research question and the previous choice of adopting a hermeneutic perspective, as it is consequently commonly applied (Bell et al., 2018). Further, semi-structured interviews provide the researcher with rich contextual information regarding the respondent's experience as it allows for the interviewer to get a good understanding of the research area without influencing the interviewee with any preconceived notions (Bell et al., 2018). Additionally, it is a collection technique widely adopted in information system research (Schultze and Avital 2011; Sharma et al. 2013).

The interview guide mentioned earlier was developed by iterating the suggested guiding questions provided by Božič and Dimovski (2019). The final semi-structured interview guide included questions framed around value drivers uncovered from the literature, as well as general questions regarding the personal views of success of an implementation and inhibitors to value. The questions were broad and open-ended to allow respondents to freely discuss what they considered necessary when answering (Bell et al., 2018). Moreover, by utilizing this type of interview technique, it provided the ability to ask follow-up questions to add interesting ancillary considerations. Semi-structed interviews were conducted in-person to ensure that rich and in-depth answers where gathered. Participants were contracted via email the day before each interview and provided with a copy of the interview template so that thoughtful and rich responses could be provided (Mays & Pope, 2020). Before each interview began, the interviewees were made aware of the essence of the research and asked to consent of the recording of the interview (Walsham, 2006). As all of the respondents accepted this, it allowed for the possibility to thoroughly listen and interpret their answer after the fact, as all interviews were transcribed. The participants were also assured of their anonymity in the paper.

In anticipation of "theoretical saturation", we selected fourteen expert interviewees (key informants) in positions within the variety of Business Analyst, Information Officer, IT manager roles. However, while additional ones could be perceived as beneficial, much empirical evidence had been repeated by the 14th interview, pointing to a clear indication of saturation (Baker & Edwards, 2012; Bell et al., 2018; Saunders et al., 2018). Each of the interviews had a duration of approximately 60 to 90 minutes. All of them possessed and actively used BA in their everyday work. To the extent feasible, the interviews were chronological arranged to begin at roles which were operationally/tactically focused to roles which were more high level and strategic, so that knowledge gained from earlier interviews could be expanded on. These interviews were conducted face-to-face, at client sites, from the 21st of August 2019 through to 14th of October 2019, and thankfully prior to any lockdowns due to Covid-19.

Table 1: Research Participants with Job titles

Strategic Level

Respondent	**Title**	**Affordances with BA**
1	General Manager of Information Technology	High
2	BI & Transformation Manager	High
3	Commercial Manager	High
4	Customer Analytics & Insights Manager	High
5	Business Analyst / IT Manager	High
6	Decision Support Manager	High
7	Business Intelligence Manager	High
8	Data Engineering Manager	High
9	Data Scientist Consultant	Moderate
10	Senior Business Analyst	Moderate
11	Senior Business Analyst	Moderate
12	Senior Business Analyst	Moderate
13	Business Analyst	Low
14	Business Analyst	Low

2.4 Data Analysis

As the interviews with the participants were recorded and transcribed, this enabled thematic analysis to be conducted on the qualitative data in a semi-structured manner (Basit, 2003; Bell et al., 2018; Leung, 2015). Braun and Clarke (2006) describe thematic analysis as "Thematic analysis is a method for identifying, analysing, and reporting patterns (themes) within data. It minimally organises and describes the data set in (rich) detail. However, it also often goes further than this and interprets various aspects of the research topic" (Braun & Clarke, 2006, p. 6). This research followed a more exploratory qualitative approach. We applied abductive scientific reasoning by identifying new trends in addition to verifying and extending existing theoretical knowledge uncovered. The coding was done using interviews using the semantic tool NVivo. NVivo has been selected as it is designed for qualitative researchers working with rich text-based data where deep levels of analysis is required and has thematic analysis capabilities (Bazeley & Jackson, 2013). Additionally, this analytical approach allowed for the comparison of the derived findings with the outcomes of prior research and theory (Sharma et al., 2013).

3 Analysis and Discussion

3.1 Thematic Analysis

As previously mentioned, all 14 practitioner interviews for this paper were recorded and then later transcribed verbatim. In order to aid with answering the research question, thematic analysis was chosen to analyse the collected data in a structured and systematic manner (Bazeley & Jackson, 2013; Bell et al., 2018). Thematic Analysis allows an expansion of our research model in figure 1 into terms, vocabulary and semantics expressed by practitioners who were interviewed. Thematic Analysis can either be theory-driven or data-driven, where the analysis either starts with theory derived from the literature or raw data/ interview transcripts (Braun & Clarke, 2006). This paper employed both approaches. Using mainly a theory-driven approach was utilized at the beginning, where indications in the findings were structured around the research model. This was followed by a more empirical approach, exploring the raw data to identify new trends and indications within the contexts not identified by prior literature (Bazeley & Jackson, 2013).

The themes discovered during our analysis were subsequently split into two categories outlined below following established research processes (cf. Braun et al., 2019; Fereday & Muir-Cochrane, 2006).

Primary theme: A primary theme was categorised as a theme within the data which was bold and distinct. This was given to themes which resonated between many participant responses or academics.

Secondary theme: A secondary theme was not as prevalent in the data set; however, the theme was still corroborated by another participant or academic, therefore was notable.

3.2 Thematic Analysis of Research and Practice

The *Data Assets* value driver which relates to analytical tools and software packages which enable BA use, this also encompasses backend infrastructure such as data storage and processing (Grover et al. 2018). The findings show that corroborations between research and practice exist, corroborations included the need for 'well-governed data', 'data integrity', the use of 'cloud-based services' which are scalable in nature and continuous hardware improvement to data assets within the organisation. Highlighting the extant literature surrounding this, (Conboy et al. 2018; Grover et al. 2018; Llave et al. 2018; Tamm et al. 2013; Wang et al. 2015; Wixom et al. 2013; Ylijoki and Porras 2018) point towards an organisational need for 'well-governed data' in order to deliver value for their BA operation. With Conboy et al. (2018, p. 3) stating that "Data governance is essential to maximising value from business analytics". In addition, the literature supported the use of 'Cloud-based data' assets which are scalable services based on demand (Cao and Duan 2017; Chen et al. 2012; Grover et al. 2018; Llave et al. 2018).

Potential value inhibitors for *Data Assets* include 'siloed systems' being present within organisations, leading to possible fracturing and duplication of data sources/ islands of automation which do not interoperate, inhibiting BA use. The incorporation of 'legacy systems' into a BA pipeline, which introduces throughput and compatibility challenges, and data quality, with this having a flow-through effect as to the accuracy of insights generated. Secondary themes also included the spanning the growing amounts of 'tech debt' generated through BA use due to the rapid evolution of the industry, and the extensive 'fracturing of technology' and tools which is now existent in the industry, with organisations now having to adopt a growing range of analytical tools from vendors.

3.3 Human Capabilities

Next, we examine the *Human Capabilities* value driver, this refers to employees and contractors that are trained to work with analytics and skilled to decode output are highlighted as critical assets that enable organisations to realise business value (Božič and Dimovski 2019; Lamba and Dubey 2015; Sharma et al. 2007; Stevens 2017; Wang et al. 2019). Many studies have suggested that an organisation's human resources are a vital driver for BA success (Côrte-Real et al. 2019; Holsapple et al. 2014; Seddon et al. 2017; Tamm et al. 2013; Trkman et al. 2010; Wang et al. 2019). The findings support what previous research has identified within this value driver; however, on the contrary, several new factors were found. Corroborations for this value driver existed, surrounding the need for 'deep domain knowledge' to be present within analytical professionals. Which is highlighted by previous research by surrounding the need for a high level of 'business knowledge' and business functions is critical (Akter et al. 2016; Božič and Dimovski 2019; Chen et al. 2012; Soh and Markus 1995; Wang et al. 2019; Wixom et al. 2013). With Božič and Dimovski (2019, p. 96) pointing out that "...employees with strong business knowledge and technical skills are more efficient in recognizing and valuing new external knowledge, therefore, increasing the knowledge level in the firm". In conjunction Vidgen et al. (2017 stating that "The business analytics function will need to build a deep understanding of the organization and its business domain if it is to create lasting value".

Potential value inhibitors that were analysed for *Human Capabilities* included a primary theme around the current shortage of 'skilled analytical staff' possessing the experience and qualities that the industry currently requires. Two secondary themes were also present, which relate to the primary theme. The first which was uncovered surrounded 'staff retention' and the struggle some organisations are facing in retaining their quality staff due to the competitiveness of the industry. In conjunction, the second theme identified relates to a disconnect of the current 'remuneration' some organisations are budgeted to pay, compared to the remuneration skilled analysts can command in the market. In summary, this highlights a lag between what organisations are budgeted to pay versus what prospective employees expect in terms of remuneration, which can also lead to the other inhibiting factors identified.

3.4 Business Analytics Impacts

The *BA Impacts* value driver refers to the output of BA use, so of which can include improved performance, operations efficiency, targeted products, process alignment and expansion into new markets. The main corroboration for this value driver surrounds the need for 'timely decisions and actions' to be made from BA generated insights. From this analysis, the first primary theme uncovered surrounded 'timely and decisive' use of BA generated insights in order to create value (Caya and Bourdon 2016; Grytz and Krohn-Grimberghe 2018; Ramamurthy et al. 2008; Wang and Byrd 2017; Wang et al. 2015). With value being generated through using "Business Analytics to drive efficiency in strategic and day-to-day decision making Krishnamoorthi and Mathew (2015, p. 2). 'Timely decision' making was found to provide an organisation with the ability to fully exploit possibly underutilised parts of the business through acting on insights derived from organisational data and analysis, however 'timeliness' is a vital aspect of this as insight derived must be current.

Value inhibitors found for this driver included two primary themes, the first emphasised the importance of 'accuracy' when presenting results and avoid distorting or enlarging the results, with participants noting that if not followed this can impact trust in data. The second primary theme surrounded the difficulty in 'measuring value' derived from BA insights in monetary terms. A secondary theme was also present surrounding the requirement of meaningful reporting were organisations should focus on reporting that is meaningful and will result in value, rather than mundane reporting, which does not result in value. In summary, these inhibitors suggest that when reporting, results should not be 'cherry-picked', instead they should be reported at face value so that integrity and trust in data is retained. In conjunction, fiscal benefits directly resulting from a BA initiative or insight should be measured on an organisational wide level, as benefits are often realised in departments throughout the organisation

3.5 Business Analytics Operations

As stated earlier, the *Business analytics Operations* value driver concerns Business Analytics processes, work practices and routines performed within the organisation to support BA use. The findings present corroborations between theory and practice for this value driver supported the need for a 'data-driven organisation' present (Akter et al. 2016; Ashrafi et al. 2019; Chen et al. 2012; Grover et al. 2018; Llave et al. 2018; Van Rijmenam et al. 2018; Vidgen et al. 2017) as stated by Llave et al. (2018, p. 7) "consumer insight can help enterprises to focus on the right customers, identify customers with high churn probability" and Enders, (2018, p. 4) stating that "value-exchange process is based on the needs of the consumers". The other corroboration identified surrounded the benefits of working in 'multidisciplinary BA teams' and the use of 'agile' project workflows. (Božič and Dimovski 2019; Capellá et al. 2012; Côrte-Real et al. 2019; Duan et al. 2018). The last corroboration identified surrounded the need for responsive, 'agile' practices to be present within the organisation to aid value creation as well as to respond quicker to insight (Ashrafi et al. 2019; Conboy et al. 2018; Llave et al. 2018; Sharma et al. 2007; Stevens 2017; Tamm et al. 2013; Van Rijmenam et al. 2018; Vidgen et al. 2017; Wixom et al. 2013; Ylijoki and Porras 2018). Two secondary themes were also present during the analysis; the first that appeared was the use of 'multidisciplinary teams' in BA use.

Probing the inhibiting aspect of this value driver, the following themes were uncovered within the *BA Operations*. The first theme present supported the ideology of focusing on 'value delivery', where organisations should focus on BA tasks which will derive immediate value. Where the analytics departments with organisations should focus on tasks which will deliver the most impact, rather than trivial reports which do not deliver the same level of value. The second theme emphasised the fiscal and 'budgeting challenges' that BA departments and teams currently faced within organisations, which can inhibit insight generation from occurring. The third theme present placed importance on the 'documentation and knowledge management' of BA system enhancements so that these are safeguarded in detail if a staff member departs from the organisation. Other secondary inhibitors were found, which include the 'growing saturation' of BA vendors and tools available for organisations to select from was present. With organisations having a challenging time selecting technology that is best fit for their use. The second theme present involved the need for a 'collaborative workflow' to be present within the organisation, with it being beneficial for BA departments and teams to involve other parts of the business in their work.

3.6 Organisational Factors

Organisational factors encompass organisations' size, scope and absorptive capacity as well as strategic factors to assist with the successful adoption and use of BA. Corroborations for this value driver include the need for 'strong executive sponsorship' behind BA use within the organisation. This executive commitment and championship towards BA within the organisation should be strongly considered before undertaking such initiatives, as pointed out by the literature (Božič and Dimovski 2019; Grover et al. 2018; Kiron and Shockley 2011; LaValle et al. 2011; Ramamurthy et al. 2008; Seddon et al. 2017; Sharma et al. 2007; Tamm et al. 2013; Vidgen et al. 2017; Wang et al. 2019; Wixom et al. 2013). Grover et al. (2018, p. 419) states that "Successful initiatives are usually championed through an integrative BDA strategy and strong leadership". In addition to this literature and participants noted the need for an analytic and 'evidence-based' making culture within the organisation (Chen et al. 2012; Duan et al. 2018; Grytz and Krohn-Grimberghe 2018; Holsapple et al. 2014; Krishnamoorthi and Mathew 2015; Lamba and Dubey 2015; LaValle et al. 2011; Stevens 2017; Vidgen et al. 2017). Lamba and Dubey (2015, p. 1) referenced a survey conducted by MIT Centre for Digital Business and McKinsey's business technology office reveals that data-driven organizations are 5% more productive and 6% more profitable than their competitors.

Some additional challenges and were also identified from the semantic analysis; value inhibitors for organisation factors include the 'importance for a company to place and build up trust in its data'. Respondents noted that this could take up a long time to build up within the organisation; however, this can be quickly lost if integrity is compromised. Also, a theme which supported an organisation with a culture supporting 'data-driven decisions' was also present; otherwise BA insights risk not being acted upon.

Table 2: Highlights of the research findings

Value Driver	Value Drivers	Value Inhibitors
Definition	People as essential enablers of BA	Culture of Distrust
Data Assets	**Corroborations:** Well Governed Data, Data Integrity, Cloud-Based – Scalable services, Continuous Hardware Improvement. **Theoretical Gaps:** High-quality BA/I Technology to fit organisations task and data strategy. **Practice Gaps:** Raw Granular Data, Well Documented	**Primary:** Siloed Systems, Legacy Systems, Data Quality. **Secondary:** Tech Debt, Fracturing of Technology
Human Capabilities	**Corroborations:** Deep Domain Knowledge. **Theoretical Gaps:** Analytical Training. **Practice Gaps:** Influential People and Negation Skills, Experimental Nature, Critical Thinking, Strong Data Story	**Primary:** Skilled Analytical Staff to fit industry's needs. **Secondary:** Staff Retention and Remuneration
BA Impacts	**Corroborations:** Timely Decisions and actions. **Theoretical Gaps:** Competitive Position. **Practice Gaps:** Business Agility, Defining the Scope of Solution	**Primary:** Accurate, not distorted Presentation, Measuring Value. **Secondary:** Meaningful Reporting
BA Operations	**Corroborations:** Data-Driven Organisation, Multidisciplinary Teams, Agile Workflow. **Theoretical Gaps:** Innovative workflow. **Practice Gaps:** Self-service analytics and reports / Personalisation	**Primary:** Focus on Value Delivery, Budget and Investment in BA, Well Documented system enhancements. **Secondary:** Vendor Saturation and Tool selection, Non-Collaborative Workflow
Organisational Factors	**Corroborations:** Executive Sponsorship, Continued Investment in BA within the Organisation. **Theoretical Gaps:** Alignment of BA capability with business strategy. **Practice Gaps:** Risk-Taking	**Primary:** Company trust in Data. **Secondary:** Culture surrounding data-driven decisions

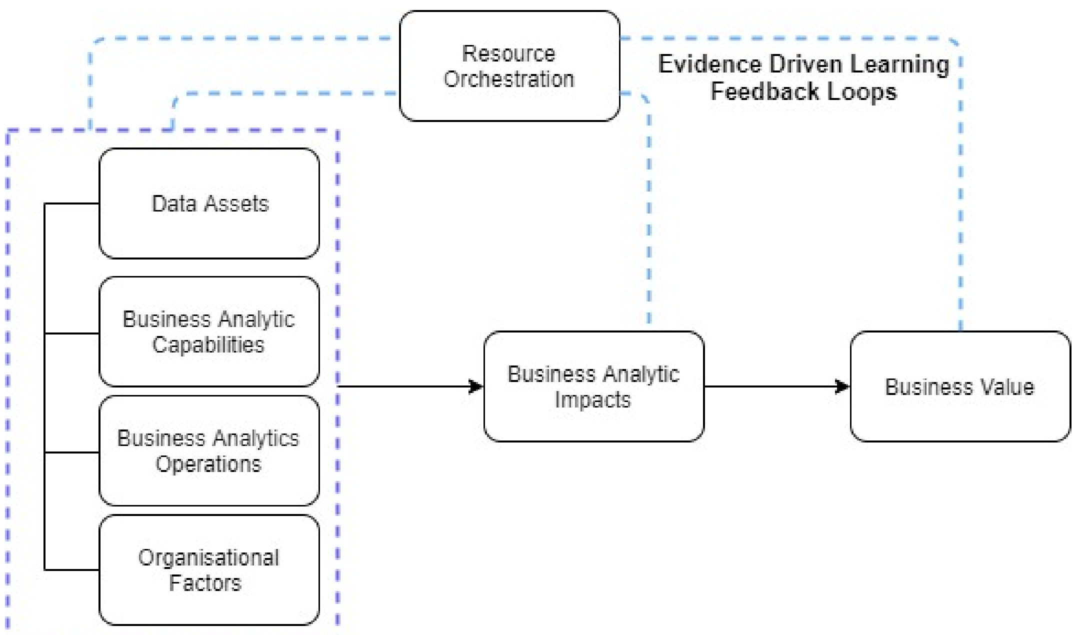
4 Conclusions

This paper gained insight into what ways business analytics can create value and developed an understanding as to what factors influence this. Based on analysing scholarly literature and real-life in-depth interviews, we can conclude that value contribution from a business analytic is highly influenced by all factors uncovered in our paper. From this, five factors were found to impact and influence value generation, Data Assets, Human Capabilities, BA Impacts, BA Operations and Organisational Factors. By collecting qualitative data from business analytic professionals, these factors were subsequently assessed analysed from corroborations and gaps in order to answer the research question - *"How does Business Analytics contribute to business value in organisations?"*

4.1 Theoretical Contributions:

Emerging from this paper, it is evident that there is a gap between the academic and professional stream of knowledge and the factors supporting value generation. We believe that positive results could be achieved by bridging them together to a greater extent. By conducting research with a greater socio-technical approach, more applicable and transferable findings could potentially occur. Hence, this paper provides the first step in the aim of bridging these literature streams and an initial attempt in addressing the encountered gap. As previous theory is lacking a more comprehensive view on the factors that influence value generation from business analytics within organisations, due to prior studies primary focusing on one or two aspects of, this paper by testing and validating prior studies in this domain and by providing a holistic view. Thus, this paper contributes to the existing literature on Business Analytics use.

Figure 2: Business Analytics Value Generation Model



Drawing from our conclusions, we theorise the model shown in figure 2, synthesising the steps in which business analytics generates value in organisations. To develop our model further, we use the resource orchestration framework as a lens to explain business analytic value generation and orchestrate analytic assets and factors. Key learnings within this point towards the cyclical nature of business analytics and business value, mechanised through evidence driven learning feedback loops.

4.2 Implications for Practice:

This paper provides managerial implications for utilising or adopting business analytics within their organisation. It can be used by managers and executives for making implementation strategies and analysing the impact of each factor and relating drivers. The role of absorptive capacity within an organisation is key in order for organisations to constructively build decision making processes to drive strategy, with adaptive learning being a cornerstone in this cycle. From the research analysis, 'People' has been highlighted as a critical success factor; being classed as drivers of assets as well as capabilities within the organisation. After all, it is the capabilities of people (known as human capital in the knowledge management literature) which interpret the data, using absorptive and transformative abilities.

Resource orchestration theory provides a contextual view of the environment and factors through the structuring, bundling and leveraging divisions. However, one should be aware that the framework itself is rather broad and mainly ignores the technical factors. This paper can further be used by other players in the ecosystem, such as the data professionals or organisations looking to adopt the technology, as the results touch upon potential value drivers or inhibitors coming from the collaboration with them. This could help the ecosystem to think how to ease the processes of implementing a successful and sustained business analytics program without the high degree of failures within organisations currently present. The resource orchestration framework as a managerial tool provides a good sense for creating implementation strategies and reviewing the contexts.

4.3 Limitations:

This research has some limitations that need consideration. Firstly, the participants interviewed with our paper were based within New Zealand. Although this was not seen as a large issue as participants included within the paper brought experience from working in other countries, this aspect could have been potentially studied further, as some themes in factors may have been affected by this. Secondly, the framework used for this paper is rather broad in nature, as a great wealth of information is contained in each of the five factors which were studied. As an alternative, we could have focused solely on one or two factors. However, as the previous research is lacking a holistic view of channels for value generation and the pitfalls towards reaching this, thus we wanted to address this gap by exploring the influence of all five factors. Hence, future research is encouraged to validate the findings further.

4.4 Future Research:

We believe that this paper contributes to the existing body of literature within Business Analytics, Value generation and inhibitors. Other researchers interested in the topic can replicate the research framework it for their own field studies by building upon our findings. Future studies could investigate BA value orchestration by taking the perspective of other organisations in differing ecosystems and countries, or by including more entities in the paper. Especially contrasting our findings against similar studies from other academic's perspectives would presumably provide valuable insights. Although this paper touched upon the domains of implementation and setting, the main focus of this paper was on the role of the factors and subsequent value generation. Hence this leaves room for fruitful avenues for research which would be practice oriented.

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