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An Empirical Investigation of Big Data Analytics: The Financial Performance of Users versus Vendors

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***Abstract*—**In the age of digitisation and globalisation, businesses have shifted online and are investing in big data analytics (BDA) to respond to changing market conditions and sustain their performance. Our study shifts the focus from the adoption of BDA to the impact of BDA on financial performance. We explore the financial performance of both BDA-vendors (business-to-business) and BDA-clients (business-to-customer). We distinguish between the five BDA-technologies (big-data-as-a-service (BDaaS), descriptive, diagnostic, predictive, and prescriptive analytics) and discuss them individually. Further, we use four perspectives (internal business process, learning and growth, customer, and finance) and discuss the significance of how each of the five BDA-technologies affect the performance measures of these four perspectives. We also present the analysis of employee engagement, average turnover, average net income, and average net assets for BDA-clients and BDA-vendors. Our study also explores the effect of the COVID-19 pandemic on business continuity for both BDA-vendors and BDA-clients.

***Keywords*—**BDA-clients, BDA-vendors, big data analytics, financial performance.

I. Introduction

An organisation does business by exchanging goods and services for money. The purpose of a business is to enhance the wealth of its owners, maximise sales and profits, and achieve its target market share. At the same time, a business should also provide a healthy working environment for its employees to learn and thrive and offer quality products to its customers. It should also ethically engage with its business partners and stakeholders, such as manufacturers, suppliers, customers, etc., and contribute towards achieving sustainable goals [61]. Traditionally, organisations utilised information systems (IS) to acquire data related to the business's internal processes, employee productivity, customers, external stakeholders, and the market. The IS systems extract valuable insights to drive business activities and enhance financial performance. However, the opportunity to gather, process, and analyse high-frequency/high-volume unstructured big data and present it in a digital format rendered the traditional IS systems quite ineffective in deriving comprehensive insights. Firms realised that if they did not extract crucial information, then they would have difficulties responding to the changes in the business market. This would impede their ability to upgrade products, improve operations, meet customer needs, sustain competitiveness, etc., resulting in a decline in their financial performance. Thus, adopting BDA systems became an absolute necessity for firms to derive relevant insights, transform their business, and achieve financial performance [77].

Businesses always explore new dimensions that would help them discover new knowledge, enhance decision making, and strengthen strategic planning from big data. Although there has been a great interest and substantial investment into BDA accompanied with anecdotal evidence of both success and failure, there has been little substantial research on the strategic contributions of BDA [10], [19] and the aim of this study is to fill-in the void by delving into the financial performance of the BDA-related firms. BDA projects rely on firms' existing technological infrastructure, staffs' data-skills and capabilities to process big data and transform it into strategic insights and forecasts to gain competitive advantage [19]. The adoption of analytics solutions which convert data into a valuable asset carries a significant financial burden for any firm. For example, the cost of three-year subscription to BDA applications such as, 'IBM PureData System for Analytics' and 'Cloudera Hadoop cluster' is $39 million and $50 million, respectively [68]. These figures pose a very important question: Do the investments in BDA payoff? Are the investments in BDA reflective of firms' financial performance? This is the first contribution this study will be making to empirical literature. Hence, in our attempt to tackle the first question this study defines BDA-clients as business-to-consumer (b2c) companies that invest in and utilise BDA-technologies.

Most of the literature studies (e.g. [37], [59], [75], [100], [101], [107]) focus on the BDA implementation, usage and benefits from BDA-clients perspective and how the BDA implementation assists the companies to deal with processing the vast amount of unstructured and raw data. Although BDA assists companies in dealing with the vast amount of data generated daily and responding to dynamic market conditions, the empirical studies investigating the impact of BDA on financial performance are still scarce. One of the reasons for the scarcity is that current research investigates the relation between BDA and its impact on the internal firms processes through the lens of information technology (IT) which discusses that the implementation of the BDA as an IT system that positively transformed the businesses or in some cases, even entire industries [66], [68], [84], [85]. The empirical evidence is not only scarce but tends to focus on a qualitative case study approach to examine how BDA provides informational support for decision-making, planning and management and the challenges which firms face in using BDA [13], [68], [92]. The case study approach revolves around firms developing big data analytics capabilities (BDACs), which are

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defined as "the ability of a firm to capture and analyse data towards the generation of insights by effectively orchestrating and deploying its data, technology, and talent" [65]. These capabilities emphasise the technical aspects of BDA but do not help understand the mechanisms and processes through which BDA contributes to business value [66]. Hence, to account for this very business value, it is essential to look at the financial performance of the businesses. Further, BDA is not a standalone technology, and instead encompasses a variety of tools, software, applications, and methodologies [71], and our study expands on this context in the "Technology Background" subsection. The "Technology Background" section discusses how each of these technological applications differs and how/ why each of them can be relevant to the nature of business.

Another aspect of this study is to shed some light into the suppliers as the empirical literature has focused almost exclusively on users and the theme of suppliers has not been addressed in the literature at all. Hence, we focus on BDA-vendors, which are business-to-business (b2b) companies that are service providers of BDA-technologies to BDA-clients. Although studies such as [23], [39], [62] discuss BDA-vendors as one of the determinants of BDA-adoption, these studies do not investigate the BDA product offerings and whether the vendors create value for themselves and whether they are financially viable. According to [27] and [11], organisational capabilities are a result of accrued knowledge gathered through interactions between the firms' technical (IT), human (employees) and intangible (expertise and business processes) resources. Since vendors are not directly involved with client firms, they rely on third-party resources and clients to acquire knowledge regarding BDA-clients' organisational processes to provide BDA-services. Our study contributes to the empirical literature by expanding the first research question into the financial viability of the BDA-vendors. These considerations pose another very important question: Do the investments in BDA payoff for BDA-vendors? Are the investments in BDA reflective of vendors' financial performance? This is the second contribution this study will be making to the empirical literature. Hence, in our attempt to tackle the second question this study defines BDA-vendors as b2b companies that invest in and try to create financial value by utilising BDA-technologies.

Most of the literature review studies explore BDA-implementation as a package rather than separate entities, such as BDaaS, descriptive, diagnostic, predictive, and prescriptive analytics [42], [62], [82]. However, no study to the best of our knowledge explored the different technologies embedded in BDA and their impact on the users and suppliers of the service. This study makes an attempt to shed some light into this uncharted area of different BDA technologies and financial performance as well. Hence, this study tries to address these gaps and brings together BDA-vendors, BDA-clients and how BDA-related technology packages affect their financial performance. Further, our study goes beyond the determinants of BDA-adoption explored in technology acceptance model theories, such as the Technology Adoption Model (TAM by [98], [99]). Instead, our study shifts the focus to what happens after BDA-models are adopted, i.e., do firms achieve positive returns?

Hence, our study addresses these two research gaps by utilising a sample of BDA-clients and BDA-vendors operating in the UK to account for how BDA-technologies impact on different performance-related perspectives emphasising "Internal business processes perspective", "Learning and growth perspective", "Customer perspective" and "Financial perspective". Each of these sections discusses different aspects of BDA capabilities and the subsequent impact on improving information quality and enhancing decision-making. Also, under these sections, our study provides an analysis of the BDA-clients' and BDA-vendors' financial performance trends before and during the COVID-19 pandemic. The BDA-clients' and BDA-vendors' financial performance analysis is based on their financial report filings with the UK government's company house [38]. Thus, our study contributes to the literature by extending BDA research in accounting as well as exploring BDA impact during the COVID-19 pandemic through empirical findings.

II. Theoretical Framework

BDA originates back to the seminal paper by [35] which conceived the term of "Decision Support Systems" (DSS) to describe a class of IS that are meant to assist humans in making decisions when faced with the situations full of unstructured problems (for example, sales growth or production planning) [68]. Since the DSS, more data types and technologies have been introduced that help managers to utilise data and extract knowledge for supporting decision making [1]. It is very common these days for managers and data scientists to use BDA applications enabling them to explore, uncover, and predict business activities. For example, by using a survey of 32 companies, [25] reported a positive association between intensity of usage the of analytics and a firm's growth rates. Similarly, IBM's survey amongst 3000 executives discovered that top-performing firms utilised BDA five times more than low-performing firms [55].

Also, Internet-of-Things (IoT) sensors collect data at minute levels (from mobile devices, social media, blogs, emails, etc.), generating a huge amount of data, resulting in data deluge. However, immense amount of data does not mean quality information and requires filtering to derive facts [7], [11]. Hence, firms invest in business analytics applications that scrutinise and transpire big data to predict plausible events and future trends, which can be capitalised by firms to generate socio-economic business value [57]. Thus, BDA refers to the adoption of business analytics solutions by the firms to derive value from big data [68]. However, BDA is a varied and complex field that often relies on several algorithms, specialist software, and automation processes. As the business environment grows competitive and increasingly complicated, companies search for ways to implement BDA technological solutions to handle large volumes of data and extract valuable insights to survive and thrive [57]. Nowadays, almost all companies use cloud computing platforms and one or more of the business analytics processes discussed in the "Technology

Background" subsection [71], [54].

A. Technology Background

BDA is not a standalone technology but encompasses a variety of tools, software, and applications: the so-called collection of technologies [71], [57]. A large number of firms have increased their BDA initiatives to derive insights for achieving competitive advantage. BDA is categorised as a prospective frontier for innovation, competition, and productivity by practitioners and scholars. According to [64], compared to the corporations that are less analytically driven, highly driven analytical corporations experience three times more growth [110]. Hence, for our research study, it is crucial to understand the significance of each of these BDA-related technologies as the involved parties may show preference to invest in several of these technologies depending on their liquidity and business needs. These technologies are complementary, and when used in combination, increase the efficiency of a business. Hence, BDA collectively refers to the technologies discussed in Fig. 1. The latter shows the connection between big data, cloud computing, and business analytics. Fig. 2 on the other hand illustrates the increasing relevance of each business analytics technology for the business.

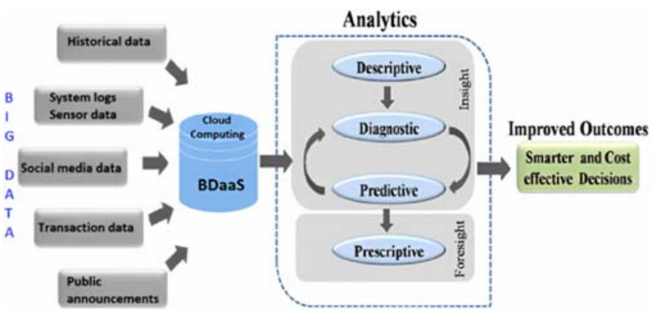

Fig. 1 Big data, Cloud and Business Analytics [24]

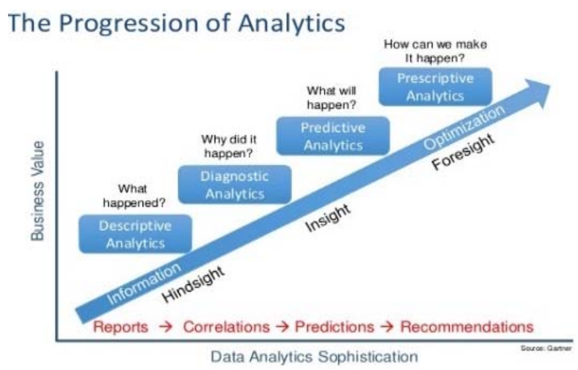

Fig. 2 Analytics and business value [70]

Big Data and Cloud Computing: Big data is defined as the massive amount of unstructured data characterized by five “Vs” i.e., volume, velocity, variety, veracity, and value [68]. Traditional IS lack the capacity of obtaining and moving large big data sets over database networks, require longer processing time and have limited storage space [88]. Cloud computing resolves these challenges by offering storage and processing capabilities to collect and process these unstructured data from various sources [9]. In cloud computing, technologies such as storage and networking equipment are the building blocks of the service and companies no longer need to invest in IT infrastructure. Instead, they rely on third-party (vendor) infrastructure that enables access to virtual "cloud" resources such as remote servers, interfaces, applications, networks, and on-demand services [52]. This combination of the cloud with big data is known as big-data-as-a-service (BDaaS), which companies can access 24x7 from multiple devices—desktop, laptop, and tablet; enabling them to have flexible and streamlined operations [10], [54].

Descriptive Analytics: It is the foundational starting point of business analytics that collects and organizes data from the relevant data sources, extracts the necessary information, and displays it on dashboard visualizations. Historical review of the organisation’s operations is provided by inventory, sales, workflow, and revenue reports, which are various illustrations of descriptive analytics [2]. Hence, 90% of companies invest in and frequently use descriptive analytics as it is the most basic and well-understood approach for analysing data [104]. For example, an annual revenue report may appear financially satisfactory on its own, but when compared with the reports of previous years, can reveal the differences in net profit/losses [2].

Diagnostic Analytics: It is the natural follow-up of Descriptive Analytics focusing on determining previously unknown correlations, such as why a particular event occurred or why a trend is developing [69]. It presents the full spectrum of causes behind the events and trends, ensuring that the firm has the whole picture [81]. It employs scorecards, dashboards, and data visualization tools as well, to acquire insights for taking corrective actions and solving dilemmas [104]. For example, the sales team can determine why certain consumer segments generated more profit the previous year compared to the current year [89].

Predictive Analytics: After knowing what happened and why it happened, comes predictive analytics, which provides the best estimations of what might happen in the future [29], [47]. Despite its complexity compared to descriptive and diagnostic analytics the share of users seems to be increasing, although not at a great pace [104]. Its complexity stems from implementing it in conjunction with machine learning to conduct a rapid and iterative analysis of past performances to determine the probability of various outcomes and anticipate the future [47], [80]. However, predictive analysis is not entirely accurate as it depends on probabilities, but it is a vital tool for better planning, avoiding unnecessary risks and setting realistic goals [89]. For example, the sales team can also predict the revenue potential likely to be achieved from a particular customer segment [2].

Prescriptive Analytics: It is the most advanced form of analytics and operates on the forecasts from predictive analytics [89]. It utilises artificial intelligence, business rules, operational algorithms, and simulations to provide adaptive, automated, time-dependent, and optimal decisions [58]. Hence, less than 3% of companies use it as it requires much more specialised analytics knowledge and is quite sophisticated to implement [104]. It has the ability to process new incoming information and refine its prescriptions, helping firms discover valuable opportunities, mitigate future risks, fix problems, and improve performance [8]. For example, it processes the public announcements from large corporations and real-time market data to re-estimate the prescribed business activities and investments [58].

It comes as a natural step to classify the aforementioned technologies into 2-sections: *(i) basic analytics* (BDaaS, Descriptive and Diagnostic Analytics) and *(ii) advanced analytics* (Predictive and Prescriptive Analytics). The former deals with processing big data and deriving valuable insights whereas the later embarks on data insights to forecast future predictions and recommend actions/decisions, respectively see Fig. 3.

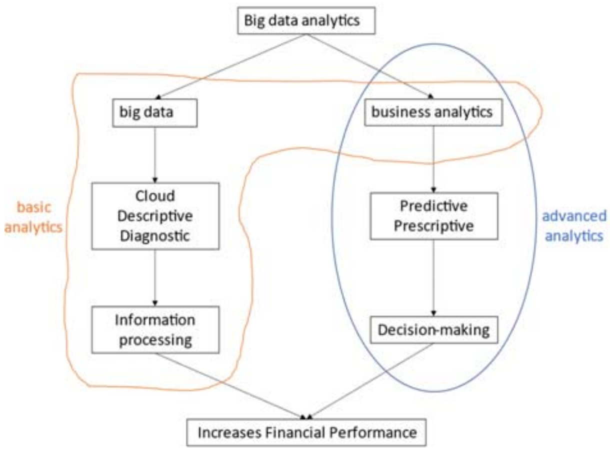

Fig. 3 Basic analytics and Advanced analytics

As mentioned earlier, both BDA-clients and BDA-vendors can invest in either one or several of the above technologies based on their business needs and financial means. The motive of the BDA-clients would be to increase their revenue, market share, operating efficiencies by using BDA while the motive of the BDA-vendors would be to retain and increase their BDA-clients which in turn increases their revenue and the necessary means to further enhance their products. Both BDA-clients and BDA-vendors will also focus on four perspectives: (i) internal business processes, (ii) learning and growth, (iii) customers, and (iv) finance perspective. The internal business process perspective discusses the implementation of BDA-technologies, while the learning and growth perspective discusses employee engagement with BDA-technologies. The customer perspective refers to the role of BDA in customer retention, customer acquisition, and customer satisfaction, while the financial perspective discusses financial outcomes stemming from using BDA technologies. This study focuses on the latter. Hence it comes as a natural evolution to analyse the financial performance of 10 BDA-clients and 20 BDA-vendors (discussed in the later parts). Out of ten BDA-clients, two are small-sized while remaining eight are large-sized companies. Out of twenty BDA-vendors, eleven are small-sized, five are medium-sized, and four are large-sized companies.

III. Business Perspectives

A. Internal Business Perspective

The internal business process perspective focuses on the integration of BDA technologies with the existing IT infrastructure of the organisation [48]. This perspective helps measure whether the implementation of BDA technologies has improved the efficiency of the internal business processes to collect and analyse big data and generate valuable insights to make informed decisions [8]. The internal business perspective looks into BDA-packages offered by BDA-vendors and whether these BDA-packages are customisable across different industry sectors, along with the value-added services (maintenance, support, licensing) and updating/upgrading BDA-packages. In the case of BDA-clients, the internal business process perspective refers to areas of BDA implementation, i.e., CRM (customer-relationship management), SCM (supply chain management), ERP (enterprise resource planning), etc.

In the case of cloud models, big data with cloud computing is a powerful combination that creates a BDaaS model to reap all the advantages of the cloud [74]. Implementing this model across cloud computing platforms creates three models, i.e., Big-data-Software-as-a-Service (BDSaaS), Big-Data-Platform-as-a-Service (BDPaaS), and Big-Sata-Infrastructure-as-a-Service (BDIaaS) [5]. BDA-clients can opt for either one or a combination of the BDaaS models depending on their business needs [9] as BDaaS models increase the scalability and efficiency of IT resources to manage big data traffic and deploy other advanced business analytics technologies across the organisation quickly. Further, BDaaS models enable easy installation of updates, ensure regular data back-up, and provide flexible data accessibility from any location, any device, and at any time [73], [17]. This leads to the effective execution of business activities, workflow coordination, and resource optimisation [54]. In principle, these models are likely to exercise a (positive) impact on companies' financial performance.

After using BDaaS, comes descriptive analytics, which consists of two main techniques, i.e., operational intelligence (analysis of real-time incoming data) and business intelligence (analysis of historical data). Both of these techniques work together to process, retrieve, sort, and correlate real-time and historical data sets to extract actionable information and provide a comprehensive overview in the form of charts, graphs, and dashboards [95]. Hence, it improves the efficiency of internal data processes, data dissemination, and information value chains across the organisation [36]. Hence, this study offers an insight into whether descriptive analytics provides BDA-clients and BDA-vendors with knowledgeable information on dashboards and increases the speed of their operations.

BDA-clients cannot find solutions to all their questions merely by observing the data obtained from descriptive dashboards. They need to delve deeper into the data to understand hidden correlations and patterns [104]. Hence, diagnostic analytics plays a crucial role in helping companies perform root-cause analysis and discover causal relationships [40]. It uses business intelligence, exploratory analysis, and machine learning algorithms to dive deeper than descriptive analytics to find hidden patterns, evaluate facts and figures, investigate the root cause of unfavourable outcomes. By doing so the process minimises humans' unintentional bias and reduces errors [26], [102], [46]. Hence, our study explores whether diagnostic analytics enables BDA-clients to reflect on their past losses/negative events/incorrect-decisions and improve their existing business operations.

After performing data diagnosis, comes predictive analytics, which upgrades internal business processes to predict future values related to productivity, profits, return-on-investment, etc. [8]. Predictive models utilise cognition and build upon the knowledge and insights from basic analytics to predict/ benchmark future performance [104]. In order to predict future values, predictive simulations run in two stages, i.e., first to extrapolate current business activities to forecast future outcomes and second, to test hypothesised correlations and observe the impact on future performance [53]. As predictive analytics is forward-looking, it enables internal business processes to be constructive and thrive on future predictions rather than traditional assumptions [30]. Hence, our study explores whether predictive models enable BDA-clients to respond effectively to market uncertainty and recommend accurate predictions which in principle will be reflected on financial performance.

Prescriptive Analytics further operates on the results obtained from predictive analytics and increases the efficiency of internal business processes to devise actions [8]. Based on the outcomes of predictive analytics, it provides two levels of data-driven decisions, i.e., decision support and decision automation. The former recommends actions, and if approved by humans, the latter implements the prescribed actions [58], [31]. These models utilise optimisation and simulation techniques to assess the past and current dynamics of the market and validate the robustness of the outcomes [53]. Thus, prescriptive analytics optimises the internal data processes to maximise the revenue and profit outcomes and reduce the costs, expenses, and losses [104]. Hence, our study explores whether prescriptive models enable BDA-clients to respond effectively to the dynamic market conditions and improve their market position.

However, different businesses across different industry sectors have different data needs. For example, the retail industry collects customers' behavioural and purchase data for better customer management and building customer relationships, whereas the healthcare industry collects medical data and performs diagnoses to make accurate medical decisions [83], [101]. On the other hand, the manufacturing industry might focus on enhancing its supply chain operations to sustain its performance [44], [62]. Most of the literature review studies explore BDA-implementation as a package rather than separate entities, such as BDaaS, descriptive, diagnostic, predictive, and prescriptive analytics (see for example, [62], [42], [82]). There are other studies (see,, for example, [104], [81]) which provide a brief distinction between BDA-related technologies (descriptive, diagnostic, predictive, and prescriptive), however, these studies again do not discuss the implementation of basic and advanced BDA-models and their impact on performance. Very few studies such as [59], [58], [54] have investigated only *one* particular BDA technology such as prescriptive analytics, predictive analytics and cloud based BDaaS, respectively. However, these studies do not address the BDA as a package because of which they do not analyse the relationship and complementarity of one BDA technology with another. Neither do these studies investigate the perspective of BDA-vendors.

B. Learning and Growth Perspective

With the learning and growth perspective, our study tries to investigate how BDA-technologies enhance employee productivity and create business value [49]. We explore the roles and expertise of various employees, such as data scientists, data analysts, data engineers, etc., in operating, upgrading, and deploying BDA technology-related models. Further, we explore whether organisations provide training to these employees, labour costs, and outsourcing of BDA-based projects. Employees can provide insight on whether the organisation's BDA adoption has aligned with its internal business processes [8], enhanced their capabilities [49], and generated reliable insights and forecasts to undertake strategic decisions for sustaining performance [73].

BDaaS enables organisations to have a seamless and timely flow of information between various business processes. However, BDaaS implementation requires upskilling of employees to rethink their operations and adapt to the BDaaS-based cloud computing environment [12]. Employees must have skills and training to access BDaaS-based tools, applications, and functions to process big data and extract insights [105], [54]. Hence, our study implicitly investigates whether employees can utilise the scalability feature of BDaaS models to incorporate data deluge and respond to dynamic market conditions. The implicit assumption is straightforward and echoes the propositions put forward by [94]: If employees tune BDaaS with the company’s objectives the operational performance is likely to increase.

Descriptive analytics, as it was stated above, analyses, interprets and filter crucial data from BDaaS models and report information through visual dashboards at various organisational levels [96]. Hence, employees need to be familiar with descriptive analytics techniques such as statistical methods, data aggregation, and data mining [93], [24]. The implicit hypothesis is straightforward: if the companies and their employees utilise descriptive analytics capabilities (such as automated reporting processes and intuitive dashboards) then they can leverage their research and development activities through better business performance [8]. Furthermore, descriptive dashboards evaluate dynamic market conditions and automatically report a sharp change (e.g., an incline or decline) in trends/patterns of sales, customer purchases, or productivity [14].

After knowing the status of performance metrics, diagnostic analytics plays a crucial role in retrospecting why certain trends/events occurred. This is especially applicable when unfavourable market circumstances, such as negative economic events (recession, COVID-19) take place. In such scenarios, diagnostic analytics can help companies navigate through the uncertainty of decision-making by performing the root cause analysis of previous events and provides a comprehensive picture of business activities [87], [70]. To perform diagnostic analysis, employees must know advanced data mining techniques such as regression analysis, anomaly detection, and clustering analysis [34]. Our study hypothesis that employees are able to utilise diagnostic analytics before and during the pandemic and refine strategies revolving around sales, revenue, profit, risk analysis, and simultaneous cost-cutting [95]. These skills should be reflected on the financial performance.

The limitation of basic analytics (BDaaS, descriptive and diagnostic) is that it does not provide the possibility of future outcomes related to current investments in technology adoption and employee training [8]. Hence, predictive analytics is essential to evaluate risks and opportunities and estimate various target variables (returns, profit, etc.) across different business areas, such as employee training, inventory levels, customer purchases, product innovations, etc. [80], [28]. Employees must be skilled in statistical modelling, machine learning algorithms, time series regression, and probability theory models to build predictive analytics models [22], [8]. Hence, our study echoes the proposition put forward by [44] and explores whether employees can maintain, monitor, and modify the predictive models and if they do so then the financial performance of the organisation should be maintained.

Prescriptive analytics adds the most value to the business as it shifts the focus from forecasting decisions to the actual opportunity/problem at hand and protects business value [16]. Prescriptive analytics resolves the time gap between predictions and actual actions by generating proactive decisions based on forecasts and helps enhance business value [58]. For example, if the forecasts show positive results, it prescribes the best possible decisions to achieve the desired outcomes. Alternatively, if the forecasts show unsatisfactory results, then it prescribes advice to attain better outcomes [76]. Employees need to be familiar with artificial intelligence, simulations, programming, business rules, and computational modelling to administer prescriptive analytics [58]. Hence, our study echoes the proposition put forward by [76] and explores whether the employees utilise the prescribed decisions and actions to enhance their organisation's products, customers, and market performance.

The aforementioned discussion tells us the various employee skills and knowledge that are crucial for operating different basic and advanced BDA-technologies. However, given the customisation and implementation of BDA-technologies across different industry sectors, it is important to determine whether BDA-vendors and BDA-clients hire employees on a salary basis or a contract basis, and the labour costs of these employees. Further, in the real world, it is essential to investigate how the different job roles (data scientists, architects, analysts, etc.) contribute to building, maintaining, and updating different BDA-models. Our study also investigates the learning and development, training, and competency courses offered to the employees across both BDA-vendor and BDA-client firms. We also explore the possibility of whether some BDA-client firms outsource their BDA-based operations to their BDA-vendors. Further, since these employees work closely with BDA-models, they can help us determine whether building (BDA-vendors) and using (BDA-clients) basic analytics and advanced analytics have helped them derive better insights and more accurate forecasts, respectively.

C. Customer Perspective

With the customer perspective, our study investigates the degree to which BDA-clients are satisfied by using BDA-services (B2B) to increase and retain their customers (B2C). In the case of BDA-clients, we explore their turnover, and the extent to which they are satisfied with the customer-data collection, product and service innovation, customer-related forecasts, and customer retention [49], [73]. In the case of BDA-vendors, we explore their turnover and the extent to which their BDA-package has helped their clients with market performance (i.e., B2C customer satisfaction).

Numerous companies across the globe have started using the cloud's BDaaS in conjunction with their CRM and ERP systems [45]. This collaboration enables them to use the processing and storage power of the cloud platform to collect and store data about their customers and build their knowledge repositories regarding customers' characteristics, behaviour, demographics, and purchasing history without worrying about on-premises storage. Companies gather such knowledge during customer interactions such as purchasing, after-sales services, customer feedback surveys, cookies, and third-party sources [37]. Hence, our study echoes the proposition put forward by [20] and looks into certain financial data such as revenue and net incomes in order to assess the impact of BDA on certain financial performance indicators.

Descriptive Analytics filters the unstructured data gathered from various data sources such as company websites, forums, social media platforms, customer feedback, daily transactions, etc. [8]. Then, it extracts and summarises the information for products and services through intuitive dashboards that display daily sales, ratings, reviews, likes, product-views, product return rate, defect rate, warranty claims, etc. [28]. It enables the sales department to analyse customer trends/events over time, such as purchase history, purchase patterns, abandoned shopping carts, product returns, relevant feedback, etc. [41]. Some companies also use techniques such as textual ETL (extract, transform, load) to obtain customers' satisfaction levels (beliefs, pleasure, emotions, compliments) and expectations (suggestions, sentiments, cultural values) from text content [79], [40]. Hence, our study explores how BDA-clients' can use descriptive analytics to generate customer insights to evaluate their brand value, customer loyalty, improve their goods, launch new products, enhance service quality, etc. [109], [41].

Diagnostic Analytics builds upon descriptive dashboards by performing diagnoses across various products and consumer segments such as demographics, locations, purchasing behaviours, etc. [18], [21]. It helps companies understand the customer experiences (unique or repetitive) with the brand and customer preferences for products and services [97], [40]. Hence, our study explores whether diagnostic insights help BDA-clients to understand customers' behavioural patterns and adapt to customer needs, improve the quality of products and services, and provide efficient sales services to their customers [15].

Basic analytics (BDaaS, descriptive and diagnostic) offer customer insights, however, predictive analytics equips BDA-clients with customer-related future forecasts and recommendations [59]. Predictive models assign scores to the customers based on their needs for products and services, satisfaction levels, value, revenue, and maintenance costs. The score indicates what a customer is most likely to purchase in the future. Hence, companies can predict customer preferences, develop leads, and formulate optimal pricing strategies [91]. As per the predictions, if the customer makes the purchase, then predictive models identify other customers within the same segment and with identical scores, who are more likely to make a similar purchase, and proactively reach them. This leads companies to create personalised ads for each customer segment at a lower cost, improve their strategic planning and enhance customer engagement [111], [63]. Therefore, our study explores whether predictive models' forecasts are accurate and provide BDA-clients with a better understanding of customer needs, enhance their product and service offerings, and achieve customer satisfaction.

Fig. 4 Average Turnover for BDA-clients

Prescriptive analytics further enhances customer satisfaction by enabling BDA-clients to keep up with all customer-related factors [49]. It involves quickly responding to customer requests, improving product quality, optimising pricing, and mitigating risks while managing budget constraints [8]. It helps avoid customer churn due to dissatisfaction with products and services and lowers customer acquisition rates [51]. Based on predictive forecasts, prescriptive analytics can prescribe recommendations, cross-selling (complementary products), and up-selling (upgrade to the higher version at a discount) opportunities [91]. Amazon's recommendation engines are a classic example of predictive-prescriptive analytics, driving 35% of their sales [3]. Hence, our study explores whether prescriptive analytics recommendations help BDA-clients anticipate and respond to customer needs, acquire new customers, and achieve customer loyalty and retention.

Our study puts the aforementioned discussion into actual perspective and records the financial performance of 10 BDA-clients coming from various industry sectors such as retail, hospitality, health-care and finance. Out of the 10 BDA-clients, we have turnovers available for 5 companies from 2016-to-2021. The remaining half have either reported turnover for the last 2-or-3 years or have not filed their financial statements with the company house [38]. Based on the data available for 5 BDA-clients, we have plotted the histogram in Fig. 4 which shows average turnover for BDA-clients. The average turnover shows a gradual increase from 2016 to 2020 followed by a downturn in 2021. The latter is explained by the adverse effects of COVID-19 closures and restrictions [38]. Based on the above data shown in Fig. 4 and the fact that all the aforementioned companies have been using BDA technologies, we can confidently state that the basic and advanced BDA technologies did contribute to their business operations (as all the companies have been using BDA) and BDA probably mitigated the adverse effects of COVID-19 downturn as the latter was not as severe as initially thought. On the other hand, the average turnover for BDA-vendor firms from 2016-to-2021 helps us determine whether BDA-models are sold and accepted by the BDA-clients in the market.

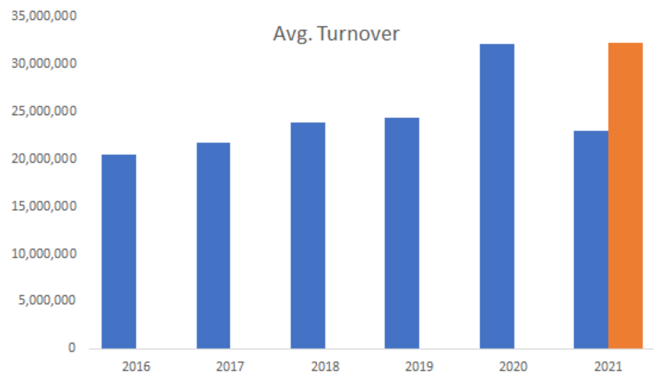

Fig. 5 Average Turnover for BDA-vendors

Fig. 5 shows that from 2016 to 2020, the average revenue of the BDA-vendors steadily increased and in 2020 there was a significant increase in demand for BDA technologies as the BDA-vendors significantly increased their turnover. In 2021, we have data available for only six firms but using linear regression, we are able to see that turnover for BDA-vendors in 2021 would be similar to that in 2020 (shown in orange). The steady increase in turnover suggests that BDA-vendors are building new products and services and there is a demand for BDA-models in the market. Also, the average turnover during 2019 and 2020 is quite significant, given the lockdowns due to the pandemic, insinuating that the restrictions in the market-place augmented the demand for BDA-products and services on behalf of the market participants. Therefore, our results verify the aforementioned hypotheses: BDA technologies (basic and advanced) do collect and analyse volumes and varieties of market data and generate apparently accurate customer insights and forecasts for BDA-clients. As a matter of fact, the demand for BDA-products, which in turn increased the turnover for BDA-vendors has been on the rise and the market restrictions in 2020 helped the clients to sustain their operations.

D. Financial Perspective

The financial goal for both the BDA-vendors and BDA-clients would be to increase their revenue and profit-margin [49]. In the case of BDA-vendors, their financial performance is directly dependent on their customers. A higher number of customers (i.e., BDA-clients) signifies higher subscription rates, which ultimately increases their revenue. In the case of BDA-clients, their financial performance depends on customers, business productivity and cost savings. It is crucial to note that both basic-BDA (BDaaS, descriptive, diagnostic) and advanced-BDA (predictive, prescriptive) contribute differently towards financial performance. The basic-BDA provides insights on financial aspects such as revenue, sales, productivity, profits, returns, and growth [73] while the advanced-BDA not only generates forecasts on these financial aspects but also helps enter new markets, develop new products, and gain new customers [80], [8].

The adoption of BDaaS models enables BDA-clients to rely on cloud architecture and have minimal IT set-up, saving them from incurring additional IT costs [56], [50]. Also, because of the pay-as-you-go option, BDA-clients can utilise the cloud services as per their convenience and alter their expenditure based on their demand for IT services. Thus, cloud scalability and flexibility increase the return-on-investment (ROI) of the BDaaS models [94]. Further, since cloud service providers (vendors) deal with the issues related to software purchases, legal rights, licensing, real-time server maintenance, and backup, BDA-clients can focus more on developing their products and services and increase their profit margin [20]. The recent market surveys amongst companies that have used cloud-based services from Oracle and Amazon Web Services (AWS) reported an overall 30%-to-50% savings on IT infrastructure and operational costs [33], [43]. Hence, our study explores how BDaaS helps BDA-clients with IT cost savings and revenue growth.

Descriptive analytics provides an overview of the overall financial performance of the company to the stakeholders. The financial dashboards illustrate the real-time profit, sales, customer transactions, etc. Setting up a dashboard with meaningful key performance indicators (KPIs) displays real-time updates on the ratio analysis of the company, such as current ratio, burn rate, net profit margin, gross profit margin, ROI, etc. [32]. It compares current financial ratios with both the company's historical financial ratios and industry benchmark ratios, indicating the growth of the company and its competitive advantage, respectively [8]. It highlights any performance inconsistencies and enables companies to take instant actions, thus protecting them from incurring losses (see for example, [32], [90]).

Diagnostic analytics focuses on determining the underlying correlations behind the financial outcomes [72]. It helps BDA-clients analyse correlations between sales patterns and determine why some marketing channels generate more leads than others, enabling them to formulate cross-selling strategies [91]. BDA-clients can compare the attributes of high-performing social media ads with low-performing ones to figure out why they worked differently and how they influenced sales [89]. Further, BDA-clients can break down sales and gross profit for various customer and product segments and their subcategories to understand why they missed the overall profit margin [6]. It enables BDA-clients to identify products that do not have sufficient demand, for which they can either improve the product quality or offer suitable products that meet customer needs. Thus, BDA-clients can evaluate product value to enhance their market performance and sustain their competitive advantage [103]. Also, diagnostic analytics is the interim gateway for building predictive models because organisations cannot move to advanced analytics without relevant data [72], [67]-. Hence, our study explores whether basic analytics has helped BDA-clients with their revenue growth and improved their business productivity, especially during the COVID-19 pandemic, as diagnostic analytics might have helped them identify various correlations for business continuity.

In the financial perspective, firms use predictive analytics to utilise their resources more efficiently and achieve their financial goals, such as target revenue, profitability, sales growth, customer retention, and operational performance. Predictive analytics increases the efficiency of utilising the insights from basic analytics and generating forecasts, enabling firms to undertake timely and accurate decisions and sustain their competitive advantage [8], [82], [108]. Hence, managers can improve their strategies on price optimisation, profit maximisation, reducing unwanted costs and improving ROI [4], [59]. After tracking customer behaviour, predictive analytics segments customers based on customer loyalty, from high-value (most profit-generating customers) to low-value, and helps companies predict the revenue [103], [106]. Thus, predictive analytics plays a crucial role in preserving loyal customers because gaining new customers costs five times more than retaining the existing ones [106], [60].

Companies feed predictions/forecasts from predictive models into prescriptive analytics to draw upon a range of optimal solutions, i.e., it not only prescribes best actions but also prescribes an alternate set of actions. These prescriptions are crucial for business growth when exploring new markets, innovating new products, acquisitions, partners, and gaining new customers [78], [76]. All these allows companies to understand the impact of their actions on their future financial performance [58]. It then recommends cost-effective solutions without compromising the quality of products, meets customers' needs, fulfils demand and supply, and generates profits [86]. Further, it analyses social media, news, profile and market data related to various business partners, such as manufacturers, suppliers, vendors, etc. It helps choose business partners who offer reasonable prices on maintenance, support, and services. These partnerships are beneficial for increasing revenue and enhancing the long-term business value [8].

Putting the aforementioned discussion into perspective for both BDA-vendors and BDA-clients sheds further lights into the impact of BDA on their financial performance. We have already established an upward revenue trend for a typical company involved with BDA technologies (see Figs. 4 and 5). When it comes to BDA-clients the increase in revenues (Fig. 4) is not accompanied with an increase in net income (Fig. 6) and its seems that the costs are running ahead of revenues. Average net income for the same BDA-clients is shown in Fig. 6 where the downward trend is noticeable. Deeper financial analysis shows an increase in the average cost-of-sales (CoS) and selling, general, and administrative (SGA) expenses from 2016-to-2021. It seems that the BDA-clients were able to expand their business operations (turnover), but the latter was achieved with a higher cost. Of course, it is quite difficult to peer into the role of BDA technologies on costs, but a possible explanation is that the BDA-technologies tend to focus more on external and market wide factors (analysis of unstructured and raw market data) at the expense of internal and company specific factors.

According to our analysis of BDA-vendors' average turnover from the customer perspective (Fig. 5), the turnover seems to have increased steadily. However, the average net income for the BDA-vendors, shown in Fig. 7 gives a different perspective. Out of 20 BDA-vendors, we only have data for six BDA-vendors for 2021. From 2018 to 2020, the average net income is significantly affected by a major negative net income from one of the major BDA-firms which acts as an outlier. Therefore, we have 3-different colours in the histogram. The green-colour shows the average net-income for all the firms, including the outlier. The blue-colour shows the average net-income for all the firms, excluding the outlier. Further, we use linear regression to determine the average net income for BDA-vendors including the outlier (represented in yellow-colour).

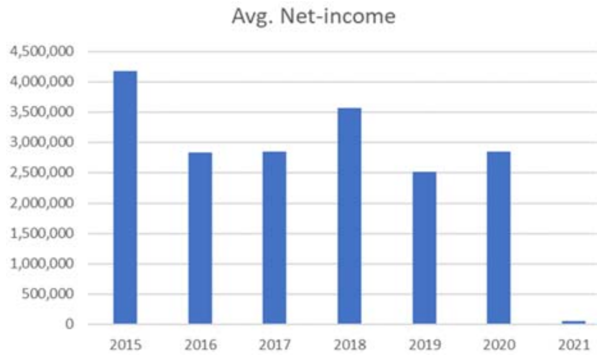

Fig. 6 Average Net income BDA-clients

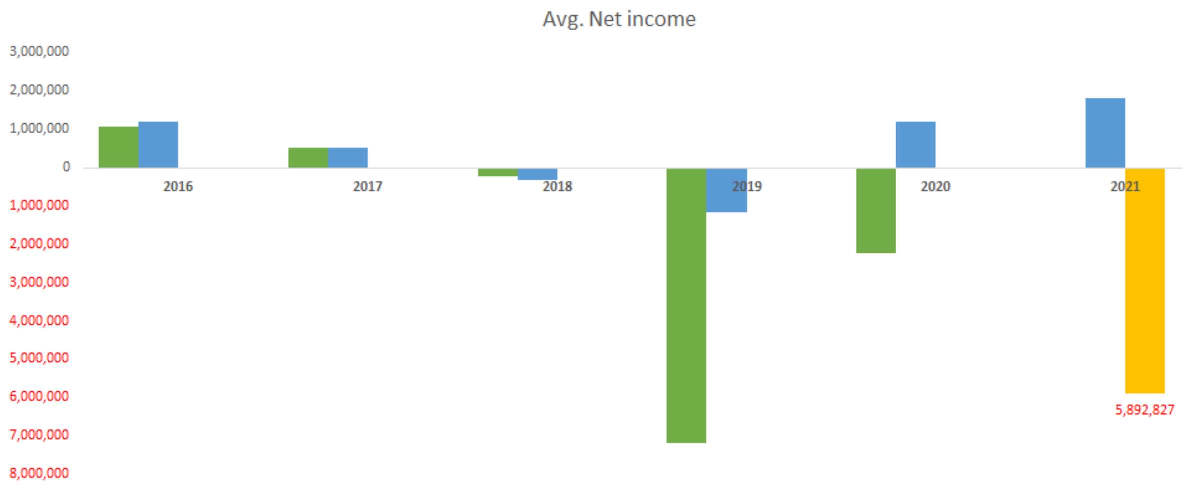

Fig. 7 Average Net income BDA-vendors

From 2016-to-2019, all firms, excluding the outlier, show a gradual decrease (blue-colour) in their average net income. Further, if we exclude the outlier, all other firms show a rise in their average net income in 2020 and 2021 (blue-colour). A deeper analysis into the performance of the outlier shows a significant increase in SGA expenses impacting the net income. Hence, the outlier's net income brings down the average net income for other firms in the negative range, especially in 2019 (green-colour). Further, linear regression shows the effect of the outlier and the other three BDA-vendors on the average net income to be sharply negative in 2021, similar to 2019 (yellow-colour). One of the reasons for the decrease in net income is the high amount of SGA expenses, especially during the pandemic period. This insinuates that maybe during lockdowns, there was a high demand for BDA-services as the majority of businesses had shifted online, employees were working from home, and purchases for goods and services were mostly done online. The BDA-vendors also faced the same challenges during pandemic as every single business entity. BDA-vendors are destined to be building new BDA-models to address the changing market conditions and provide necessary maintenance, upgrade, and support to their clients, but these very changing market conditions come at a significant cost. Hence, although the average turnover shows a gradual positive increase, due to high SGA costs, the average net income shows losses.

Fig. 8 histogram represents the average net assets (or shareholder's equity) for BDA-vendors as we want to see the value of the business as reflected by the shareholder equity.

Remarkably the average net assets for the BDA industry sector also increases (blue-colour). However, for 2021, only six BDA-vendors have reported their average net assets (blue-colour). Therefore, we use linear regression to determine the average net assets for 2021 (orange-colour), which is consistent with the average net assets of six firms. This indicates that the BDA-vendors have expanded and had more shareholder investments, especially during the pandemic. It shows that the value of the assets is running ahead of its liabilities. It also shows that the BDA-vendors depend on equity financing rather than debt since the Net Assets have been steadily increasing.

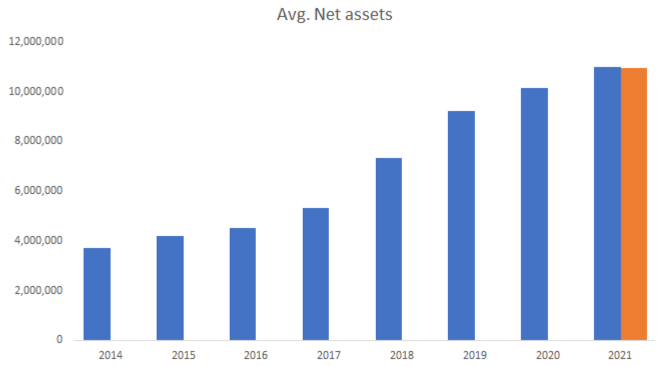

Fig. 8 Average Net Assets BDA-vendors

IV. Conclusion

Companies implement BDA technologies to collect and process large amount of unstructured data for deriving valuable insights and making evidence-based decisions to enhance their business value. Most of the studies [65], [77], [100], [62] explore BDA as a single entity. On the contrary, our study has segregated BDA into tools and applications that together make up the BDA technology. These tools and applications are BDaaS cloud models, descriptive analytics, diagnostic analytics, predictive analytics, and prescriptive analytics. Our study discusses the application and importance of each of these BDA-related technologies in the "Technology Background" section. Further, our study classifies these technologies under two categories, i.e., basic analytics and advanced analytics. Basic analytics consists of BDaaS, descriptive analytics, and diagnostic analytics, while advanced analytics consists of predictive analytics and prescriptive analytics. Further, our study explores the BDA industry sector from the perspectives of both BDA-vendors, who offer BDA services, and BDA-clients, who consume BDA-services. Since BDA-clients can invest in BDaaS, basic analytics, or advanced analytics, based on their business needs, our study explores how BDA-vendors might offer their BDA services.

We use four perspectives i.e., internal business processes, learning and growth, customer, and financial perspective, to discuss how each BDA-technology affects the performance measures of these four perspectives. Under each of these four perspectives sections, we discuss BDA implementation and offerings from the viewpoints of both BDA-clients and BDA-vendors, respectively. Further, our study also discusses and presents the analysis of employee engagement and financial performance of BDA-vendors and BDA-clients from the lens of average turnover, average net income, and average net assets. This analysis is based on the secondary data obtained from the financial report filings of BDA-clients and BDA-vendors with the UK government's company house [38]. Our study would explore more about the recruitment, skills, training, and labour costs of the staff for both BDA-vendors and BDA-clients from the primary data collection through interviews and surveys.

In terms of the average turnover of BDA-vendors, we see a gradual rise from 2016 to 2020. This shows that BDA products are received well in the market by the BDA-clients. However, the average net income of BDA-vendors provides a different picture, as we see the average net income decline during the years. We speculate that the reason for this decline is that BDA-vendors have high SGA expenses. This indicates that BDA-vendors spend a huge amount on innovating and developing BDA-products. Negative average net income during the pandemic (2019-2020) suggests that BDA-vendors might have faced challenges as every other business organisation as well as incurred additional costs to provide services and support to their clients due to high demand for BDA. We will further explore the reasons behind increase in turnover, decrease in net income, and SGA expenses from the interviews and surveys with BDA-vendors. In terms of average net assets, BDA-vendors show a consistent and gradual increase, denoting that BDA-vendors rely on equity financing.

In the case of the average turnover for BDA-clients, it shows gradual increase and consistency from 2016 to 2020, with a slight decrease in 2021. This is due to the closures and restrictions during COVID-19 pandemic. Since these companies utilise BDA technologies, it indicates that BDA assisted them with managing their business operations. The average net income of BDA-clients shows decrease from 2016 to 2020 with a huge drop in 2021, which is attributed to high CoS and SGA expenses during pandemic. However, we will explore further about the effect of BDA usage on BDA-clients in our interviews and surveys. After the collection of primary data, our study will present empirical findings on BDA-offerings, BDA-attributed business continuity during the COVID-19 pandemic, and BDA's impact on financial performance of both BDA-vendors and BDA-clients.

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