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Data Analytics Diffusion in the UK Renewable Energy Sector: An Innovation Perspective

Abstract

We introduce the BDA dynamics and explore the associated applications in renewable energy sector with a focus on data-driven innovation. Our study draws on the exponential growth of renewable energy initiatives over the last decades and on the paucity of literature to illustrate the use of BDA in the energy industry. We conduct a qualitative field study in the UK with stakeholder interviews and analyse our results using thematic analysis. Our findings indicate that no matter if the importance of the energy sector for 'people's well-being, industrial competitiveness, and societal advancement, old fashioned approaches to analytics for organisational processes are currently applied widely within the energy sector. These are triggered by resistance to change and insufficient organisational knowledge about BDA, hindering innovation opportunities. Furthermore, for energy organisations to integrate BDA approaches, they need to deal with challenges such as training employees on BDA and the associated costs. Overall, our study provides insights from practitioners about adopting BDA innovations in the renewable energy sector to inform decision-makers and provide recommendations for future research.

Keywords: Big Data Analytics, energy sector, renewable energy, diffusion of innovations, field study

1   Introduction

Over the last years, there has been significant attention by scholars and practitioners to Big Data (BD) and analytics (BDA) (Wang et al., 2016; Gunasekaran et al., 2017; Batistic and Van der Laken, 2019; Papadopoulos et al., 2021). Sena et al. (2019) define BD as "large volumes of data extracted from a number of sources including documents, social media and sensors among others" (p. 219). BD is described using the terms volume, variety and velocity (Chen et al., 2014; Wang et al., 2016): *a host of data, which is unstructured, large in volume, continually flowing and requires subjective analysis techniques such as machine learning (ML)* (Davenport, 2014). BDA has to do with the "ability to gain insight from data by applying statistics,

mathematics, econometrics, simulations, optimisations, or other techniques to help business organisations make better decisions" (Wang et al., 2016, p. 99).

The popularity of BDA is because of the advancement of technology infrastructure, which accelerates the growth rate of data. IDC (2018) has predicted that the global data volume will increase to 175 Zettabytes by 2025, showcasing an overall increase of 430% and an average yearly increase of 61%. The increase in data propensity, properly managed, can lead to critical insights guiding informed business decisions. The utilisation of these insights is encapsulated through the term Business Intelligence and Analytics (BI&A) (Chen et al., 2012). Therefore, incorporating analytics into an organisations' strategy is becoming the norm in modern business operations. Data-driven innovations can enable the development of new industries, processes, and products (Akter et al., 2020; Wamba et al., 2017) and bring social and economic benefits for industries and societies (Kusiak 2009; Sorescu 2017) while they transform the service systems (Akter et al. 2019).

Data is highly prevalent within the energy sector through sensors, wireless transmission, network communication, and cloud communication (Zhou et al., 2016), which are fundamental to energy companies' survival. There is, hence, a need for BDA in the energy sector to increase its sustainability (Akter et al., 2019, 2020; Wamba et al., 2017) and identify areas of opportunity for managers. As the levels of fossil fuels left at a global expense are diminishing and the renewables' share of electricity generation increasing by 3.8% between 2017 and 2019 (GOV, 2019), the demand for technologies and analytics is evidently flourishing.

Literature concerning the use of BDA within the energy sector has mentioned its use in tackling different challenges in the industry, such as power generation side management, renewable energy management, demand-side management (DSM) and smart grid (SG) optimisation (Altin et al., 2010; Escobedo et al., 2017; Ceci et al., 2014; Ericsson, 2014). BDA, therefore, has positive impacts on the generation, distribution and optimisation of renewable energy sources. Data-driven innovations were used to induce a behavioural change of electricity users in reducing their energy usage (Jetzek et al., 2014), improvement of reliability of energy simulation outputs in residential buildings (Causone et al., 2019), and development of sustainable urbanism (Bibri 2018; Bibri and Krogstie 2020).

However, there are few, if any, studies that investigate the challenges associated with BDA for the energy sector. Such studies discuss issues as adequate storage and management of energy BD, the most cohesive analysis techniques for unstructured energy data types, how to

turn the data into practical insights that can improve daily operations of renewable energy firms, and how to prevent risk with regards to consumer data privacy (Zhou et al., 2016). Therefore, there is a need for studies investigating in detail how BDA is diffused in renewable energy organisations. Hence, our research question is: How is data-driven innovation *diffused through BDA opportunities within renewable energy organisations?* To answer our research question, we embarked on a qualitative field study conducting semi-structured interviews with experts. We provided evidence on the implications of data-driven innovation aspects and the associated impact of adopting data analytics systems in renewable energy companies.

The paper structure is as follows: Sections 2 and 3 introduce the prior research and the background of the study, Section 4 provides the research design of the field study, while Section 5 outlines the study's main results. Ultimately, Section 6 discusses the findings and Section 7 elaborates on the conclusions and limitations of the study.

2 Prior Research

Big Data (BD) can be defined as an enormous dataset that cannot undergo standardised management and processing using normalised IT tools in an optimised time frame (Chen et al., 2014). According to Sagiroglu and Sinanc (2013), BD has the following characteristics the 3 Vs: Variety, Volume, and Velocity. Data retrieved from various sources can fall under structured, semi-structured, and unstructured terms. Khan et al. (2016) further mention that structured data has predefined fields that allow for seamless categorisation, formed through either human or machine generation – it is the method of storage and characterisation that defines this variance. Unstructured data has no predefined schema to its data model, which causes additional complexity, existing in the form of audio, video and weather data, for example. Semi-structured data does not allow for direct categorisation but incorporates tags, which separate the data elements (Gunther et al., 2017). The remainder of this section gives an overview of the prior research and the background of the study.

2.1 Big Data Management

Advancement in information systems has produced mass data sources, which leads to an exponential increase in the volume of data. Meaning data storage and analysis cannot be conducted through traditional techniques. Due to the induced velocity, it is essential to capitalise on data immediately after it reaches possession by the organisation or individual. Otherwise, data that is stored for extended periods of time with no use becomes an adverse asset to an organisation (Sagiroglu and Sinanc, 2013). With these characteristics in place,

opportunities and problems arise. BD Management alongside BDA are the processes taken by organisations to propel their effectiveness in leveraging said data.

To fully capitalise on the 7V's, it is in the best interests of data users to collect the BD-set effectively, utilising less hardware and software requirements (Chen et al., 2014b). A significant challenge for companies is data management, which provides effective foundations for the Data Analytics process. It can be observed that effective data management is achieved when said BD-set is seamlessly accessible, harnesses categorised data and is correctly secured (Oussous et al., 2018). The main processes underlying data management are storing data securely; cleaning data, ensuring reliability and consistency; aggregating data for organisation and further credibility. During this procedure, role-based access would be asserted to distributed endpoints (Mikalef et al., 2013, Spanaki et al., 2021, Karafili et al., 2018).

While the procedures and challenges of BDA were explained, more detail is also required on the opportunities and challenges that firms face when adopting BDA. According to Watson (2014), BDA can be harnessed using: descriptive analytics and predictive analytics. These are detailed in this section alongside organisational adoption characteristics.

Descriptive Analytics: Watson (2014) mentions that descriptive analytics are at the core of Business Intelligence (BI). These use reporting, dashboards and data visualisation to generate intel for an organisation based on past data. Agreeing and adding to this, Sivarajah et al. (2017) suggest that descriptive analytics scrutinises data, allowing for reporting and defining the current business state. The authors mention that the end-users are required to utilise said dashboards, connecting the insights with the relevant decision-making processes, hence ensuring the business perspective is ascertained. Sivarajah et al. (2017) state that most BDA is descriptive, hence exploratory, and requires businesses to use statistical methods to identify patterns.

Predictive Analytics: This analytics method concerns constructing statistical models to generate sufficient forecasts as an enabler of querying possibilities in the future (Sivarajah et al., 2017). Khanra et al. (2020) also state that predictive analytics also incorporate empirical models aiming to create empirical pre-distinctions and methods of judging the prediction quality harnessing predictive power, for example. Gandomi and Haider (2015) further suggest that predictive analytics can be categorised into moving averages, aiming to investigate historical patterns in the outcome and extrapolate this for the future; linear regression, aiming to seek the dependency between the outcome and explanatory variable. Therefore, this

approach roots for statistical significance heavily, resulting in knowledge-heavy associated tasks, meaning organisations need to ensure sufficient operatives to use statistical techniques.

BD and BDA tools effectively enhance traceability, optimisation, forecasting, classification, and clustering. Lavalle et al. (2011), a heavily cited journal in the analytics space, comprises a survey of 3000 executives, managers and analysts across 30 industries and 100 countries on BDA adoption at their organisations. Their survey's findings highlighted that 50% of respondents found that analytics was a top priority for their organisation, alongside more than 20% saying they were under intense pressure to adopt analytics. Kwon et al. (2014) suggest that a firm's competence to maintain high-quality corporate data positively influences its affinity to adopt BDA. The article suggests that organisations who have previously utilised internal organisational data may oppose adopting BDA, contrary to firms who heavily rely on external source data, such as environmental data, which are more likely to adopt BDA. Wang et al. (2018) indicate that maximising business value from data analytics capabilities can be achieved through sufficient speed to insight. Gupta and George (2016) have highlighted the importance of BD-specific technical and managerial skills in organisations. They have argued that effective use of BD and BDA in addition to hardware and software investments, collecting hordes of data, and having access to sophisticated technology, requires a shift in organisational management and implementation of a data-driven culture where insights are extracted from data are valued and acted upon.

Benefits achieved from firms of different sizes and different sectors do not differ. The security risk, therefore, shows industrial prevalence between Raguseo (2018) and theoretically through Bello-Orgaz et al. (2016) and Tankard (2012), where Agrawal and Srikant (2000) provide an effective way to harness a data mining strategy securely. Similarly, Ramanathan et al. (2017) research the adoption of business analytics and the impact that technology has on business performance.

Dremel et al. (2020) studied the link between effective applications of BDA and associated organisational preconditions. They argue that besides organisational resources and capabilities for DBA essential for the effective use of BDA, organisations must also know to generate business value through BDA. Mikalef et al. (2019) also investigated the configurations of resources and contextual factors that lead to BDA investments' performance gains. Using complexity theory, they argued that one of the significant obstacles in BDA adoption is attributed to 'organisations' failure to realise performance gains. Mikalef et al. (2020) also explored how different inertial forces during big data analytics deployments hinder

the emergence of dynamic capabilities. They argued that one of the main issues in BDA projects is related to governance. They highlighted that resource orchestration mechanisms to handle individual-group-industry dynamics are essential to leveraging resources into value.

Albeit concentrating on a different industry, the study of Schoenherr and Speier-Pero (2015) also endeavours to investigate the adoption and usage of Data Science and BD within the Supply Chain Management sector – surveying 531 professionals in the space. The resultant data compiled these individuals into one of three usage groups: no current use but plans for the future; to some extent. This is a similar approach taken by Lavalle et al. (2011), who provide a three-tiered model in their study, highlighted previously. Across the three categories, Schoenherr and Speier-Pero (2015) found that security issues, lack of data and the ability to find data, which is useful during predictive analysis, were the most prominent barriers. Therefore, organisations that had not adopted BDA were more likely to verify that security issues were the prominent reason not yet to adopt BDA. This study focuses heavily on exploratory data science; however, it still shows cohesion with the other studies critiqued in this review. Kwon et al. (2014) mention that firms that heavily utilise external source data in their operations, such as environmental data, are more likely to incorporate BDA into their strategies. The following section provides an overview of the diffusion of BDA in the energy sector.

2.2   Diffusion of BDA in the Energy Sector

There is a growing awareness among stakeholders that opportunities brought by BD are shifting the paradigms of the energy sector, particularly in terms of methods of energy production and the pattern of energy consumption (Zhou et al., 2016). A common theme among the papers looking at data analytics within the renewable energy sector is the focus on smart grid (SG) optimisation, which aims to utilise the large volume of energy data and integrate the information from assorted sources, for instance: weather, consumer information and geographical data (Hu and Vasilakos, 2016). According to Diamantoulakis et al. (2015), an SG allows for biflow of power and data between the source and sink (suppliers and customers) to allow for power flow optimisation with regards to economic efficiency, reliability and sustainability. The systems used in SG's consist of consumers home participation through energy management systems, smart metering, and demand response (DR) algorithms. These systems accumulate data through sensory nodes; hence load classification (LC), through data mining, can be used to distinguish load patterns and categorise accordingly, then using predictive analytics and ML to abide by real-time data dispersal. With sensors acquiring mass data on a real-time basis, the variety and volume of the data can be excessive;

however, Jeffery et al. (2006) confirm the use of Extensible receptor Stream Processing (ESP) to automate the mitigation of erroneous data.

Although Alahakoon and Yu (2016) do not delve into the enhancement of DR through BDA, the authors mention smart metering and the use of load forecasting, which would assist LC, similar to Diamantoulakis et al. (2015). Additionally, Alahakoon and Yu (2016) endeavour to cluster analysis from alternate smart metering devices, attain information on average energy consumptions and changes in day-to-day readings, allowing for more structured forecasting. In terms of practical implications, Balac et al. (2013) research energy consumption using a Time Series Approach, which detects anomalies in the energy models from the offset. This research builds a direct relationship with Diamantoulakis et al. (2015); Alahakoon and Yu (2016) highlight clustering to remove erroneous data from energy profiles.

The work of Tannahill and Jamshidi (2014) also seeks to utilise clustering in the protocol; however, utilising photovoltaic (PV) device data rather than SG optimisation. To achieve clustering, the researchers utilise the MATLAB toolkit to construct scripts – to conclude, the authors suggest investigating the use of cloud storage to generate models for more massive datasets. Overall, it is evident that researchers are investigating the optimisation of SGs through effective data analytics. This topic shows significant potential to deliver improvements in practice. However, research into end-to-end data analytics models within the renewable energy space has not endeavoured. It is essential to advance the understanding of which organisations are currently harnessing the advantages of effective data analytics for optimising SGS and the obstacles they face.

This article addresses that gap by providing evidence about the implications of challenges and opportunities and their impact on adopting data analytics systems in renewable energy companies.

2.3   Diffusion of Big Data Analytics – A Conceptual Framework

The conceptual framework applied in this study will allow data interpretation and underlying effects of BDA adoption to be revealed, further highlighted by Grant and Osanloo (2014) as one of the most critical aspects of the research process.

There have been some frameworks developed in the literature. Alahakoon and Yu (2016) provide the framework designed by C3 energy to manage and optimise energy data using artificial intelligence (AI) whilst addressing data-mining techniques that can be employed within the industry. A common theme among existing studies is demand forecasting for

renewable technologies to ensure effective delivery models. Diamantoulakis et al. (2015) show that demand response (DR) is directly coordinated with SG's, hence stating that the DR algorithm's success depends on demand, price, load, and renewable energy forecasting, which has led to the construction of signal processing methodologies.

The Technology Acceptance Model (TAM) constructed by Davis (1985) profiles the chances of technology adoption as the potential adopter's perception and attitude of said technology influencing the organisation. This model is built using the adopter's expectations – how easy the technology is to use and the potential usefulness. Davis (1985) mentions that the perceived ease of adoption is directly related to the usefulness, as the perception of usefulness comes as a subsequent attitude to the adoption of the technology.

The Diffusion of Innovations (DOI) theory, compiled by Rogers (2003), showcases the process of an innovation being communicated to provide people knowledge of the innovation. The social system acting around the adopters/ non-adopters and the adoption process which organisations take is described. The theory defines an innovation-decision process consisting of Knowledge, Persuasion, Decision, Implementation and Confirmation. The Persuasion stage is particularly interesting, providing the five attributes of organisations' perceptions to innovations: Relative Advantage, Compatibility, Complexity, Trialability and Observability (Rogers, 2003). Similarly, the DOI theory considers the usefulness of the innovation as the 'Relative Advantage' characteristic to the TAM model. However, unlike the TAM, the model does not directly relate to the 'ease of use'. However, it can be incorporated into the 'Compatibility' and 'Complexity' perceptions.

The impact of data-driven innovation in operations and supply chain management fields has been a topic in various studies (Lee 2018). The innovations cycle, as described by Lee (2018), includes three key areas in improving existing processes in operations by a) using BD tools and methods, b) leveraging insights and value propositions through expansive usage or incorporating historical data, and c) allowing companies to create new processes or business models to serve customers in new ways.

Data-driven approaches triggered in operation management often appear in value propositions and business model innovation opportunities (Akter et al., 2019; Manyika et al., 2011; Wamba et al., 2017). Data and information products can provide multiple operations and supply chain management opportunities with a strong focus on innovation outcomes (Spanaki et al., 2018). However, there are multiple challenges in the diffusion of innovative

data-driven approaches, requiring multidisciplinary approaches and methods sothat already existing theories can be extended towards this direction.

The DOI theory will be used as a lens for this research due to elevated scalability and broader nature – analysis will be optimised and heavily aligning to BDA being adopted by organisations. With a multitude of variables in adoption rates of BDA, further insights can potentially be gained through the use of the DOI. This is the case even though the simplicity of the TAM model would allow for more streamlined analysis and reflection.

To utilise Rogers (2003) work effectively, relevant elements of the 'Diffusion of Innovations' are utilised to construct this framework below. Concerning the aim and objectives, the priority for this research is to find the reasons for adoption; hence, these factors, given in Appendix 2A, have been selected for this framework, depicted in Figure 1.

Diffusion of Innovations (DOI)	Aspects	Interview Question
Rate of Adoption	Relative advantage	What are the perceived advantages and disadvantages that can arise during BDA incorporation?
	Compatibility	Is BDA suitable for analysis in the renewable energy sector?
	Complexity	What is the difficulty of incorporating BDA? What are the challenges?
	Trialability	Would a trial period be deemed as an incentive for adoption?
	Innovation decision	Who makes such decisions at the organisation?
Internal characteristics	Centralisation	Does the limitation of power to a few individuals in the organisation impact the likelihood of BDA adoption due to the increased/decreased innovativeness?
	Size	What differences are there in the likelihood to adopt BDA based on assorted sizes of organisations?

Figure 1 – Conceptual framework

The following methodology is derived from exploring the reasoning behind the BDA adoption of organisations in the renewable energy sector. A data collection section is included in order to justify the reasoning for the study approach, followed by the sampling strategy, interview design, the method of data analysis and ethical considerations taken during this research process.

3   Research Design

This research follows the tenets of qualitative research. Our aim was to provide a detailed interpretation and a realistic perspective (Miles and Huberman, 1994; Denzin and Lincoln, 2013; Bell et al., 2019) to study how BDA is diffused in renewable energy organisations.

We followed a field study approach. A field study approach allows for the entire scope of a study to be ascertained (Merriam, 1998; 2002). Field research allows the researcher to observe or interview multiple participants in their natural setting – this, therefore, means that a broader range of comprehensive perspectives is gained through varying sources, however convergent to the same topic area (Babbie, 2013). The field study approach has been used by Huberman (1990), showcasing credibility, where assorted individuals from different organisations in the renewable energy space act as participants representing the organisation where they have a key management role. Whereas attaining conceptual justifications can be a challenge of the field study method (Aggarwal et al. 2013), a field study approach aligns with the research questions where a full range of organisations are investigated, enabling a broader view of the adoption rates of BDA across the renewable energy sector. Following a qualitative approach, we conducted interviews (King, 2014) with the view to delve into questions as to how and why a participant has a specific view based on the surrounding context.

3.1   Interview Design

Data were gathered through semi-structured interviews. They are used to prompt responses through questions, to obtain more effective dialogue (Edwards and Holland, 2013), allowing for real-world research capabilities (Gillham, 2000). With the open-ended questions, a reduced number of questions are asked, enabling the participant to fully endeavour their viewpoints and experiences with reduced friction (Turner, 2010).

We followed a 'purposeful' approach to sampling (Patton, 2005; Suri, 2011) to increase credibility and ensure data sufficiency. Patton (2002) mentions that purposeful sampling entails the need to strategically deliberate, reaping the most remarkable result from a limited number of individuals in a sample – convenience, time, and cost are factors that should not

be prioritised comparison. Delving further into the strategy encompassed in this research, Palinkas et al. (2013) mention using a stratified purposeful method to measure the major variations in the space, allowing for core similarities to be exposed during analysis.

We conducted eight semi-structured interviews within the renewable energy sector, representing the views of 8 organisations within the field. Most candidates hold postgraduate qualifications and experience in the field, which provides credibility in their responses. The duration of the interviews was 1 hour on average. The individuals shown in Table 1 represent the sector because of the range of job roles the participants have (e.g., consultants, analysts and directors). Table 1 also shows the varying functions of the renewable energy sector the participants reside in and the size of the organisation they are working in. Through studying these individuals, a quality-intensive study in the renewable energy sector is confirmed. The confidentiality of the discussions and the participants' anonymity was explicitly stated and agreed to by each participant. The theoretical underpinning of the questions was the 'Diffusion of Innovations' (Rogers, 2003). The theory explains the rate at which individuals in a space proceed to harness changes in technology, arguing that 'diffusion' allows for innovation to have conversed throughout a system. Interviews were transcribed ad verbatim.

Table 1 - Interviewee sample characteristics

Participant Profile			Organisational Information	
Participant	Job Role	Years in Industry	Function	Size (employees)
P1	Senior Technical Consultant	9	Renewables Consultancy	1,001–5,000
P2	PV Performance Analyst	5	Solar	501-1000
P3	Associate Director	11	Energy Efficiency	51-200
P4	Renewable Energy Modeller & Analyst	9	Wind, Solar, Hydro, Hybrid	10,001+
P5	Developer	2	Energy Efficiency	11-50
P6	Head of Production Operations	8	Fuel Cell / EV	11-50
P7	Data Analyst	2	Solar	11-50
P8	Senior Controls Engineer	5	EV / Solar	10,001+

3.2 Thematic Analysis

We applied thematic analysis to analyse the interview data, allowing for themes to arise from the interview data (Boyatzis, 2009). The arising themes can reflect the context and allow for further means of inference (Marvasti et al., 2012). The thematic analysis used was deductive (Braun and Clarke, 2006), where a theory-based approach is capacitated (Boyatzis, 2009) – therefore heavily aligning to the theoretical basis, that is, 'Diffusions of 'Innovations'.

We followed the following steps in conducting the thematic analysis (Braun and Clarke, 2006):

1. Familiarisation with the data
2. Generating initial codes
3. Searching for themes
4. Reviewing themes
5. Defining and naming themes
6. Producing the report

The coding process followed a hybrid mode of NVivo and manual processes (Bazeley & Jackson, 2013) where codes, themes, and meanings were extracted after the transcription of the interview data. After the themes had been outlined, following the 'conclusion drawing' stage (Miles and Huberman, 1994), a reiteration of the results with the literature review progress –consolidates and enforces any themes across the study took place.

4 Research Findings and Analysis

The procedure recommended by Braun and Clarke (2006) and also suggested by other qualitative studies (Marvasti et al., 2012; Patton, 2005; Boyatzis, 2009) is followed in this research. In utilising the 'Diffusions of Innovations' theory, by Roger (2003), the main thematic clusters which arise from the interviews in conjunction with the responses are:

a)   Perceived benefits of BDA to the energy sector

b)   Alignment of BDA tools to organisational strategy

c)   Challenges of BDA incorporation

The three thematic directions mentioned outline the structure of the chapter and provide insight into the interview data and the field study results. The respective participants provided views of renewable energy organisations through questions regarding the diffusion of BDA in the organisational processes and the challenges and opportunities arising from integrating such tools.

4.1 Benefits of BDA to the energy sector

This theme is closely related to the 'Relative Advantage' perceived attribute arising through the 'Diffusion of Innovations' theory. Relative advantage is associated with the degree to which an innovation is considered better than the prior approach (Rogers, 2003). The subthemes identified are introduced in Table 2, along with their frequency throughout the interviews.

Table 2: Perceived benefits of BDA in the energy sector

Sub-Themes	Interviewee	Example Quotes
More informed business decisions	P2, P3, P4, P5 and P8	*"Data analytics is important as firms have a huge amount of data and firms 'don't use It properly. Good BDA can result in quicker and better decisions by looking at trends and patterns in the large datasets" (P3)*
Trends and forecasts for profiles	P1, P2, P4 and P6	*"A company in the renewable energy space is not different to any other company – they need to have a strategic business model and act in a competitive market" (P4)*
Investment analysis	P2, P4 and P7	*"With the rise of energy storage, it is very useful …. generating better reports for better investing opportunities." (P2)* *"It helps predict performance RE projects and gives confidence to investors on how their investments are going to go, based on the generation, so definitely at my organisation it is very helpful and does align" (P1)*
More effective pricing	P2 and P7	*"With the rise of energy storage, it is very useful to see whether energy prices will be stagnant and when prices will rise in order to know when to sell etc., generating better reports for better investing opportunities." (P2)*
Utilising real-time data	P5 and P8	*"You can be more proactive and dynamic in your feedback cycle, so you have an issue, you can get an idea of what the issue is, before it happens, using feed analytics." (P8)*
Energy supply and demand	P2	*"With the rise of energy storage, it is very useful to see whether energy prices will be stagnant and when prices will rise in order to know when to sell etc.…" (P2)*
Peak loading calculations	P6	*"With renewables, because you 'don't have the typical, reliable generation, as 'you're dependent on things like the sun or the wind, understanding the likelihood of power available at any time is critical to being able to make it reliable in the first place" (P6)*

High-quality data retrieval	P1	"In an Energy firm, measuring data and the quality of data is high, so Data Analytics would be useful in acquiring historical data – backdating a lot more using the traditional energy data" (P1)
Improved metering through insights	P3	*"If 'you're a solar energy firm and monitoring solar energy data through metering – you can look at the different types of solar panels, their specifications and also performance characteristics such as degradation and yield" (P3)*

Overall, it is possible to notice the importance managers are giving BDA for decision-making. The most highly frequent benefits stated by the are related to more informed business decisions and the development of trends and forecasts, enabling organisations to understand more about the market and implement improvements. Different interviews also mention investment analysis, more effective pricing, and the availability of real-time data as interesting applications of BDA implementation. Less frequent but still relevant benefits are associated with particular activities that provide valuable information about the situation, including the balance of supply and demand of energy, peak loading calculations, high-quality data retrieval and enhanced insights obtained from metering.

The most frequently stated benefit identified in the interviews was that 'More informed business decisions' can arise through the use of BDA. Because of the power of BDA, the capacity to analyse and operationalise information can support efficient and effective decisions for different stakeholders involved (Zhou et al., 2016). For instance, P4 specifically suggests: "BDA can be used in the HR function, for analysis and selection of the best candidates". This aligns with the findings from Halper (2014), who states that through 'Better business decisions', operations can be improved. This also indirectly agrees with Raguseo (2018) study, which highlighted that improved products and employee productivity were results of introducing business analytics. Therefore, the findings of this research stress the importance of BDA to improve decision-making, which supports the findings from Awudu et al. (2020) in the renewable energy sector.

Bose (2009) mention the importance of 'Understanding customers' as a significant benefit of BDA stemming from their study. Although the aspect does not resemble the sub-themes identified at first glance, it is important to unpack the meaning. The author mentions that through the use of retention analysis, it is possible to identify trends that can have a richer picture of customers and their profiles. Indeed, Zhou et al. (2016) argue that BDA can help

monitor and forecast demand analysis, customer engagement, targeted marketing, and optimise and understand energy consumption. Looking at the findings in Table 2, half of the participants highlight the importance of BDA to develop trends and forecasts, allowing them to have more accurate profiles. Particularly, P2 and P4 showcase knowledge of concrete BDA adoption characteristics.

Bose (2009) also suggests that 'Usage of organisational data' is a relevant advantage. The sub-themes 'Investment analysis', 'More effective 'pricing' and 'Improved metering through insights' account for it because these represent applications in which organisational data has been used to deliver actions. For instance, in the smart-grid operation, price forecasting can be a significant challenge that can be addressed using BDA (Yousefi et al., 2019), and BDA has shown the potential to support these activities. Hence, P2, P3, P4 and P7 arise as individuals who align to Bose's different advantages (2009).

The data managed by BDA has enormous potential for energy companies. For instance, Diamantoulakis et al. (2015) suggested that SG's can undergo optimisation with the use of better insights. Similarly, Kotu and Deshpande (2014) state 'utilisation of sensor data', which involves the use of real-time data, can be valuable for managing supply and demand. Additionally, Sharmila et al. (2019) propose the optimised distribution of energy resources through the use of machine learning and BDA. Bearing in mind the inconsistency of power generation, P5 and P8 confirm that utilising real-time data can be significantly beneficial in the renewables sector.

Finlay (2014) suggests 'Provides a scalable format' and 'Consistency of predictions' as other relevant benefits of BDA use. These aspects can be associated with the sub-theme 'High-quality data retrieval', voiced by P1. This could be due to the technical background of P1, coming from the consultancy industry, where these extremities are comparatively persistent.

Therefore, across the board, it is deemed prevalent that the knowledge about the benefits of BDA exists throughout the renewables sector, with the results of this paper aligning heavily with current literature. However, further knowledge dispersion in the sector could be beneficial in driving BDA to extend the reach of some of the advantages identified.

4.2   Alignment of BDA tools to organisational strategy

With all organisations subject to the incorporation of BDA to their organisations, it can be said that a faddist approach is being taken, according to Mortenson et al. (2015). With P2 and P7 showcasing a more neutral outlook, it can be said that the organisations seemed to acquire a

middle-ground between the faddist and isolationist approaches – deemed necessary for leveraging adoption (Mortenson et al., 2015). Extracting from Kwon et al. (2014), it seems that organisations in the renewables sector aim to maintain high-quality corporate data, ensuring an easier adoption. On the other hand, the misalignment between BDA and the organisational strategy can generate issues for organisations. For instance, P7 was uncertain about the alignment of BDA to their organisation, which was reflected in the comment that when low-cost assets and devices are bought, insufficient data can be retrieved. This, therefore, has an adverse effect on BDA due to the inconsistency of data.

Lavalle et al. (2011) found that 50% of respondents said BDA was a top priority at their organisation through analysing individuals from various industries. This paper suggests that in the renewable energy industry, BDA can be considered important, as the majority of participants agree on the top priority of BDA. The reasoning is that the renewable energy sector is increasingly becoming accustomed to modern technologies in improving business performance. Additionally, survival in the energy sector requires the capacity to evolve and adapt to technological changes. The view of P8 confirms this view as "…renewable energy firms are nimble and more tech-savvy, younger, that is the impression I get at this organisation. So, they are more used to building their resources from the ground up, using the latest technology available".

However, even with the capabilities of organisations in this sector, complete adoption is a pending challenge. Our results found that only P4 and P8 are fully transformed hence accustomed to BDA, even when most companies are trying to align their strategies to BDA. However, even with the capabilities of organisations in this sector, complete adoption is a pending challenge. Our results found that only P4 and P8 are fully transformed hence accustomed to BDA, even when most companies are trying to align their strategies to BDA. The use of Python seemed attractive to some of the participants, which supports the idea of Diamantoulakis et al. (2015), suggesting the optimisation of smart grids using predictive analytics and ML, which harnesses Python coding. Further knowledge of how Python can be effective for renewable energy organisations dealing with smart grids should be delivered.

Coming from an engineering background, P6 and P8 agree with Tannahill and Jamshidi (2014), who use MATLAB to construct their scripts for PV optimisation. The authors utilise this due to inclined clustering, also endeavoured by Diamantoulakis et al. (2015) and, Alahakoon and Yu (2016). In this respect, it should be in the best interests of organisations in the solar industry

to incorporate clustering to improve their PV devices. A summarising table for the sub-themes and quotes of the findings is presented in Table 3 below.

Table 3: Sub-Themes and Example quotes for the integration of BDA in the business strategy.

Sub-Themes	Example Quotes
Alignment of BDA tools to organisational strategy	*"I would say that our company strategy is definitely to try and use BDA as we go, but there is no defined objective that specifically encompasses BDA for improvement." (P7)* *"Yeah so what we say is that data analytics is embedded in our company strategy, it is part of our DNA" "…" it is essential to our development strategy and how we deliver our services to clients" (P3)* *"Yes, they see it as a huge potential. They look at the implementation of BDA as a long journey. So, not disruptive innovation but incremental innovation ." (P4)* *"Frankly, if you want to be competitive in this environment, you have got to have the edge" (P8)* *"Data analytics is something that can really change your business model and 'it's a matter of reflecting on the revolutionary aspect for many companies" (P4)*
Resultant Tools (e.g., Excel Bespoke Python MathWorks – MATLAB SQL VBA Tableau)	*"We do a lot of work in Excel because it is relatively simple, compared to Tableau, and clients are used to using Excel so 'it is useful for workbooks to share with clients"." (P3)* *"We only use mostly Excel, more recently, not really using but we have been exploring the benefits of BI software, more specifically Microsoft Power BI. I think it was mostly explored in terms of data visualisations for certain graphs during decision making and showing to senior management" (P2)* *"MathWorks, using the basic software, to do some large-scale BDA, which is critical as you have to have the capability in it, so the guys need to know what they are doing in writing the program" (P6)* *"We are using Python, but less for analysis, and more for data munging and handling the large amounts of data. Certainly, we are using some open-source software to do some basic PV modelling formulas in order to speed up the analysis" (P7)* *"I wanted to clarify that Excel is the most used tool in the solar industry, and still is, and the main reason behind this is the flexibility and the use of data manipulation… if you are a small business, you want quick, accurate answers, so Excel comes in handy" (P7)*

	"We use Tableau quite a lot; we have a whole team of Tableau trained consultants who use them for ad-hoc data analysis developing, specific dashboard for clients." (P3)
	"We use a couple of different types; we use JupyterHub for Python and Github for more developing. I personally use a lot of MATLAB" (P8)

4.3 Challenges of BDA incorporation

The use of organisational data is an interesting aspect because research has identified a struggle between gathering data and operationalising it. Wang et al. (2018) mentioned the importance of turning raw data into manageable and useful information, but our findings highlight the problems caused by the lack of those capabilities. Organisations know they have data at their disposal which can be utilised to their benefit but struggle to use it properly, as expressed by P3: "…firms have a huge amount of data and do not use it properly." This finding supports Chen and Zhang's (2014) statements, who argue that organisations can go to the extent of deleting useful data due to insufficient storage and analysis knowledge. Finlay (2014) suggests that 'Data can be unstructured', and Zhou et al. (2016) mentions the complexity of data integration and sharing, aligning with the 'Flexibility with data variety' sub-theme. P1, who voiced this challenge, coming from a consultancy background, is heavily involved in retrieving and making sense of said data for clients. Albeit, this is also agreed extensively throughout literature, an example being Wu et al. (2014) and Fan et al. (2014), who collectively state that having various fields for the same function can lead to domain errors during aggregation of multiple sources.

Lavalle et al. (2011) propose a three-tiered model of BDA capabilities. Based on this model and the tools and perceptions stemming from the analysis, Table 4 is produced. All organisations in this study outlined multiple barriers hindering the adoption of BDA. The primary challenges in the renewables sector given in Halper (2013) and Bose (2009) are the 'Lack of skills' and 'Organising to execute', along with the lack of professionals of BDA and energy management available (Zhou et al., 2016). These aspects heavily align with the findings in this study, where several participants mentioned that 'Educating employees' was the most dominant barrier alongside 'Cost'. An example of that was presented by P3, who confirmed that they are facing difficulties currently. Similarly, the findings agree with the study performed by Raguseo (2018), in which out of 200 organisations, one of the most prominent reasons preventing the adoption of BDA was minimal IT expertise.

Table 4: Challenges of BDA incorporation in the energy sector

Sub-themes	Interviewee	Example Quotes
Educating employees	P2, P3, P6 and P8	*"That is the biggest hole, insufficient knowledge, however that was a few years ago" (P8)* *"…it takes time to learn these new skillsets" (P3)*
Cost	P2, P3, P5 and P6	*"…there's also time and expense,… and if you can't see the value of it then you won't want to spend that time and money." (P3)* *"Cost… in any industry… unless you have specialists working in, but we're quite a small company, and we don't have a team dedicated to doing data analysis tasks. So yeah, it is expensive to do – in order to harness something like tableau, that is a very expensive package." (P5)*
Alignment to strategy	P2, P3 and P4	*"The challenge is to understand that BDA is not just cosmetics, you don't just add numbers and say, 'we are doing BDA', BDA can really change at the core any business…" (P4)*
Resistance to Change	P3 and P4	*"…and if you can't see the value of it then you won't want to spend that time and money." (P3)*
Flexibility with data variety	P1 and P6	*"The team took our feedback and worked on it, and they have something similar they now use where they go over the basics, and one-point source of information with FAQ's and that has helped a lot."(P8)* *"…we deal with different technologies, and they have different measuring equipment. It, therefore, needs to be flexible in dealing with different types of data and different types of data sources" (P1)* *"Consistency of data is something which is needed for data science, one reason we don't have data science here because data coming from different data loggers all in a different format, getting it into the same format so you can run analysis is a challenge" (P7)*
Lack of standards	P7	*"…there is a lack of standards in the renewable energy space since it's been built from the ground up. Growing industry, which requires more standards" (P7)* *"…. there is the lack of standards in data hardware; one of the things we face is that we have 200 plants over the world that have their own monitoring system, data loggers, through individual communication protocols" (P7)*

Lack of performance indicators	P7	*"Buying cost-effective assets may be a problem to run optimisation of the asset as if you buy cheap plants, you won't have the best hardware" (P7)*
Variety of software available	P2 and P7	*"…another problem is the lack of performance indicators when one person is talking about the same performance indicator, they might end up with different value, as there are not distinct calculating methods" (P7)*

To overcome the relative difficulty of BDA tasks, 'Trialability' can be an important factor. It can improve adoption rates – a key theme being 'Utilising training manuals and FAQs'. This suggestion is also provided in Halper (2014), who states the co-creation of centres of excellence (COE) to converge organisational knowledge.

Further, P1, for the first theme, mentioned: "*…setting up training manuals, as in organisations information should not just be left with one person. The information should be delivered from one person to another in case of a handover.*" This shows that adopters need to have sufficient information on the technology for relatively large organisations, as mentioned by P8.

P4 mentions the requirement to align and integrate BDA to the strategy fully. Bose (2009) mentions the challenge of 'Insufficient business case or organisational buy-in', which is also displayed in the results of this paper, as some participants mentioned that 'Alignment to strategy' is a barrier to BDA adoption. This is particularly interesting because all of the participants said that their organisation is currently aligning BDA to their strategies, where P2 and P7 responded in a neutral manner. P2 was a participant who also suggested said challenge; however, a distinct relationship cannot be formed. This is a relevant finding because it shows that even though organisations acknowledge the importance and value of BDA, they struggle to align it to strategy successfully.

Additionally, the results from Kotu and Deshpande (2014) are associated with the challenge' resistance to change' through mentioning 'Organisational culture' as a challenge. Kotu and Deshpande (2014) go on to mention that the changes in cultural aspects incrementally resonate throughout the business. P4 confirmed the existence of this challenge – this could be due to coming from a large organisation, where the process of change is executed over an increased period of time.

A sub-theme of 'Disruptive changes to operations' arose in the 'Trialability' theme, where most participants highlighted said challenge. Based on this, it is evident that sufficient knowledge of implementation exists in the renewable energy sector.

5 Discussion

To cohere with the organisational characteristics dimension of the 'Diffusion of Innovations' theory, we investigated the characteristics of the decision-making processes and the structure of the relevant department at the respective organisations. In doing so, we explored the various views which exist for a renewable energy organisation and the associated decisions to adopt BDA effectively.

Table 5 shows whether the renewable energy organisation has adopted advanced analytics in conjunction with the number of stakeholders which are required to make decisions. The 'Diffusions of Innovations' theory suggests that 'Centralisation' is negatively related to an organisation's innovativeness – with power being concentrated to fewer individuals, the leaders have insufficient positioning to be able to suggest relevant innovations to meet the needs of the organisation. Therefore, analysing the table (Table 5) shows that the number of decision-makers is relatively proportional to the organisation's size. For reference, Table 1 bases 'advanced analytics' as complete incorporation of BDA.

Table 5 - Decision makers against the adoption of advanced analytics and organisation size

Interviewee	No. of Decision-makers	Organisational Size (No. employees)	Renewable energy specialisation	BDA adoption decision
P1	15	1,001–5,000	Renewables Consultancy	Yes
P2	4	501-1000	Solar	No
P3	4	51-200	Energy Efficiency	Yes
P4	30	10,001+	Wind, Solar, Hydro, Hybrid	Yes
P5	1	11-50	Energy Efficiency	No
P6	2	11-50	Fuel Cell / EV	No
P7	5	11-50	Solar	No
P8	36	10,001+	EV / Solar	Yes

Further, based on this, it can be correlated that the fewer decision-makers in an organisation lead to a reduction of BDA adoption taking place, hence less innovation. Using examples of P1, P4 and P8, 37.5% of the sample all carry a relatively larger number of decision-makers, spreading the need for knowledgeable decisions to be made whilst incorporating BDA. In the

case of P3, a company that utilises BDA does not align with this notion, with 4decision-makers at the organisation. From Table 5 we also observe that those decisions are not relevant to the specialisation of the organisation in the renewable energy sector, although a few differences in the perceptions for BDA were identified during the interviews.

5.1   Research implications

According to the literature, big data and operational analytics tools and techniques have become very popular in OR communities over the past two decades. Operations research, as a field devoted to decision-making analytics via optimisation, modelling and statistics (Hazen et al. 2018), has benefited the most from the advances of big data discourse. During the last few year big data analytics and OR disciplines have become more and more intertwined and are moving forward hand in hand. Recent trend in scholarly academic publications shows that with the increase in application of big data analytics for decision making, the interest in Operations Research has decreased. The advances in big data analytics have provided numerous opportunities for OR scholars (De Coninck, 2017).

Findings from the literature have outlined several potential advantages of BDA analytics for the renewable energy sector (Zhou et al., 2016) and made great strides on smart-grid optimisation (Hu and Vasilakos, 2016; Diamantoulakis et al., 2015). Less attention, however, has been placed on end-to-end data analytics models for the implementation of BDA in the sector. More empirical evidence in the sector is necessary to account for managers' perceptions to support the successful implementation of BDA.

Rogers (2003) outlined five aspects affecting the adoption rate of innovations: complexity, trialability, observability, relative advantage, and compatibility. This section links the findings from this research to provide insights using the case of eight renewable energy companies about BDA implementation in the sector

The primary finding obtained from the analysis highlights the paramount importance of 'Relative Advantage' from the DOI theory (Rogers, 2003). The different cases showed that the majority of organisations feel that incorporating BDA can return better business decisions, with different potential benefits aligned with previous research (Raguseo, 2018; Halper, 2014). For the renewables sector, several participants mentioned the importance of improved business decisions and the theme of 'Trends and forecasts for profiles' as advantages. These were highlighted due to the mass volume of data retrieved through the devices, collecting 'real-time data' which is retrieved through the devices, and collecting 'real-time data' mentioned by participants P5 and P8. Sun et al. (2020) argue that relative advantage is

reflected in improved business opportunities, customer service and competitiveness. Looking at the benefits outlined in this research, the themes extracted provide evidence about the potential value of BDA to improve the company's practices, gain understanding about the customers and enhance business decisions. Hence, this research found that relative advantage significantly impacts managers' interest in adopting BDA, which aligns with previous research findings (Baig et al., 2019).

Regarding the 'Compatibility' attribute of the DOI theory, all participants mentioned that BDA did align with their strategy and showed interest in pursuing BDA integration to support their operations. Nevertheless, just a couple of participants are involved in fully integrated companies. This is reflected in their current practices. For instance, the majority of participants mentioned that they are still accustomed to using Excel for their analytics. It can be said that organisations in this space need to apply BDA to their company's core to incorporate the technology fully. Hence, companies have to be aware of the potential challenges of misalignment between strategy and BDA. Concerns about infrastructure, such as the quality of assets and devices, could have an adverse effect on BDA due to data inconsistency. This finding agrees with the results from Sun et al. (2018), who highlights the importance of considering 'compatibility' as an antecedent for BDA implementation.

Complexity has been stated as an important element affecting the adoption rate of BDA in previous literature (Sun et al., 2018; Baig et al., 2019). Our findings align with those because when mentioning the capital required to incorporate BDA, it is imperative in this study to ascertain the challenges which conformed to the 'Complexity' attribute. 'Cost' and 'Educating employees' equally attained several responses from the sample. No other sources found the 'Cost' to be a significant factor in the literature, but it makes sense because of the investment needed before ripping benefits. However, 'Educating employees' boded with other studies such as Raguseo (2018) and Halper (2014), proving margin for grounding. Hence, this result helps to configure the perception of organisations in the renewables sector on BDA adoption.

By investigating the 'Trialability' attribute, it was evident that incorporating trials of technologies would improve their adoption process instead of findings from Sun et al. (2018). Although their finding suggests 'Trialability' is of low priority for scholars and practitioners, the analysis presented here concludes that organisations within the renewables sector perceive that trialability mitigates 'Disruptive changes to operations' and can be improved through 'Utilising training manuals and FAQs', which is supported by Halper (2014). Halper (2014) states that centres of excellence (COE) allow for improved organisational knowledge;

however, including BDA as a catalyst to a strategy is not enough to reap benefits. Actionable processes should have ensued, which are heavily dependent on BDA. By ensuring a sufficient trial period, it is possible to mitigate the disruption of business operations, hence perform sufficient integration of BDA. With such a large amount of data available to organisations in the renewable energy space, it is required to use tools more advanced than Excel. This finding, therefore, proves to be ancillary to the objectives of this research – rather than solely exposing the perceptions of organisations.

While critiquing perceived advantages, it was evident that participant P4 was drawn to believe that BDA implementation and advantages are the same for all organisations whilst expressing the importance of alignment. When coming from a relatively large organisation of 10,001+ employees, it can be said that this viewpoint is derived through the size and willingness of the organisation to use BDA for their decision making, aligning to results from Malladi (2013) and Sun et al. (2018), who find that the increasing size of the organisation, is positively related to the rate of adoption. Hence, small organisations fulfilled a lower degree of innovation, even though there were fewer decision-makers. Similarly, larger organisations are more accustomed to uptake BDA into their processes. With innovativeness greater at these larger organisations, based on the 'Centralisation' attribute, the larger organisations evidently have a greater capital to ensure effective BDA tools. This result suggests that the study meets its objective in analysing stakeholders' perceptions and deriving the dynamics involved in BDA adoption.

An interesting item to highlight is the absence of comments related to privacy and security issues identified by Raguseo (2018), Zhou et al. (2016), and Schoenherr and Speier-Pero (2015). This research did not find risk and security as one of the main barriers to BDA implementation. The subthemes identified can be due to the early stage of implementing the organisations involved in the analysis, which are more focused on the modifications necessary for implementation rather than looking at the risks of implementing the technology. This finding highlights the importance of giving thorough information about BDA's implications to inform decision-making from managers.

Last but not least, as sustainability is becoming more complex, dealing with its challenges are also becoming challenging and costly for stakeholders. Big data analytics could be valuable in providing understanding and insight for coping with systems that have high levels of complexity and uncertainty. Hence, recent literature shows that sustainability is gaining significant attention among OR and analytics scholars and practitioners (Dubey et al. 2019;

Jable et al. 2018; Zhang et al. 2020). Over the last decade, advances in OR and big data analytics solutions research have made a significant contribution to understanding and implementing sustainability criteria in various industries. According to Gupta et al. (2019),, one of the challenges of dealing with sustainability and implementing circular economy in manufacturing and supply chain is the lack of functionalities that can help practitioners generate insights for highly complex and integrated sustainability processes. Kristoffersen et al. (2020) argue that smart technologies, such as the Internet of Things (IoT) and big data analytics tools and techniques, could work as essential enablers and facilitators for the successfull implementation of the circular economy. Their study shows that predictive models based on historical and real-time data can help circular economy practitioners to deal with the challenges of analysing sustainability criteria in organisations.

Despite the recent advances in this area, findings of this research show that the empirical research in this area is still in its infancy; particularly, within the context of the energy sector.

5.2   Practical implications

The findings mentioned bode with the objectives of this research in gaining an overview of the perceptions carried through the renewables industry of BDA adoption in their respective functions. At the same time, this research provides a set of practical implications for managers:

- 'Relative Advantage' is key for the implementation of BDA in the renewable energy sector – Our findings outline different advantages of BDA in the sector related to the improvement of practices inside the company, gaining understanding about the customers and enhancing business decisions. Managers can use this finding for motivating the investment in BDA and harnessing relevant benefits for the company.
- 'Compatibility' has to be carefully considered whilst deciding to implement BDA in the renewable energy sector to avoid neglecting 'complexity' - The benefits to be had from implementing BDA often obscure the complexity of its inherent challenges. Our findings suggest it is important to integrate BDA to the core of the business to reap real benefits, given that partial or poorly planned implementation can lead to insufficient infrastructure or preparation, affecting the inconsistency of data and the effectiveness of BDA. That becomes important when considering cost and educating employees are the two most prominent perceived barriers to BDA. This result can warn managers about the dangers of limited planning when investing in BDA and provide advice about aspects to consider in the investment.

- 'Trialability' is an important attribute for BDA in the renewable energy sector - Considering the visibility of energy provision and the problems created by operational disruptions, an appropriate trial period is essential to integrate BDA fully and successfully. This finding can inform managers about the need to integrate a 'trialability' period to ensure the organisation is ready to deploy BDA and reduce service disruption.

Overall, our findings can encourage managers in the renewable energy sector to critically evaluate their readiness and commitment to implement BDA in their companies. The research has highlighted relevant drivers and barriers to consider in order to benefit from the use of BDA in this sector. Additionally, this research has delved into the experience and perception of managers regarding BDA implementation. The findings highlight the role of alignment between BDA implementation with strategy. This can make managers aware of the importance of embedding BDA in the company's core structure to ensure a successful implementation in the long term.

6   Conclusions

This study has focused on the opportunities and challenges for implementing BDA in the renewable energy sector. Using the DOI theory as a lens, this research provides empirical insights to advance understanding regarding the implementation of DA in the renewable energy sector through the analysis of interviews with practitioners.

The results highlight clarity and understanding of several of the benefits of DA across the sector. Particularly regarding the impact on business decisions and the value for trends and forecasts. However, challenges related to appropriate training and education of the workforce, investment cost, and integrating this in the organisation's strategy have to be carefully considered by managers to reap those benefits.

This work extends current knowledge on the implementation of BDA in the renewable energy sector. However, different limitations need to be presented. Although considering the UK renewable energy sector was decided because of its relevance and context, that also complicates generalisability. The results of this analysis have to be carefully considered for countries to account for the context and regulatory framework. Moreover, although we were careful to gather a meaningful sample of participants, the use of purposeful sampling is vulnerable to bias.

One of the limitations of this research could be attributed to the sample size. Although the sample showcased credibility, with the participants, employees of organisations of different sectors, the result showed that the alternate perspectives proved hard to adjourn grounding and hence allow to derive appropriate propositions. For example, the Solar industry, of which 4 of the organisations were members, was the highest in this study. Further benefit could have been retrieved if a single function was studied, rather than the sector as a whole. This can also lead to an increase of sampling size, to account for the variance in functions in the sample.

Additionally, with limited previous research studies within this space, forming a discussion section proved more difficult due to the misalignment with industries other than the renewables industry. Albeit, the results provide strong grounding on the perspectives of BDA adoption within the space, hence fully aligning to the aim of this research.

There are several opportunities for further research. The study of specific sectors rather than the whole renewable industry would provide more actionable guidelines based on the context of the sector. Further studies could incorporate a 'case study approach as the research methodology attempted to acquire a plethora of suitable participants. Finally, the 'Diffusion of Innovations' theory by Rogers (2003) proved to carry many facets during analysis, so a more refined model, such as the TAM model, could facilitate analysis based on its malleability in the context.

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