Software Quality Journal
https://doi.org/10.1007/s11219-024-09665-5

RESEARCH

Enhancing big data analytics deployment: uncovering stakeholder dynamics and balancing salience in project roles

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Accepted: 20 February 2024

Abstract
Deployment constitutes a pivotal aspect of data science projects, such as big data analytics (BDA). A comprehensive definition of successful deployment necessitates the integration of perspectives from both the project stakeholders and the end-users. However, adequate consideration of project stakeholders remains notably absent within the broader view of project deployment. This paper investigates the role of stakeholders in the deployment of BDA projects by applying an ethnographic research design throughout a 12-month period within a large multinational organization. The study employs critical systems heuristics concepts to identify stakeholder roles, which are subsequently classified and analyzed according to the salience model. The empirical findings point towards the missing link between the technical and the business aspects of a BDA project. The organizational function and product management, (capable of comprehending both the technical and business dimensions) must undertake a highly salient stakeholder role to effectively guide the project toward the successful deployment. Additionally, this role will be able to identify the exact beneficiaries, thus enabling them to increase their salience and their interests to resonate across the spectrum of project stakeholders. This study advances the knowledge and understanding of BDA deployment through the lens of a stakeholder perspective and systems thinking. It uncovers the necessary resources by mapping the social roles of a project and assessing their salience. Balancing role-based salience contributes to successful BDA project deployment.

Keywords Big data analytics · BDA · Deployment · Project management · Stakeholders · Stakeholder management

1 Introduction

The application of big data analytics (BDA) impacts organizational performance (Elgendy & Elragal, 2014; Manyika et al., 2011; Wamba et al., 2017), including supply chain performance (Bag et al., 2020; Tan et al., 2015), innovation (Lee et al., 2014; Niebel et al., 2019)

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Published online: 13 March 2024

sustainable competitive advantage (Shah, 2022), enterprise decision-making (Kościelniak & Puto, 2015), and organizational knowledge (Pauleen & Wang, 2017; Shabbir & Gardezi, 2020). Additionally, the application of BDA can support project management in decision-making (Ahmed et al., 2022; Angée et al., 2018; Kabanda, 2020). Big data analytics refers to the process of examining and interpreting large volumes of structured and unstructured data by utilizing advanced technologies, machine learning, and algorithms to reveal patterns, correlations, and trends (Chen et al., 2012). Evidently, literature presents vast opportunities presented by BDA usage, which organizations can capitalize upon by discovering business opportunities, making data-driven decisions, and enhancing operational efficiency (Jensen, Persson et al., 2023). However, to extract value from big data initiatives, organizations must not only develop BDA capabilities and employ technologies such as AI (artificial intelligence) to create business value but also ensure successful execution (Tsoy & Staples, 2020) and deployment (Davenport & Malone, 2021) of their BDA projects. Deployment, involving the successful implementation of a system within the organization, is a critical discipline throughout all phases of a data science project like BDA (Davenport & Malone, 2021). Unfortunately, deployment is often considered only in the final stages, leading to potential failures (Davenport & Malone, 2021). Despite the increasing adoption of BDA technologies and the development of capabilities, just one in 10 companies achieve substantial financial benefits from their efforts (Ransbotham et al., 2020). Regardless of the brilliance of an algorithm or model, without deployment, an organization receives minimal value from the efforts and the job cannot be considered done (Davenport & Malone, 2021).

While the technological characteristics and maturity of big data solutions can be evaluated from the perspective of domain experts and application developers, determining the parameters of a successful deployment should be considered from the viewpoints of stakeholders and end-users (Osinga et al., 2022). Thus, BDA can be considered as a complex social phenomenon with inherent duality (Someh et al., 2019). Regardless of project type, whether BDA, IT, or technology-related, organizations seek value through projects (Eskerod & Jepsen, 2013).

Project success (Pinto & Slevin, 1987) draws from a rich literature and practical field of project management that provides tools and approaches to meet objectives in terms of time, cost, scope, and quality (Atkinson, 1999; PMI, 2013; Pollack et al., 2018). Beyond measuring the projects' success based on the triple constraint (Chow & Cao, 2008; Jha & Iyer, 2007; Lee & Xia, 2010), projects are expected to align with and contribute to the organization's strategy (Meskendahl, 2010; Patanakul, 2020; Too & Weaver, 2014). Despite the considerable investments, many projects fail to deliver the expected benefits or face premature termination (Eskerod & Jepsen, 2013). A recurring theme in project deployment failures is the lack of attention to project stakeholders (Eskerod & Jepsen, 2013; Sutterfield et al., 2006). Stakeholders encompass various individuals and entities that influence or are impacted by project outcomes (Freeman, 2010), including project team members, end-users, clients, decision-makers, project sponsors, top management, suppliers, and the public (Achterkamp & Vos, 2008; Davis, 2014; Vos & Achterkamp, 2006). Neglected end-user adoption, reduced interest or budget by top management, and attempts to disrupt projects by concerned entities contribute to deployment challenges (Eskerod & Jepsen, 2013). Hence, a project's success criteria must consider the perceptions of multiple stakeholders across the project lifecycle (Achterkamp & Vos, 2008; Davis, 2014, 2017; Turner & Zolin, 2012).

Similarly, studies underscore the significance of critical success factors related to organization, technology, process, people, human and analytics capabilities, data management, and governance for the successful deployment of BDA projects (Adrian et al., 2017; Al-Sai et al., 2020; Gao et al., 2015). While organization and people-related factors indirectly address the stakeholder dimension, some studies delve into stakeholder perspectives in relation to BDA projects (Miller, 2022; Osinga et al., 2022; Someh et al., 2019). Additionally, stakeholder analysis and change management are pivotal skills for deployment (Davenport & Malone, 2021). However, data science teams and organizations tend to underestimate deployment-oriented skills (Davenport & Malone, 2021), and a robust discussion of BDA projects' effects on stakeholders is lacking (Miller, 2022).

In this paper, we empirically investigate the role of stakeholders in the deployment of BDA projects through an ethnographic research design over 12 months within Vestas Wind Systems A/S, a large multinational organization in the renewable energy sector. Utilizing concepts from critical systems heuristics (CSH) (Ulrich & Reynolds, 2010), we identify stakeholder roles (Vos & Achterkamp, 2006) and guide data collection, followed by stakeholder classification and analysis based on the salience model (Mitchell et al., 1997). Our research question is: *"How can a stakeholder management perspective that integrates systems thinking ensure an understanding of stakeholder roles and their contributions to the successful deployment of big data analytics (BDA) projects?"* In doing so, we uncover the characteristics and practices of the project social roles of a BDA project and evaluate the salience of each resource with attention to balancing the salience of each role to ensure successful BDA project deployment.

This contributes to the growing body of BDA literature; specifically in terms of stakeholder management perspectives for ensuring the deployment of BDA projects, an area that has not yet received adequate attention. Moreover, we provide valuable insights and knowledge to organizations and practitioners engaged in the execution and managerial aspects of BDA projects.

The remainder of this paper is organized as follows: Sect. 2 provides an overview of BDA deployment implications and perspectives on stakeholder management. In Sect. 3, we outline the research design, encompassing data collection methods and the analysis process. Moving on to Sect. 4, we present the analyses conducted and the resulting data insights. Section 5 discusses the results, implications, future work, and limitations. Lastly, Sect. 6 concludes.

2 Background and related work

In this section, we outline the relevant literature. We begin by providing an overview of the deployment aspects of BDA. Following this, we examine the literature relevant to stakeholder aspects of BDA projects. Subsequently, we present our approach grounded in stakeholder management theory, detailing stakeholder identification to guide the data collection process, along with the application of the stakeholder classification model. This frames our interpretation and discussion of the results of our study.

2.1 Deployment of big data analytics

The BDA lifecycle consists of different phases that guide the progression from initial ideas to completion, covering developmental, deployment, and utilization stages (Chen et al., 2012; Larson & Chang, 2016). The conceptualization phase involves activities such as scoping and project definition, progressing to data acquisition and discovery, where analysts evaluate the value and utility of data sources and repositories (e.g., "data lakes"). Subsequently, this leads to the analysis and visualization stage. The developmental stages encompass activities related to design and modeling, including descriptive, predictive, and prescriptive analyses employing machine learning algorithms such as regression, clustering, or classification (Larson & Chang, 2016). The process includes iteratively fitting and validating analytical models. Upon completion of conceptualization and development, the BDA project advances to the deployment stage, subsequently transitioning to the utilization stage, where the measurement of post-project benefits becomes an integral aspect (Jensen, Persson et al., 2023).

However, the deployment of BDA is increasingly recognized as *"one of the most critical disciplines at all phases of a business data science project"* (Davenport & Malone, 2021). Deployment distinguishes itself from implementation; while implementation involves technical solutions, deployment encompasses the essential transformation in business practices required for the success of the BDA system. Despite its significance, deployment often lacks the attention it warrants. Frequently, it is only regarded as the last part of the data science projects (Davenport & Malone, 2021), even if methodologies tailored specifically for data science projects have started to emerge (Angée et al., 2018; Grady et al., 2017). Surprisingly, deployment is frequently not executed even at the project level.

The reason for this may lie in the nature of deployment itself; change is at its core (e.g. transitioning from an old business process to a new). Data science projects typically do not explicitly address change (Davenport & Malone, 2021; Jensen et al., 2019). Change is necessary for business processes due to BDA's potential to transform previously manual, heuristic-based, or seemingly challenging tasks into AI/ML-powered solutions. It is important to differentiate deployment from implementation; the latter refers to developing and ensuring the functionality of technology from a systems and data standpoint. This is the technical dimension, that often assumes the central role in many data science projects (Sfaxi & Aissa, 2020). The emphasis on deployment does not neglect the significance of technical implementation. Rather, equal attention to deployment and implementation is necessary at different stages of the data science project.

In numerous data science projects, the responsibility of deployment is initially assigned to the data scientists. However, these professionals are often not adequately equipped with the necessary skills to effectively manage the transition from old to new practices (Davenport & Malone, 2021). Davenport and Malone (2021) underscore how crucial aspects linked to successful deployment, such as stakeholder analysis and change management, are not sufficiently covered in traditional data science training programs.

This raises the question of whether data scientists are the most appropriate individuals to be assigned the deployment responsibility. One of the notable challenges with assigning deployment to data scientists is that they are expected to anticipate and address deployment issues, despite not having been trained for such tasks. To accommodate this, some organizations assign the task of deployment to other roles, so that the data scientist can focus on coding and developing analytical models. These roles include product managers, data/analytics/AI strategists, and data engineering or analytics translators (Davenport & Malone, 2021; Henke et al., 2018). These roles underscore the growing recognition among organizations that deployment should not rest solely on the shoulders of data scientists. However, even with these newly defined roles that prioritize deployment, a significant proportion of BDA projects still encounter failure.

Essentially, there are different roles in a data science project that each contribute to its success (Beck et al., 2019). The expectation that a data scientist can excel in both the development of technical models and their deployment raises questions. From a socio-technical perspective, the socio aspects (deployment) and the technical facets (AI models) are inherently different yet linked and interdependent for achieving success (Mikalef et al., 2020). Xu and Pero (2023) present a framework for BDA adoption concerning the interaction of socio-technical elements, such as organizational resources and capabilities, in relation to the process of resource accumulation, stabilization, and coordination. This framework challenges the notion that BDA adoption should only begin once all the necessary resources are established. Instead, Xu and Pero (2023) propose that the needed resources can be developed gradually with purposeful resource management actions. Thus, expecting a data scientist to navigate both the socio and the technical domains, solely based on their technical background, may overlook the complexity of the task, as evidenced by various instances of deployment challenges. For example, a survey conducted by MIT Sloan Management Review/BCG in 2020 (Ransbotham et al., 2020) highlighted the significance of the final stage of data science maturity (e.g. AI projects), for unlocking value. Successful orchestration of interactions between humans and machines requires a broad spectrum of skills that extend beyond the technical domain (Granzen, 2020). The outcome of a data science project, such as AI, is by nature a learning system (Ransbotham et al., 2020), which then requires broad expertise in the areas of both technical development and deployment -incorporating aspects of business change management (Granzen, 2020) and the underestimated importance of stakeholder management (Davenport & Malone, 2021).

Although the possibilities of BDA on the organizational performance from a business perspective are well recognized, the investigation of the influencing factors on the deployment success merits attention and the orchestration of the needed resources (Adrian et al., 2017) with an emphasis on stakeholders (Osinga et al., 2022).

2.2 The stakeholder aspects of BDA projects

Undoubtedly, the deployment of big data is a complex endeavor and is influenced by various factors, ranging from enterprise data management to corporate culture, and demands more preparation compared to other technology projects (Cato et al., 2015). Several studies point toward the influencing factors related to the organizational and people-centric aspects. These can be aligned with the stakeholder perspective, considering entities or individuals that can influence or be influenced by outcomes (Freeman et al., 2010). The effective execution of BDA projects requires significant engagement with institutional stakeholders (Kee et al., 2022).

2.2.1 Collaboration, support, and trust among BDA stakeholders

Among the organizational factors influencing the deployment of BDA projects, the close collaboration between IT and business emerges as a pivotal driver. Bringing data scientists, business experts, and IT professionals together, and fostering frequent interactions with the end-users becomes imperative to achieve synchronization in project endeavors (Al-Sai et al., 2020; Cato et al., 2015; Osinga et al., 2022; Reggio & Astesiano, 2020). Additionally, the configuration of organizational structures, particularly the integration of IT and analytics teams within the organizational framework, significantly influences the success of deployment initiatives (Cato et al., 2015). Moreover, the endorsement of executives' support (Reggio & Astesiano, 2020) and the cultivation of trust among management and stakeholders serve as foundational cornerstones for successful deployment (Davenport & Malone, 2021).

2.2.2 Process transparency and alignment

The governance mechanisms encompassing processes, practices, and policies, which are undertaken by various organizational actors across the organizational and departmental boundaries, influence the deployment of BDA projects (Al-Sai et al., 2020). The establishment of a well-defined process towards deployment, whether adhering to agile principles (Larson & Chang, 2016; Reggio & Astesiano, 2020; Tsoy & Staples, 2020) or a stage gate product development approach (Davenport & Malone, 2021), holds substantial value. Such processes enhance transparency and alignment among organizational stakeholders. Particularly, agile principles and development methods are gaining ground in analytics projects (Tsoy & Staples, 2020) by promoting close collaboration and interaction between stakeholders to ensure clearer requirements, understanding, and joint accountability (Larson & Chang, 2016). This enables more devoted time to explore possibilities rather than determining information requirements (Larson & Chang, 2016). Reggio and Astesiano (2020) further underscore critical components for mitigating the risk of BDA project failure, including project management related components in favor of agile methods with short iterations and frequent interactions with users. This approach ensures the synchronization of development endeavors with evolving business needs.

2.2.3 BDA stakeholder roles and identification

Deployment and the related influencing factors should be considered throughout the course of the project (Davenport & Malone, 2021). Concurrently, stakeholder identification and involvement should be considered both early in the design processes during the development stage (Penn et al., 2019) and the usage stage to accommodate the user needs and ensure synchronization (Miller, 2022; Osinga et al., 2022). However, it is important to pinpoint that stakeholders at the development stage hold a distinct capacity to address the concerns of all stakeholders (Miller, 2022).

The stakeholder perspective entails the ability to identify and classify the roles of various stakeholders throughout the course of the project. Miller (2022) identifies the stakeholders affected by AI projects and AI system applications, and what stakeholder roles are involved in the decision-making and acting in AI projects. Throughout a systematic literature review, Miller (2022) applies the salience model (Mitchell et al., 1997) to identify stakeholders, and includes the harm attribute to provide an ethical dimension to the three fundamental attributes of the salience model, namely, power, legitimacy, and urgency. While the stakeholder group at the development stage possesses the legitimacy and power to decide upon features and functions of the AI system, the stakeholder group at the usage stage holds legitimacy and power relevant to the deployment of the system and its impact on external stakeholders (Miller, 2022). Additionally, external stakeholders encompass individuals and societal entities that may experience harm during the development or operation of the AI system (Miller, 2022).

Someh et al. (2019) adopt a stakeholder perspective on BDA to identify and develop key theoretical concepts underlying ethical issues for three interrelated stakeholder groups: individuals, organizations, and society, all of which are engaged in BDA. By employing the prominent salience model (Mitchell et al., 1997) within the stakeholder theory, the study elucidates the salience of each stakeholder group: their power to influence big data analytics, the legitimacy of their relationship to big data analytics, and the urgency of their claims on big data analytics (Someh et al., 2019). This understanding of the salience of each stakeholder group facilitates discussions on the interactions between stakeholders and suggests methods to harmonize those interactions (Someh et al., 2019).

Despite the good intentions of the use case owners and application developers, stakeholders can hold distinct perspectives and motivations for adopting big data solutions in contrast to the use case representatives (Osinga et al., 2022). Yet, achieving alignment between the viewpoints of use case representatives and stakeholders within BDA projects can be intricate due to the challenges in pinpointing the needs of stakeholders (Osinga et al., 2022). Consequently, a systems-thinking approach coupled with a comprehensive and interdisciplinary process becomes imperative for the creation and implementation of solutions (Osinga et al., 2022).

2.3 Application of stakeholder management theory

Stakeholder theory serves the dual purpose of explaining and guiding the structure and operations of organizational entities, involving multiple participants with diverse and sometimes conflicting objectives (Donaldson & Preston, 1995). There are three aspects of stakeholder theory: descriptive, instrumental, and normative (Donaldson & Preston, 1995). The descriptive aspect provides an empirical understanding of stakeholder behaviors and their relationships with phenomena. The instrumental aspect establishes a link between effective stakeholder management and the achievement of corporate objectives. Meanwhile, the normative aspect encompasses moral and philosophical principles guiding corporate management. While both the instrumental and normative viewpoints could be considered prescriptive, the former is hypothetical in nature, prescribing actions to achieve specific goals, while the latter is categorical, prescribing actions based on ethical principles.

The instrumental view aligns with the management-of-stakeholders approach (Eskerod & Huemann, 2013), endorsed by project management standards (PMI, 2013), and is fundamental in several prominent two-dimensional matrix models (Freeman, 2010; Friedman & Miles, 2002; Polonsky & Scott, 2005; Savage et al., 1991). The normative view, on the other hand, embraces the management-for-stakeholders approach (Eskerod & Huemann, 2013), acknowledging external, passive, and marginalized groups without the ability to influence outcomes but are impacted by them (Di Maddaloni & Davis, 2017; Nguyen et al., 2019). While these three stakeholder theory aspects may appear distinct, they should not be isolated, as they are mutually reinforcing and interconnected (Donaldson & Preston, 1995).

In this study, we adopt the salience model as presented by Mitchell et al. (1997) to classify stakeholders, providing insight into their salience and framing our analysis. Similarly, the salience model (Mitchell et al., 1997) has also been employed by other investigations focusing on stakeholder perspectives within BDA projects (Miller, 2022; Someh et al., 2019). Stakeholder classification is based on the possession of one, two, or all three attributes: (1) the stakeholder's power to influence, (2) the legitimacy of the stakeholder's relationship, and (3) the urgency of the stakeholder's claim (Mitchell et al., 1997). The classification typology allows predictions and recommendations concerning managerial behavior in relation to each stakeholder class. A combination of the attributes (power, legitimacy, and urgency) gives rise to seven distinct stakeholder types. Among these, three types possess a single attribute, three types embody two attributes, and one type embodies all three attributes. The low salience classes are latent stakeholders, who possess only one of the attributes (Mitchell et al., 1997). The moderately salience classes are expectant stakeholders, who possess two of the attributes. Lastly, the highly salient class are definitive stakeholders, who possess a combination of all three attributes. Stakeholder salience, reflecting the degree to which managers prioritize competing stakeholder claims, is positively related to the cumulative number of stakeholder attributes perceived by managers (Mitchell et al., 1997). While the salience model effectively accommodates the descriptive and instrumental views, we endorse all three views by allowing us to reconsider the positioning of stakeholders in the light of situational and contextual nuances.

2.4 CSH research approach

In the present inquiry, we align with the concepts derived from critical systems heuristics (CSH) as articulated by (Ulrich & Reynolds, 2010) to identify the roles of stakeholders. This methodology, also evident in other studies such as the work of Vos and Achterkamp (2006), is selected for its efficacy to reveal different perspectives and elucidate the diverse roles assumed by stakeholders. We utilize these concepts to guide our data collection process. Subsequently, the stakeholder classification and analysis are based on the salience model. This model provides a structured framework through which the significance of stakeholders is systematically evaluated, contributing to a nuanced understanding of their respective roles within the studied context.

Critical systems heuristics (CSH) provides a conceptual framework for establishing critical practice and awareness (Ulrich, 1983) and aims to intervene in potentially problematic social situations to improve them. Rooted in critical systems thinking, a paradigm that emerged in the 1980s, CSH considers human intervention and broader organizational aspects both in relation to social complexity and technical issues, making it an interesting theoretical perspective for examining BDA project stakeholders (Ulrich, 1983). CSH considers diverse perspectives and stakeholder interests, in both understanding and improving problematic situations – such as BDA deployment challenges. The application of CSH to the BDA project offers a comprehensive exploration of social and stake-holding aspects across design, implementation, and utilization stages. Stake-holding aspects make explicit the various considerations and dimensions associated with stakeholders within a given system, for example a BDA project.

CSH explicates the broader socio-political landscape, the interrelations, and the power dynamics among stakeholders in system design (Ulrich, 1983). Given that BDA projects encompass stakeholders from various domains, such as technical, business, and financial, it is noticeable that very few BDA projects have a methodology in place for stakeholder inclusion to ensure success. As previously described, BDA projects tend to rely on development methodologies not specifically tailored to the particularities of such projects. To this, CSH emphasizes pluralism as well as boundary critique in establishing the multiple viewpoints from those involved and affected by the system, while questioning and making explicit the boundaries and assumptions these stakeholders hold of the system. In making pluralism explicit by the means of CSH towards BDA stakeholders, signifies the acceptance as well as incorporation of diverse viewpoints while acknowledging the inherent complexities in BDA projects. CSH is operationalized from 12 different questions. Each of the questions helps unfold and make explicit the everyday judgement that we unknowingly or not, depend upon to understand the challenges we face (Ulrich & Reynolds, 2020). The questions are presented in Table 1. In this inquiry we apply the questions relevant towards social roles (stakeholders) as we investigate the role of stakeholders in the deployment of BDA projects.

Table 1 The boundary categories and questions of CSH. Adapted from Ulrich (1996)

Sources of influence	**Boundary judgements informing a system of interest (S)**			
	Social roles (Stakeholders)	Specific concerns (Stakes)	Key problems (Stakeholding issues)	
Sources of motivation	*1. Beneficiary* Who ought to be/is the intended beneficiary of the system (S)?	*2. Purpose* What ought to be/is the purpose of S?	*3. Measure of improvement* What ought to be/is S's measure of success?	**The Involved**
Sources of control	*4. Decision maker* Who ought to be/is in control of the conditions of success of S?	*5. Resources* What conditions of success ought to be/are under the control of S?	*6. Decision environment* What conditions of success ought to be/are outside the control of the decision maker?	
Sources of knowledge	*7. Expert* Who ought to be/is providing relevant knowledge and skills for S?	*8. Expertise* What ought to be/are relevant- knowledge and skills for S?	*9. Guarantor* What ought to be/are regarded as assurances of successful implementation?	
Sources of legitimacy	*10. Witness* Who ought to be/is representing the interests of those negatively affected by but not involved with S?	*11. Emancipation* What ought to be/are the opportunities for the interests of those negatively affected to have expression and freedom from the worldview of S?	*12. Worldview* What space ought to be/is available for reconciling differing worldviews regarding Samong those involved and affected?	**The affected**

Making pluralism evident from BDA project is essential in uncovering the role of stakeholders, as it allows for a more inclusive understanding of the varied interests these may hold (Ulrich, 1983). Each of the social roles as presented in Table 1 contribute to making pluralism evident. The *beneficiary* is someone that experiences an improvement from a particular system – such as a BDA project. The *decision maker* ought to be or is in control of the conditions for success from the system. Third, the *expert* acts as a skilled provider and source of knowledge for the system. Finally, the *witness* is someone who ought to be or is acting as a representative for those that potentially may be negatively affected by the system as these may not be directly involved in the system. As an example, the roles that are not directly assigned in the project.

Altogether, our stakeholder perspective endorses the descriptive, instrumental, and normative views by balancing both the management-of and management-for-stakeholders approaches, where we apply the concepts from critical systems heuristics to identify the stakeholder roles that should be classified and analyzed according to the salience model.

3 Methods

In addressing our research question, *"How can a stakeholder management perspective that integrates systems thinking ensure an understanding of stakeholder roles and their contributions to the successful deployment of big data analytics (BDA) projects?"*, we opted for an ethnographic design, recognized for its depth in investigating real-life cases through methods such as interviews and participant observation (Myers, 1999). Our study focused on a large multinational organization, Vestas Wind Systems A/S, that invested significantly in BDA technologies and initiated several internal BDA projects at the time of this study. Thus, our methodology was contextual and interpretive employing various techniques of organizational ethnography (Agar, 1980, 1986; Van Maanen, 2011) extended over a 12-months period. The data was collected on the premise of the organization through participant observation, semi-structured interviews, documentation review, field notes of participating in several departments and BDA project meetings (e.g. steering committee meetings) as well as informal social interactions with the participants. This amounted to more than 33 interactions, apart from the interviews, contributing an additional 51 h of analyzable data. The interviewees were chosen based on their in-depth knowledge of BDA projects both pertaining to technology as well as to business requirements. The participants were involved in different BDA projects in which we specifically followed one of these in greater detail. The participants spanned Vestas' hierarchical levels from sales to finance managers, project managers, and senior managers. Informal data was also collected from key informants like department managers, BDA developers, and product managers.

Eight in-depth interviews constituted the primary data source for our study. These interviews followed a semi-structured format and were based on the questions proposed by CSH (Ulrich, 1983) in making explicit the social roles engaged in defining a system. The questions were asked in two modes; "*as-is*" and "*to-be*" to make explicit the judgments by those included in the system. The system of interest in this study was BDA projects with a specific focus on deployment and the roles undertaken by various stakeholders. Thus, we focused on CSH questions about social roles and stakeholders. The questions were 1*) "Who ought to be/is the intended beneficiary of the system?"*, (2) *"Who ought to be/is in control of the conditions of success for the system?"*, (3) "*Who ought to be/is providing relevant knowledge and skills for the system?"*, and (4) "*Who ought to be/is representing the* *interests of those negatively affected by but not involved with the system?*". The interviews lasted between 60 and 90 min and included the participants listed in Table 2. All of the interviews were audio recorded and transcribed.

3.1 Data coding

From CSH and the questions concerning stakeholders, analytical themes were as such already given. Therefore, the data was analyzed through a directed content analysis (Assarroudi et al., 2018; Hsieh & Shannon, 2005), which is guided by a more structured process compared to a conventional approach (Hsieh & Shannon, 2005). Starting with established theory, we applied directed content analysis by identifying key concepts as initial coding categories (Potter & Levine-Donnerstein, 1999). Following this, we undertook stepwise coding which consisted of open, axial, and selective coding in identifying themes. Our objective was to elaborate and make explicit the judgments of those involved and affected by the BDA projects, specifically in relation to deployment and BDA stakeholders. The stakeholder questions from CSH are considered in two modes: an ideal model (what "should" be), and a descriptive mode (what "is"). By contrasting the responses between these two modes, we aimed to uncover any disparities, which could indicate unresolved matters. CSH is useful in unfolding selectivity from multiple perspectives. Our focus in this study was on exposing the selectivity of those involved in BDA projects in making explicit their implicit assumptions of the stakeholders in BDA projects, particularly in the context of deployment.

4 Analysis and results

Our analysis investigates the perceived necessary roles for the deployment of BDA. It is important to emphasize that deployment differs from implementation, as deployment involves the utilization of BDA technology and analytical outcomes, thus presenting the potential value creation. Guided by CSH, we specifically explore the boundary questions relating to social roles, seeking to make explicit the implicit assumptions held by those engaged and affected by the BDA project regarding the necessary roles for successful deployment. For a BDA project to assume that the roles defined at the project level are enough for successful deployment appears to be false. While the BDA project constitutes a system with typically well-defined roles and assigned responsibilities, the same is usually not the case for deployment. From a systemic perspective, these are two separate systems, however, dependent upon each other to ensure that the organization's investment in BDA is worthwhile.

4.1 Moving toward deployment

Investing in BDA implies that the organization seeks to improve its existing practices in some manner. The basic idea of unfolding improvement in specific situations, such as from BDA, raises some fundamental issues in moving beyond the BDA project to deployment. Several of the interview participants addressed this:

"*We (in BDA projects) have the technical competencies, but what we are missing is a specialist from the business with a financial understanding and product ownership*" (Project manager, BDA projects).

Table 2 Interview participants

Participant	Functional area	Responsibilities in BDA projects
1: Design owner	Engineering, Modelling & Analytics	Technical solution specialist, management level. Responsible for the technical solutions developed within functional area.
2. Project manager	Project management	Project management is responsible for delivering on agreed deliverables within the time, budget, and scope for BDA projects.
3. Senior functional lead	Modelling & Analytics, senior functional leads	Technical solution specialist for the BDA projects. Involved directly in project work. Reports to the Design owner.
4. Sales manager	Sales	Sales representative. Defining requirements from sales.
5. Chief specialist	Product Value engineering	Defining potential data products from BDA projects with a commercial perspective.
6. Head of siting	Global Siting	Example of an internal customer responsible for the deployment of BDA.
7. Senior financial Specialist	Finance	Financial expert supporting in developing the business case for the potential benefits in collaboration with the chief specialist and the Sales manager.
8. Senior specialist	Product development	Defining market requirements towards product development.

The technical design owner elaborated further on the lack of decision architecture in moving from the BDA project to deployment in realizing the potential value of the organization's BDA investment in describing the importance of separating the analytical part from the decision rights in the business.

The issues in moving from the BDA project to deployment appear to be missing roles that connect these two. It concerns both the ethics as well as the knowledge of initiating a BDA project and planning for the improvement in the business, which is expected by those initiating and involved at the project level. From the interviews, it became obvious how the understanding of the needed resources for deployment differed between the interview participants depending on their knowledge and understanding of the BDA project. The concern is that being able to anticipate what exactly BDA may produce of output is difficult and may vary as well depending on those defining it. Moreover, the potential improvement in the organization from the BDA deployment did not mean the same to each of the interview participants, which implies conflicts of understanding. As an example, when being asked to identify the social roles that potentially could be negatively affected by the BDA project and its deployment in the organization, the answers from the participants varied greatly:

"…if they don't incorporate the improvement from the (BDA) model, then they will be negatively affected and by they, I mean finance" (Senior specialist, product development).

In contrast, the Sales manager found the Service department to potentially be negatively affected by the BDA project and its deployment in the organization:

"You need the Service guys at the table (in defining implications of deployment) when he hears that the bias of the annual energy production will be reduced, he might not understand the exact implications it has for him" (Sales manager, sales department).

The different answers from the interview participants as to who or which department could potentially be negatively affected demonstrate the fluid boundaries that BDA has in an organization. The analytical output may not only serve a certain and restricted group of people. Alternatively, it can move between departments and functions, and potentially be utilized in multiple ways that might not have been originally intended. From an ethical perspective, this raises a conflict that, however, cannot be deemed as being played out between "good" (the intended) use and "bad" (the unintended) use. Instead, any conceivable deployment of the BDA projects will encounter challenges as it may never be able to serve the different potential users of it, equally or in a restricted manner. The inescapable question is then how to manage these potential challenges in moving between the BDA project and deployment. To this, different roles may serve different purposes. Table 3 presents the types of roles that represent each of the needed sources in making implicit assumptions about a system (the BDA project deployment), explicit and hence, manageable.

4.2 Establishing roles

The roles are dependent upon if the BDA project is initiated to develop an external data product to sell to customers outside the organization or if it is initiated to develop internal BDA solutions for stakeholders within the organization. The differences are outlined in Table 3.

In summary, the resources and their types are associated with the conditions for success that need to be controlled to ensure the proper functioning of the system. We identified several stakeholder roles for BDA deployment, expanding on the roles from the BDA projects in which the interview participants were involved. The type of specific role may vary depending on the type of BDA project that is initiated. Table 3 represents generic roles that are important in ensuring successful BDA deployment. Yet, several of

Table 3 BDA project social roles for deployment

BDA project social roles – for deployment	
	Empirical roles
Beneficiary (source of motivation)	**Internal & External**: Entire value chain – a holistic perspective. External customers as well as internal in the organization depend on the type of BDA product.
Decision maker (source of control)	**Internal:** Product manager, Service, Change management expert, Data owner, Product owner, Project manager, Technical lead. **External**: Product manager, Sales, Service, Change management expert, Data owner, Product owner, Project manager, Technical lead.
Expert (source of knowledge)	**Internal:** Data scientist, Technical lead, Business analyst, Product manager, Data owner, Financial expert. **External:** Data scientist, Technical lead, Business analyst, Product owner, Product strategy responsible, Data owner, Financial expert, Market specialist. Cooperation between the roles is crucial. Here the BDA project steering committee members hold an important role.
Witness (source of legitimacy)	**Internal:** Product owner, Management team, Department managers affected by the BDA output, Data owner. **External:** Product owner, Data owner, Sales managers, Management team, Department managers affected by the BDA output.

the interview participants stressed the importance of these roles to work closely together and that the sequence of which this cooperation was initiated, was important as well. As an example:

"Product management should have the anchoring of the (BDA) product as they are right between technology, sales, and finance. The business case is what they then should navigate from as this is what they all have a stake in" (Project manager, BDA projects).

The Chief specialist from the product value engineering elaborated further:

"I believe that we have all the experts we need. What is missing is the cooperation between these and the business" (Chief specialist, product value engineering).

Several of the interview participants highlighted the BDA project's business case as a means for ensuring cooperation between the different stakeholders and this was the responsibility of the product management and financial specialist to develop. The business case could then serve as a tool in which to anchor the collaboration between the different stakeholders. However, managing the different stakeholders during the course of the project to ensure successful deployment would not be something that could be established from a business case. One of the respondents addressed the challenges of letting experts dominate the BDA project and that these may operate with a very narrow focus:

"They (the experts) don't operate at a high enough level (in the organization). They have become pigeonholed…everyone must become experts suddenly…due to our significant growth our managers have not had the opportunity to become more generalists." (Chief specialist, product value engineering).

We consider the CSH roles presented in Table 3 through the lens of the salience model to discuss their placement and who needs attention and management during the course of the project to ensure successful deployment.

4.2.1 The discretionary stakeholders

The beneficiaries, regardless of being internal or external customers, are difficult to pinpoint by the interviewees, due to the difficulties in defining the exact output that a BDA project may produce combined with the fluid boundaries of BDA outcome within the organization. The beneficiaries are considered as the users, who must adopt and use the technology to ensure any deployment. Hence, they are treated as discretionary stakeholders who, as users, possess the legitimacy of the relationship. Stakeholder groups who only possess one attribute are latent stakeholders. They have low salience and may not even be recognized, and managers may well do nothing about them. Discretionary stakeholders possess the legitimacy of their claim but have no power to influence the project and no urgent claim. The absence of power and urgency impose no pressure on managers to engage with such stakeholders, although they may choose to do so. However, each attribute is not a steady state, but a variable that may change for any particular entity (Mitchell et al., 1997). The degree of each attribute is a constructed reality based upon multiple perceptions rather than an objective one. Stakeholders may not be aware of possessing a specific attribute or, if aware, may not choose to act. The ability to identify the exact beneficiaries before deployment, optimally at an early stage of the project course, will allow such stakeholders to acquire the power attribute. Having a combination of two attributes changes the conditions from a passive to an active stance with an equivalent increase in the stakeholder's interest by other and more decisive roles in the project. Paying more attention to identifying the exact beneficiaries will provide them with the power attribute and move their status from being a discretionary to a dominant stakeholder. This is important as otherwise, nobody involved in the project will pay attention to them, which will not ensure the adoption of technology and contribute to a successful deployment.

4.2.2 The dominant stakeholders

The remaining BDA project social roles, namely the decision maker, the expert, and the witness are considered dominant stakeholders. While the degree of possession may vary between the organizational roles within each of the three CSH social roles, they all possess the combination of power and legitimacy attributes. Dominant stakeholders are both powerful and legitimate, and they will matter due to their ability to act on these claims (Mitchell et al., 1997). This is particularly due to their professional expertise and technical excellence that provides them with the ability to act and be noticed during the course of the project.

Regardless of the large pool of dominant stakeholders with a high level of subject expertise, none of the stakeholders appear to have urgency to their claim that calls for immediate attention. Throughout the data analysis, it is evident that there is a missing link to the business side, and it is implied that product management can balance the technical and the business perspectives. The expectant stakeholders, possessing two attributes like the dominant stakeholders, can become the definitive stakeholders by acquiring the missing attribute. Potentially, the product management role can acquire urgency, criticality, or time sensitivity to their claim. Stakeholders that possess both power and legitimacy will require immediate attention when such a stakeholder's claim is urgent and must be given priority. This enables the product management role to orchestrate the project by considering both the technical and the business aspects toward a successful deployment, including paying attention to the identification of beneficiaries (the discretionary stakeholders). Table 4 provides an overview of the key findings starting with the identification of empirical role according to the CSH project

Table 4 Identification of empirical roles as CSH roles and the assessment of their salience and stakeholder classifications

CSH social roles	Empirical roles	Stakeholder salience	Recommendations
Beneficiary	The users *Difficulties in defining the exact output that a BDA project may produce combined with the fluid boundaries of BDA within the organization.*	Discretionary stakeholders *Possess legitimacy of their claim but have no power to influence the project and no urgent claim.*	The beneficiaries, who are the users, are classified as discretionary stakeholders. The users (internal or external) are identified as beneficiaries (CSH role) throughout the empirical data analysis. They have low salience, possess only one attribute (legitimacy), and for this reason are classified as discretionary stakeholders. Move status from being a discretionary to a dominant stakeholder by acquiring the power attribute and having moderate salience (two attributes: legitimacy and power). *Identifying the exact beneficiaries (users) at an early stage of the project course, will allow such discretionary stakeholders to acquire the power attribute – evolve into a dominant stakeholder, and ensure that the remaining social roles in the project pay attention to them.*
Decision Maker	Product manager, Sales, Service, Change mgmt expert, Data owner, Product owner, Project manager, Technical lead.	Dominant stakeholders *Possess power and legitimacy.* *Will matter due to their ability to act on these claims.*	Several empirical roles are identified as decision makers (CSH role) in the empirical data analysis. They have moderate salience – possess two attributes (power and legitimacy), and for this reason are classified as dominant stakeholders. However, only one empirical role should progress in this CSH role (decision maker) by acquiring the third attribute (urgency) and become a high salience stakeholder (definitive stakeholder) – the product management role. The product management role must move status from being a dominant to a definitive stakeholder by acquiring the urgency attribute. *Acquire urgency, criticality, or time sensitivity to their claim. Enables the product management role to orchestrate the project by considering both the technical and the business aspects, including paying attention to the identification of beneficiaries.*

Table 4 (continued)

CSH social roles	Empirical roles	Stakeholder salience	Recommendations
Expert	Data scientist, Technical lead, Business analyst, Product owner, Product strategy responsible, Data owner, Financial expert, Market specialist.	Dominant stakeholders *Possess power and legitimacy.* *High level of subject expertise provides the ability to act and be noticed during the course of the project.*	Several empirical roles are identified as experts (CSH role) in the empirical data analysis. They have moderate salience – possess two attributes (power and legitimacy), and for this reason are classified as dominant stakeholders. The experts will matter due to their ability to act on their claims, enabled by possessing two attributes. *The empirical roles identified as experts (CSH role) should engage with beneficiaries (users) during the development stage. They should maintain their moderate salience and classification as dominant stakeholders.*
Witness	Management team, Department managers affected by the BDA output, Data owner, Sales managers.	Dominant stakeholders *Possess power and legitimacy.* *High level of professional expertise provides the ability to act and be noticed during the course of the project.*	Several empirical roles are identified as witnesses (CSH role) in the empirical data analysis. They have moderate salience – possess two attributes (power and legitimacy), and for this reason are classified as dominant stakeholders. The witnesses will matter due to their ability to act on their claims, enabled by possessing two attributes. *The empirical roles identified as witnesses (CSH role) should engage with beneficiaries (users) during the development stage. They should maintain their moderate salience and classification as dominant stakeholders.*

social roles followed by the stakeholder classification and assessment of salience and completed with a recommendation toward a successful BDA deployment.

5 Discussion

Drawing from CSH (Ulrich, 1987) we expand on the principles and guidelines that ensure the effectiveness, efficiency, and ethical implications of BDA project deployment for stakeholders. Lack of attention to project stakeholders for deployment is a recurring theme (Eskerod & Jepsen, 2013; Sutterfield et al., 2006), which we address for the deployment of BDA projects.

From the salience model (Mitchell et al., 1997), we focus on the stakeholder interactions and their interests in BDA deployment, and how these exert influence in this context. By considering both CSH and the stakeholder perspective, we make explicit the necessary roles for BDA deployment and their respective salience. Several scholars have emphasized the importance of addressing the stakeholder perspective in BDA projects and how these need to be orchestrated (Mikalef et al., 2020). Furthermore, scholars have highlighted the need for strong collaboration between IT and business, advocating for closer integration of data scientists, IT, and the business (Al-Sai et al., 2020; Cato et al., 2015; Osinga et al., 2022; Reggio & Astesiano, 2020). Our contribution lies in establishing effective orchestration among diverse stakeholders, achieved through a holistic approach that combines insights from CSH and stakeholder management, promoting the potential for successful deployment. Essentially, the stakeholder and the CSH perspectives for BDA project deployment emphasize the necessity of understanding and addressing the interests, requirements, and concerns of various stakeholders throughout the deployment process of BDA.

Our study portrays how continuously identifying relevant stakeholders for BDA deployment and evaluating their salience is crucial for successful BDA deployment. Several scholars emphasize how stakeholders may evolve in BDA projects once the project begins to materialize (Jensen, Nielsen et al., 2023; Xu & Pero, 2023). In addition, the success criteria of a project must consider these multiple evolving perceptions across the lifecycle of the project (Achterkamp & Vos, 2008; Davis, 2014, 2017; Turner & Zolin, 2012). It seems only natural that carving the stakeholders in stone at the outset of a BDA project cannot foster successful deployment as the analytical outcome of BDA projects may be explorative as well. Moreover, several researchers have addressed the orchestration of resources, both internal and external, as needed for BDA deployment (Gong et al., 2018). Our study approaches this by adopting a stakeholder perspective to assess the salience of each resource, and from that vantage point, we contribute to orchestrating these resources effectively. As an example, the organizational role, product management, that can comprehend the technical as well as the business side must become a high salience stakeholder to orchestrate the project towards successful deployment. Furthermore, this role will be able to identify the exact beneficiaries, which will enable the beneficiaries to increase their salience by acquiring the power attribute besides the legitimacy, and their interests will be considered by the remaining project stakeholders, which is beneficial to the deployment.

Moreover, successful BDA deployment may introduce significant changes in the organization in relation to the interactions between individuals, the technology, and the organization as a whole. For instance, it is expected that BDA will replace human resources in repetitive, clerical, and objective tasks (Alicke et al., 2019). The potential free-up of existing resources from repetitive tasks does not mean that these necessarily will leave the organization. Instead, the resources could potentially be directed toward other tasks. To this extent, we posit that the business representative holds a significant degree of power to establish an understanding of the reallocation of resources. The business representative must possess a comprehensive understanding of the organization's operations and comprehend the potential impact that BDA deployment, including technological and process changes, may have beyond mere technical implementation.

Indeed, much of the existing literature on BDA deployment has largely focused on topics such as performance impact and determinants of adoption intention, without delving into a more comprehensive examination. Some advances have been made in terms of a management-oriented perspective, as demonstrated by Xu and Pero (2023), from the proposed framework scrutinizing the role of management actions during BDA deployment. Through our study, we contribute to the advancement of BDA deployment knowledge by adopting a stakeholder perspective and incorporating systems thinking. Our approach involves explicitly identifying the needed resources through the characterization of social roles within a project. We further evaluate the salience of each resource with attention to balancing the salience of each role to ensure successful BDA project deployment.

5.1 Implications for practitioners and future work

Our findings present several implications for practitioners of BDA deployment. First and foremost, practitioners should acknowledge the difference between the implementation and deployment of a BDA technology. Successful deployment goes beyond the technical implementation and therefore requires that practitioners manage this differently. Our study portrays how the orchestration of stakeholders may contribute to successful deployment, but also how these stakeholders hold different levels of salience and that these should be orchestrated differently. As an example, the product management function should undertake a highly salient stakeholder role to guide the BDA project toward successful deployment. The reason for this should be viewed in the light of the tasks assigned to the Product manager, which usually entail both a technical as well as a business dimension. Thus, the Product manager would be able to comprehend the technical solution and bridge it to the exact beneficiaries. This is crucial for successful deployment since the beneficiaries must adopt and utilize the BDA technology once it is developed.

For future research, our findings point towards the missing link between the technical and the socio aspects of a BDA project with a specific focus on the stakeholders. Future research endeavors should expand upon our findings within the context of various project methodologies that are undertaken for BDA projects, such as agile methods and DevOps. By doing so, researchers can delve deeper into the specifics of the sequences and practices related to the methods in which stakeholders should be involved. Moreover, a topic that warrants exploration in future studies pertains to the allocation of different tasks within a BDA project and the associated roles of stakeholders. In evaluating the salience of each resource, future studies may point to changes in how the different stakeholders in BDA projects contribute to the tasks at what specific time in each project phase. Lastly, future research endeavors should extend the application of systems thinking, such as CSH, to investigate the dynamics between a BDA project and the success of its deployment. BDA deployment success may be regarded as a system entailing a complex orchestration between the technical and the socio-cultural elements to which systems thinking may contribute to making these manageable. This approach could offer valuable insights into how to navigate the complexities of BDA deployment and ensure its successful integration within organizations.

5.2 Limitations

Conducting an ethnographic research design entails a substantial commitment of time and resources due to its emphasis on in-depth understanding within a specific context. The emphasis on a specific context makes it challenging to extrapolate the findings to a wider population or setting. Moreover, the researcher's subjectivity may impact the data collection, analysis, and perception of participants' experiences. As an alternative approach, a comparative case study methodology could be considered to identify patterns, differences, or commonalities across various contexts. Nonetheless, the selected ethnographic research design contributes a profound and comprehensive understanding of a specific culture and communities within their natural surroundings. This allows the researcher to uncover insights that might be overlooked by other qualitative methods. The provision of thick and detailed descriptions enhances the authenticity of the research findings.

6 Conclusion

The deployment of a BDA project is complex and influenced by multiple factors and requires more preparation in contrast to other technology projects. Regardless of the effort and technical advances, if it is not deployed, the organization will receive minimal value. Yet, many projects fail to generate the expected benefits and lack attention toward project stakeholders.

In this paper, we investigate the role of stakeholders in the deployment of BDA projects by applying an ethnographic research design throughout 12 months within a large multinational organization. In this study, eight in-depth interviews served as the primary source of data and were analyzed through a directed content analysis. Furthermore, the ethnographic research design enabled a diverse collection of data, including participant observation, semi-structured interviews, documentation review, field notes of participation in several department and BDA project meetings as well as informal social interactions with the participants. This contributes to a comprehensive and in-depth understanding of the complex organizational context and environment in which big data analytics projects are initiated, developed, and ought to be deployed. We apply the concepts from critical systems heuristics to identify which roles and stakeholders should be classified and analyzed according to the salience model.

From a socio-technical perspective, the empirical findings point towards a missing link between the technical (development) and the socio (deployment, business aspect) sides of a BDA project. The product management role must become a high-salience stakeholder to orchestrate the project toward successful deployment. In addition, this role can identify the exact beneficiaries, which will provide them with the power attribute and increase their salience from being discretionary to a dominant stakeholder. This is important to gain attention from the remaining roles involved in the project, particularly the dominant stakeholders with technical excellence and expertise.

From our investigation, we contribute to the advancement of scholarly discourse surrounding the deployment of big data analytics from a stakeholder-centric standpoint and systems thinking. This explains the needed resources through the identification of the social roles of a project and evaluation of the salience of each resource with the attention towards balancing the salience of each role to ensure successful BDA project deployment.

Acknowledgements The authors would like to thank all the participants within the case organization for their contribution – both the formal and informal conversations.

Author contributions Maria Hoffmann Jensen wrote the main manuscript text excluding the literature section on stakeholder theory 2.3. Stakeholder management theory and the initial draft of the introduction. Maja Due Kadenic wrote the initial draft of the introduction, parts of the analysis and prepared the two later figures in the analysis. Both of the authors reviewed the entire manuscript.

Funding Open access funding provided by Aarhus Universitet No funding was obtained for this study.

Data availability Data obtained and processed in this study cannot be shared due to legal and ethical reasons from the case company.

Declarations

Conflict of interest The authors declare no competing interests.

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