Overcoming the AI opacity in ESG reporting: A Digital Platform-based Knowledge Boundary-Spanning Perspective

Dragos Vieru
TELUQ University
dragos.vieru@teluq.ca

Albert Plugge
Nyenrode University
a.plugge@nyenrode.nl

Abstract

Environmental, Social, and Governance (ESG) reporting has become increasingly important for organizations after the introduction of EU directives. The development of ESG platform functionality is impeded by the scattered knowledge across different stakeholders and the absence of crisp regulatory standards. Artificial intelligence-based systems, such as algorithms integrated with ESG training, can transform investment by providing precise and relevant information. Adopting an Action Design Research methodology, we use four effective knowledge boundary-spanning (EKBS) mechanisms to illuminate the practices of a team of three actors (a platform owner, a complementor, and a platform user) co-designing an explainable artificial intelligence (XAI) tool for ESG reporting in the context of a multi-boundary digital platform. Our data analysis suggests that using EKBS mechanisms is essential for ensuring explainability and trust in AI-based tools.

Keywords: ESG, XAI, Digital Platform, Knowledge boundary-spanning mechanisms, Boundary spanner, Boundary object, Boundary practice, Boundary discourse.

1. Introduction

ESG, which stands for environmental, social, and governance factors, is a set of criteria that investors use to evaluate a company's performance and sustainability. The ESG factors can help investors identify how environmental, social, and governance issues can create risks for a business and impact investment decisions (Barker & Eccles, 2019; Liao et al., 2020). ESG factors can include issues relating to climate change, resource scarcity, human rights, labor standards, corporate ethics, executive compensation, board diversity, and more (Aich et al., 2021). When companies evaluate their ESG performance, they typically assess relevant issues, set goals and priorities, evaluate risks and opportunities, design mitigation measures and transition strategies, direct resources, and perform other activities to achieve stable growth. ESG can be viewed as a concept of responsibility towards society and the environment, combined to generate profit to meet stakeholders' expectations (Hughes et al., 2021; Moodaley & Telukdarie, 2023). Various mandates require companies to disclose material environmental and social risks. This helps investors make informed decisions and helps companies become more transparent and accountable for their actions (Barker & Eccles, 2019).

As ESG data grows exponentially, making balanced decisions regarding ESG issues becomes increasingly challenging for investors, companies, and government agencies. Moreover, ESG reporting lacks crisp regulatory standards, which may result in "greenwashing," where companies falsely represent themselves as sustainable (Todaro & Torelli, 2024). This has led to questions regarding the credibility of the information provided. As the field of ESG is emerging, companies lack a benchmark for disclosing ESG information, leading to a wide variety of published data. As a result, greenwashing and few efforts with extensive campaigns pay off, and the less environmentally and socially sustainable company receives the funding (Minkkinen et al., 2022). Integrating AI-based systems such as Machine Learning (ML) algorithms with specific ESG training can revolutionize the investment industry by providing more accurate and relevant information (Chen, 2024). This technology can analyze vast amounts of ESG performance-related information, link financial statements to ESG, and predict future economic performance. It can also use real-time data from online sources, such as news articles, social media posts, or traffic, to identify trends that might impact investment decisions (Moodaley & Telukdarie, 2023).

The potential of AI is vast, and experts predict that its market value will reach $1.8 trillion by 2030 (Statista, 2023). However, the rise of AI has raised concerns about the trustworthiness of its predictions and results and who will be responsible if things go wrong. This is because the efficiency of AI models is based on complex statistical algorithms, which can be challenging to understand (Weber et al., 2023). This is known as the "black-box problem," where a system cannot provide a suitable explanation for its decisions (Lachuer & Jabeur, 2022). Entrusting important decisions to a black-box model creates the need for AI algorithms to be transparent and explainable in their decision-making process; therefore, there is a growing demand for AI systems to be transparent and accountable (Chazette et al., 2019). To meet this demand, industry professionals use the explainable AI (XAI) literature for ideas and solutions (Hassija et al., 2024). However, despite recent efforts to understand how humans interact with AI, XAI research still needs a clearer understanding of real-world user needs for AI transparency (Zhou et al., 2022). Additionally, there needs to be more consideration of what practitioners need to create explainable AI products. Our study, anchored in a particular context – an ESG digital platform - suggests that design support is required to reduce technical and practical barriers to creating transparent algorithmic tools.

It has been suggested that to support ESG reporting, the need arises to design a digital platform (DP) that can collect and analyze ESG data provided by various retrieval systems (Plugge et al., 2024). A DP represents a system that comprises a platform owner that implements technical, business, and social mechanisms to facilitate value creation on a DP between the platform owner, complementors, and DP users (Hein et al., 2020). Complementors represent external actors that join the DP and create complementary products, often called complements, and platform users can use that. For example, IBM or SAP (platform owners) offer add-on features developed by complementors on their platforms that can be applied by end users (DP clients).

Digital platforms facilitate companies to leverage distributed knowledge, collaborate with external sources, and explore new ideas, technologies, and knowledge (Hein et al., 2020; Plugge et al., 2024). However, these platforms also bring new challenges that require new ways of organizing knowledge sharing between actors to fully embrace their potential (Hossain et al., 2017). The concept of knowledge boundary spanning will be placed at the forefront to enhance understanding of knowledge sharing in this context. This paper considers boundary spanning a process involving several events and a combined effect of multiple spanning mechanisms (Hawkins & Rezazade, 2012). The knowledge boundaries between the three actors (DP owner, Complementor, DP user) involved in developing the ESG digital platform are ubiquitous, and effective knowledge sharing is vital to maximizing the platform's effectiveness. It has been shown that knowledge boundaries arise during collaborative efforts to find a solution to a problem (Levina & Vaast, 2005). The outcome, nonetheless, has yet to be discovered in advance; somewhat, it is shaped by the interaction between the actors during a knowledge-sharing process (Carlile, 2004). The work of Hsu et al. (2014) emphasizes that efficient knowledge boundary spanning, as part of an information systems development project, would significantly impact the quality of the system and projects. This leads us to argue that the level of explainability of the algorithmic ESG reporting solution would only have the required quality if it were known how efficiently the knowledge spans the boundaries between the three main platform actors.

In general, spanning mechanisms – boundary object (Nicolini et al., 2012), boundary spanner (Levina and Vaast, 2005) or boundary broker (Waardenburg et al., 2022), boundary discourse (Vaara & Monin, 2010), and boundary practice (Reissner et al., 2021) – have been found to have an impact on the efficiency of crossing knowledge boundaries. Due to the specificity of the dynamics within the collaboration between the platform actors, the implementation of mechanisms for efficient knowledge boundary spanning might differ from how they are identified and applied within a traditional organizational structure. This assumption leads us to our main research question regarding the process of implementation of such mechanisms in the context of an ESG digital platform development project:

> *How do the mechanisms for effective knowledge boundary spanning act as enablers of explainable AI during the design of an ESG reporting digital platform?*

We answered this question by drawing on the literature on ESG and XAI and using the four complementary spanning mechanisms proposed by Hawkins and Rezazade (2012) as a conceptual tool. We conducted an empirical study (single case study) that explains how a platform owner, a complementor, and a platform user as part of a DP all collaborate to design an XAI-based digital platform module that provides ESG features. The results of our analysis suggest that the platform actors used all four spanning mechanisms for efficient boundary spanning. The result of their work, as of April 2024, was an explainable AI tool for ESG reporting for three features in an environmental context (CO_2 emissions, travel emissions, and energy consumption). We aim to address Waardenburg et al.'s (2022) call for more research to analyze the impact of knowledge brokerage work on organizations due to the increasing opaqueness of artificial intelligence-powered technologies. We also echo recent calls to provide a better understanding of digital platform actors' practices during the process of value co-creation (Hein et al., 2020). The rest of this paper is organized as follows. First, we present the theoretical foundations. Next, the research method is introduced, followed by the findings and the discussion sections. Conclusions and future research are provided at the end.

2. Theoretical Background

2.1 ESG and Digital Platforms

The current state of ESG data needs to be clarified as it involves a wide range of subjective interpretations of corporate sustainability (Moodaley & Telukdarie, 2023; Plugge et al., 2024). There is still a need for concrete and verified facts and figures, and the data is often estimated or modeled, making it difficult to rely on (Aich et al., 2021). Moreover, the data is usually manipulated to reflect hindsight rather than adopting a transparent and systematic approach. ESG reporting involves analyzing the non-financial aspects of company performance. To make sustainability information as relevant as financial information, it's important to identify the financially pertinent sustainability issues, or material, to companies' business models (Eccles et al., 2012). However, this process is subjective and dependent on the choice of framework without meaningful access to the underlying raw data, which is the foundation of a company's sustainability performance. With the increasing number of companies reporting sustainability and disclosing their non-financial information, there has been a rise in the amount of non-financial information available (Hughes et al., 2021), often supported by an ESG digital platform (Plugge et al., 2024).

An ESG digital platform is a software solution that streamlines and facilitates an organization's ESG initiatives (Katsamakas et al., 2022). These platforms offer a range of features such as data collection, analysis, and reporting templates that help organizations manage their ESG performance and report it to their stakeholders clearly and concisely. The platforms employ advanced digital technologies, including ML and data analytics, to assist organizations in measuring their performance on various ESG metrics, such as carbon emissions, employee diversity, social impact, and more (Moodaley & Telukdarie, 2023; Chen, 2024). By leveraging these technologies, organizations can efficiently track their performance, identify areas for improvement, and implement strategies to enhance their ESG performance and meet their sustainability goals (Plugge et al., 2024). Additionally, ESG digital platforms often include stakeholder engagement tools to ensure that the organization's stakeholders are kept informed and engaged in the ESG initiatives, contributing to a more transparent and accountable approach to sustainability.

2.2 The Need for Explainable AI (XAI)

Explainable Artificial Intelligence (XAI) represents a set of processes and methods that aim to produce more transparent, understandable, and explainable AI systems without decreasing performance and accuracy (Arrieta et al., 2020; Silva et al., 2023). It addresses digital responsibility and social, ethical, and ecological aspects of information system usage (Sovrano et al., 2022). Many stakeholders, including algorithms experts, regulators, lawyers, philosophers, and futurologists, agree upon XAI's relevance today (Mittelstadt et al., 2019; Waardenburg & Huysman, 2022). It encompasses much more than a few individual technological methods. It is considered a movement and part of the "third-wave AI," the next generation of AI development (Waardenburg et al., 2022).

In terms of AI, understandability describes the ability of an AI model to enable human understanding of the outcomes (Arrieta et al. 2020). Explainability is one way to facilitate understanding (Chazette et al., 2019). It is expressed actively by providing and exchanging reasons and information about the functioning of a system or its behavior (Mittelstadt et al., 2019). Thus, an explanation acts as a bridge between humans and a decision-maker, enabling them to communicate effectively (Guidotti et al., 2018), which is the AI system. In explainable artificial intelligence parlance, the term "black box" is frequently used to refer to models that are opaque or difficult to interpret (Hassija et al., 2024), in contrast to "white box" or transparent models where the internal mechanisms and reasoning behind the predictions are easily accessible and understandable. Transparent models can help users better understand the system's decisions.

There is a growing emphasis on creating explainable AI models, meaning their decision-making process can be easily understood and explained to users (Waardenburg & Huysman, 2022; Silva et al., 2023). Some industries and regions are introducing regulations that mandate that AI systems be explainable to ensure accountability and transparency. Explainability is essential in building trust in AI systems, crucial for widespread adoption and use. It can also facilitate model validation, ensuring that the decisions made by AI models are free from biases and errors. Additionally, explainability can provide insights into how AI models make decisions, making identifying and addressing sources of error or bias easier. Overall, the interaction of explainability with AI highlights the significance of developing transparent, interpretable, and trustworthy AI systems for their responsible and effective deployment in various domains. (Silva et al., 2023). The decision-making process of AI algorithms should involve providing explanations and justifications for the outcomes. People usually prefer reasoning over an incomprehensible description of the inner workings of the algorithms and logic that led to the decision. XAI promises to provide predictions like black-box models while remaining explainable (Hassija et al., 2024). This means that, besides being accurate, these predictions can be trusted and held accountable for their decisions.

As a result, in our case, based on Adadi & Berrada's (2018) survey, we suggest that the explainability in AI-based ESG design and deployment workflows adhere to three principles:

1. *XAI is understandable to humans.* To achieve this, AI developers should adopt human-centered design principles and involve users in the early stages of the development process. This will allow users to participate and help create contextual and meaningful explanations. By empowering users to self-explain the logic involved in an AI algorithm, the XAI model becomes more practical and easier to understand (Chazette et al., 2019).

2. *Explanations are multi-dimensional, extending beyond mere performance*. It's essential to evaluate explanation methods beyond just their performance. This should include factors such as qualitative performance, achievement of the end task, and error analysis. Designers should aim to create an evaluation benchmark to measure both qualitative and quantitative aspects of explanations. Prioritizing goal-oriented explanations can help designers anticipate the impact on the AI algorithm (Miller, 2019).

3. *Amendments are paramount*. XAI is a new concept in technology, and as research progresses, beliefs about it will change. It's important to understand that generating an explanation is not a one-time event. Providing users with modified explanations in dynamic environments will improve explainability. Addressing questions like "How do the modifications impact the algorithm?" and "Why should I consider this explanation instead of the earlier one?" will benefit XAI designers' interactions with users. Solid foundations and necessary amendments will enhance the structure of XAI, leading to a more significant impact (Mittelstadt et al., 2019).

2.3 Knowledge Boundaries

A knowledge boundary between organizational units makes it difficult to create a joint development of knowledge from several distinct units (Carlile, 2004). This situation prevails in a digital platform-based collaborative project, such as creating an ESG reporting tool, where three groups of actors (platform owner, complementor, and platform user) need to work concertedly. In this specific environment, knowledge sharing between the three stakeholders can represent a significant challenge since knowledge has to cross the boundaries between these different entities. It is, therefore, imperative to better understand the basic concepts related to effective knowledge boundary spanning (EKBS). Adapting Hsu et al.'s (2014) definition of EKBS to the context of an ESG digital platform project, EKBS can be defined as the interactions between platform owner, complementor, and user aimed at achieving "effective syntactic knowledge transfer, semantic knowledge translation, and pragmatic knowledge transformation" (Hsu et al., 2014: p. 286). We adopt the perspective that sees knowledge as localized, embedded, and invested in practice (Orlikowski, 2002; Levina & Vaast, 2005). Given the tacit and sticky nature of knowledge (Carlile, 2004), the problems related to knowledge boundaries can be illustrated as "the knowledge delivery problems in which the tacit and sticky nature of localized knowledge may hinder problem-solving and knowledge creation across functions. In practice, this specialization of knowledge increases the difficulty of collaborating across functional boundaries and accommodating knowledge developed in other practices" (Hsu et al. 2014, p. 283). Thus, knowledge boundaries are not static; they adjust to environmental learning structures and individuals' social and material interactions (Hawkins & Rezazade, 2012).

2.4 Effective Knowledge Boundary-Spanning (EKBS) Mechanisms on Digital Platforms

To further understand knowledge sharing in the context of an ESG digital platform, it is appropriate to place the boundary-spanning concept at the forefront. In such a context, effective knowledge sharing becomes essential to maximizing the mutual performance of all three main actors (Hsu et al., 2014). To effectively manage knowledge across boundaries, Hawkins and Rezazade (2012) propose a spanning process characterized by multiple actors and the adoption of four complementary spanning mechanisms: 1) *boundary spanners*, i.e., "human agents who translate and frame information from one community to another to promote coordination (p. 1803)"; 2) *boundary objects*, i.e., "physical, abstract, or mental object that serves as a focal point in collaboration enabling parties to represent, transform and share knowledge (p. 1805)"; 3) *boundary practices*, i.e., "a boundary spanning mechanism that overcomes a knowledge boundary by engaging agents from different knowledge communities in collective activities (p. 1806)", and; 4) *boundary discourse*, i.e., "the content of knowledge that shapes the dialogue among the experts from distinct domains" (p. 1807). Thus, as knowledge boundaries arise during collaborative work, the results of such work are shaped by the interactions of individuals. The four spanning mechanisms could be integrated to analyze and clarify how knowledge crosses boundaries among the three digital platform stakeholders.

As proposed by these authors, knowledge crossing between boundaries is a process that involves and integrates complementary EKBS mechanisms: spanners, objects, practices, and discourse. Because the nature and structure of digital platforms differ from those of other organizational arrangements, how EKBS mechanisms are deployed collaboratively between the main actors of a digital platform will vary from how they are deployed elsewhere. EKBS mechanisms include first *boundary spanners*. These individuals translate and reformulate information passing from one group to another to facilitate coordination and problem-solving (Levina & Vaast, 2005). They are sometimes called 'knowledge brokers' (Neal et al., 2022). In a recent ethnographic study, Waardenburg et al. (2022) analyze how knowledge brokers labeled as 'algorithmic brokers' attempt to translate opaque algorithmic predictions. They analyzed a group of Dutch intelligence officers responsible for mediating between a machine-learning community and a user community by interpreting the results of the learning algorithm for police management. In our case, during the development of the AI-powered ESG reporting tool, AI engineers might sometimes find it difficult to express themselves in simple, understandable language during exchanges with others. Boundary spanners/knowledge brokers could better translate ESG-related knowledge passing to and from the project stakeholders. Alternatively, boundary spanners could facilitate ESG-specific communication between the complementor, the user, and the DP owner. In this way, they may increase stakeholders' trust in the results provided by the ESG reporting tool.

The second mechanism is *boundary objects*, which are everyday objects shared by different groups that allow them to represent, transform, and share knowledge (Levina & Vaast, 2005; Caccamo et al., 2023). These boundary objects could be particularly relevant in the context of the development of the AI-powered ESG reporting module. As mentioned before, AI opacity is a significant issue related to the credibility of ESG reporting. Thus, boundary objects could allow stakeholders to understand the algorithmic process outcomes better. For example, since ESG is a broad field comprising various themes, no existing blueprints may guide how to calculate ESG metrics. Using a boundary object, such as a dictionary or a glossary, would facilitate the description of these metrics as various governmental bodies sanction them. This boundary object would enable the digital platform actors to communicate their needs and constraints regarding services rendered via a familiar object common to all.

Boundary practices, the third mechanism, allow for the creation of new knowledge through the collective commitment of parties to the practice of shared activities (Hsu et al., 2014). Boundary practices are novel activities providing a context where individuals can learn, understand, internalize, and co-create tacit and situated knowledge (Reissner et al., 2021). Faced with practical problems, the ESG team members modify their knowledge collectively. However, this EKBS mechanism might be more complex and challenging to introduce in an AI-powered ESG digital platform. Indeed, the main objective of an ESG reporting tool is to create a set of disclosure standards that companies complete to communicate sustainability initiatives; by ensuring a collaborative environment, a digital platform could integrate boundary practices to share knowledge.

Boundary discourses, the fourth mechanism, refer to the content of knowledge that characterizes exchanges between experts from the three organizational actors. This relates to how language allows knowledge to cross borders (Vaara & Monin, 2010). Discourses represent persistent systems of thought (including ideas, attitudes, beliefs, and practices) that enable and constrain what can be thought, said, and done (Foucault, 1979). Thus, boundary discourse is a mechanism that can be challenging in a collaborative effort on a digital platform. Centralizing ESG expertise under one roof may encourage AI engineers on one side and ESG specialists and the client on the other side to develop specialized jargon that they can use to communicate among themselves.

While such a context characterized by the existence of different groups of actors might render the interactions among the project stakeholders more difficult and complicated (Waardenburg et al., 2022), it seems that the AI engineers would benefit from taking stock of the boundary discourses of the other actors to develop an AI solution that makes sense to everyone. Thus, AI engineers should express themselves using more accessible terms for the ESG specialists and the client to understand.

3. Methodology

3.1. Action Design Research

Action Design Research (ADR) is a research methodology combining action research and design research elements. The approach was proposed to address the gap between the design of IT artifacts and their shaping by the organizational context (Sein et al., 2011). ADR acknowledges that the artifact emerges from interaction with the organizational context, even when the researchers' intent guides its initial design. ADR conceptualizes the research process as a set of interrelated activities, which includes building the IT artifact, intervening in the organization, and evaluating the artifact concurrently. It reflects the premise that IT artifacts are ensembles shaped by the organizational context during development and use (Sein et al., 2011). The method comprises several stages and principles encapsulating its underlying beliefs and values. These stages include problem formulation, building, intervention, evaluation, reflection and learning, and formalization of learning. ADR is beneficial in fields like information systems, where the aim is to ensure the reliability of designed artifacts through adherence to a set of principles (Collatto et al., 2018). It is a cooperative and participatory approach that involves researchers and participants of a research situation in identifying problems, developing solutions, and implementing changes. Our ADR case uses primary data and a real-life cyclic design process. One of the authors acted as an action researcher and observed and tracked design challenges bi-weekly.

3.2. Case Description

We used two main criteria to select a case in which the three actors are represented (DP owner, Complementor, and DP user). First, we focus on the character of an ESG digital platform that requires knowledge of the digital technology involved, ESG features, and ESG regulations and directives. Each aspect affects the knowledge boundary-spanning mechanisms as described. Second, the role of each actor may differ in an ESG digital platform context. Some actors may only know about the digital technology (the platform) involved, while others may know both the platform and ESG regulations. Hence, the knowledge of each actor influences how knowledge is developed and who is able and willing to share knowledge, ultimately affecting the boundary-spanning mechanisms. We selected a case study in which a DP owner, complementor, and DP user collaborated to design, implement, and maintain an ESG digital platform (selection criterion one). The DP owner is a well-established global IT supplier renowned for their digital capabilities and services of digital platforms. The complementor is a European advisory and technology firm that knows both digital platforms and has deep insights into ESG aspects, such as deforestation and biodiversity. The DP user (situated in Europe) deeply understands local laws and regulations and has been experienced in providing non-financial outcomes for the last decade. All three actors are experienced in collaboration with multiple actors regarding other fields of expertise. The roles of the three actors differ as the DP owner only knows its digital platform (design and maintenance). The complementor, however, knows the owner's digital platform and ESG features. The DT client has specific knowledge of domestic regulations and can express their need concerning ESG features requirements (selection criterion two). In our case, we focus on the knowledge boundary-spanning perspective applied in designing an explainable AI tool for ESG reporting.

When applying the ADR methodology, all actors contributed to developing and sharing knowledge when designing and building the ESG digital platform. In 2021, the three actors identified and discussed a set of ESG requirements as the starting point for the design of the digital platform. An ADR team was established in 2022 based on the requirement outcomes. An initial set of Critical Design Issues (CDIs) was discussed in 2022 by the DP owner, complementor, and DP user on the subject matter expert level. In 2023, the ADR team decided to use design artifacts (i.e., architecture blueprint, user stories) to elaborate on the three features that will be developed in 2024 and 2025. The action researcher organized workshops and meetings to evaluate if the developed ESG digital platform features would match the identified requirements.

4. Findings

During the design of the ESG digital platform, the actors became aware that the degree of complexity was higher than expected. Task inputs could have been more transparent, as retrieved data sets were incomplete, unreliable, and incomparable. To overcome this challenge, the actors first created a data taxonomy and model to harmonize the data and ensure consistency and reliability. All actors provided input to establish these tasks and described the structure, methodology, and model. Next, all actors decided to use transparency as a design principle to develop and implement ESG techniques. The ESG task processes (i.e., automated workflows and machine learning) were agreed on and described step by step to create insights to explain how the platform works. By applying EKBS mechanisms, the actors prevented the learning algorithms in the digital platform from becoming opaque.

Addressing the *boundary spanners* mechanism, each actor appointed a lead responsible for coordinating internal tasks and aligning with the other actor leads. The DP owner assigned a platform architect as a boundary spanner who coordinated design activities internally (e.g., architecture guidelines and blueprints, application programming interfaces, interoperability). The complementor assigned an ESG lead architect who coordinated their employees' activities in the United Kingdom (functional leads) and India (technical developers). The DP user selected his head of sustainability as a boundary spanner, responsible for coordinating internal activities that included supply chain management, commerce, facility management department, and legal counsel. During one of the first design meetings, the complementor ESG lead architect suggested that "*the leads of the platform owner, complementor and platform user should be responsible for aligning all internal activities to avoid misunderstandings about design, build and implement tasks. In doing so, we are more effective in our operations and decrease lead times*." Using this approach, the ADR team prevented the boundary spanners from erecting new knowledge boundaries between them and the platform actors they intend to connect (Waardenburg et al., 2022).

Regarding the mechanism *boundary objects*, we found four relevant objects used to create an XAI, including the design of 1) an ESG reporting lifecycle roadmap, 2) digital platform architecture, 3) calculation models, and 4) a digital reporting dashboard. Considering the explorative approach to designing, building, implementing, and maintaining these features, the actors first created an ESG reporting lifecycle roadmap (*first boundary object*). The lifecycle roadmap comprises seven steps. First, the actors had to complete a "materiality assessment" to determine the impact of the environment on the platform user's company products and services, such as energy consumption. The deliverable of this process is a "materiality matrix." Second, based on the identified materiality priorities, the actors' established goals and targets for short and long-term initiatives. Third, metrics were defined to establish a baseline and measure progress made by selected priorities. Fourth, ESG policies and controls were set up and commonly implemented. These policies are aligned with controls to determine the degree of policy compliance and govern exception handling. Fifth, the actors identified and assessed risks to support platform user ESG managers to avoid potential risks that could delay or prevent completing company ESG objectives. Sixth, metrics were collected from a broad, diverse set of data owners across the company to track progress on ESG objectives and to compile for external reporting. Finally, to disclose ESG outcomes to investors and regulators, ESG metrics need to be reported by regulatory requirements.

The *second boundary object* was realized by designing a digital platform architecture. The architecture design is executed by the platform owner and the complementor and is based on key topics as part of the ESG reporting lifecycle roadmap. The design illustrates more in-depth building blocks of the lifecycle roadmap. For example, the materiality matrix is broken down into goals that, in turn, exist as targets and entities. The goals are directly related to metrics, which rely on metrics data. One of the ADR team designers mentioned: *"We need to dive into the metric details to understand the complexity of measurements that requires insights from the platform user on domestic regulations, complementor knowledge on measurement models, and the platform owner's knowledge of how to design automated workflows that guide the data. That's why we need representatives from all parties involved."* In addition, the building block entities, which are part of the materiality assessment, are also related to metrics data. By sketching out the relationships between the various lifecycle elements, the ADR team was able to identify what type of data is required to support different ESG features.

The three actors designed calculation models (*third boundary object*) to support the identified ESG features. The design of calculation models is essential as their results will be presented at the end and are associated with the ESG performance of the platform user. The ADR team had to redesign the calculation models regularly as they found that emission calculations were inaccurate as the baseline was grounded on many estimates. Similarly, formulas were developed to measure all emissions that apply to the platform user. As a next step, the created insights on the platform features must be represented automatically to limit the degree of manual labor. The three actors first designed a mood board translated into a digital dashboard (*fourth boundary object*), demonstrating the ESG features' outcomes. The dashboard provides a high-level overview of the E, future S, and G categories and a summary of the goals and targets. An overview of agreed disclosures and pending closures is provided. In addition, the materiality matrix illustrates material topics based on the degree of importance and impact on the platform user's company.

When considering *boundary practices,* the DP actors agreed to apply a four-D-step process (e.g., *d*iscover, *d*efine, *d*evelop, and *d*eliver) that provided opportunities to include feedback loops and redo activities when needed. Due to the explorative character of the prototype, the actors decided to use an agile way of working by organizing sprints that consist of two weeks. We found that each boundary object was divided into 'epics' (in Agile project management, an 'epic' is a large chunk of work segmented into smaller tasks) that were subsequently translated into user stories. To coordinate activities, the actors established a core team that aligned their activities during weekly stand-ups. Moreover, content-related activities were discussed every week and organized around the 'epics.' Significantly, various knowledge disciplines of all actors contributed to the content-related meetings to explore opportunities, feature functionalities, and risks. The complementor's ESG lead architect argued that *"we must develop new knowledge during content meetings as ESG standards are multi-interpretive. Therefore, we need to include employees with technical, functional, and legal knowledge to understand the consequences of our work. Let's ramp up our content team, establish multi-disciplinary design, and implement a team rapidly."* To better understand the digital platform outcomes, intermediate demos were provided to evaluate if functional and technical requirements were met.

Addressing the importance of *boundary discourse* as the fourth spanning mechanism, we found that the subject matter expertise from the complementor in ESG features is still being determined. During the design stage, various ESG 'Subject Matter Experts' were assigned to other client engagements that hindered the lead times to complete boundary objects. One of the complementor's managers argued that *"our resources are geographically dispersed across the United Kingdom, United States, and India. As client* *engagements are often unpredictable from a resource perspective, we must continuously cater to client changes to fill the gaps. Hence, we struggle to allocate the necessary ESG capabilities for this engagement."*

The action researcher suggested realigning complementor's SMEs across other engagements to continue the tasks to complete the boundary objects.

5. Discussion

In recent years, ESG issues have gained significant public and research attention. Climate change, social insecurity, and economic uncertainty have emerged as challenging problems. AI algorithms have emerged as promising tools to address ESG challenges (Todaro & Torelli, 2024). However, many AI-powered tools are complex and lack explanations of their decision-making processes, labeling them "black-box" models. One major obstacle to adopting such models is the difficulty in interpreting them, making it harder to explain their learning and decision-making processes. This requires transparency and easy predictability.

The results of this study suggest that the technical design and implementation of an explainable AI-powered ESG platform functionality were facilitated by knowledge boundary-spanning mechanisms enabling knowledge flow beyond the DP owner. Ultimately, the three platform actors (the owner, the complementor, and the user) could answer questions such as 'Why did the model produce this prediction, and what are the logic and reasoning behind the model's decisions?'

The EKBS mechanisms were developed in a challenging socio-technical environment. Since the design of ESG digital platform development is complex, we argue that the four EKBS mechanisms were required to collect and exchange knowledge between a platform owner, complementor, and platform user. In other words, developing boundary-spanning mechanisms in an uncertain context can only be achieved when all DP partners collaborate intensively.

Our study offers new insights into the literature on knowledge boundary-spanners (e.g., Pawlowski & Robey, 2004; Vieru & Rivard, 2018). Boundary spanners' practices show that, over time, they can acquire a unique position that allows them to become increasingly influential. Additionally, the study of an ESG reporting DP design highlights that knowledge boundary spanning (EKBS) mechanisms are more complex than just addressing a knowledge boundary between traditional professional communities (e.g., Carlile, 2004; Boari & Riboldazzi, 2014). This is because, in their efforts to resolve such boundaries, spanners may inadvertently create new boundaries between themselves and the stakeholders they are meant to connect (Waardenburg et al., 2022). To address this potential problem, three boundary spanners were assigned to represent the three different DP actors. This approach allowed stakeholders to effectively translate the algorithmic predictions based on more profound insights into the three different actor communities, given the ESG reporting's multidisciplinary nature.

Our research highlights that boundary spanners use different boundary practices over time. The four-D-step process with feedback loops provides new insights into knowledge boundary-spanning literature. These boundary practices lead to successful efforts to decontextualize the ESG algorithmic predictions from the AI specialists (DP owner) and contextualize them to the complementor (ESG specialist) and user groups. This averted what Waardenburg et al. (2022) call "an impassable knowledge boundary." Previous research indicates that boundary-spanning knowledge practices emerge when semantic boundaries hinder knowledge exchange between different communities (e.g., Boari & Riboldazzi, 2014). These studies suggest that boundary spanners play a crucial role in breaking down these barriers by implementing specific boundary practices. Our contribution to the boundary-spanning knowledge literature presents a dynamic perspective on how boundary-spanners implement these practices, particularly in the context of opaque AI predictions within ESG reporting DP design.

Our work indicates the emergence of practice fields involving actors from different communities. Traditionally, organization literature associates practices with specific professional communities (Orlikowski, 2002). Together, these practices form a field that enables community members to act effectively in a particular context and establish boundaries (Vieru & Rivard, 2018). Our study suggests that new practice fields can arise when actors from different communities act as boundary spanners, translating knowledge across communities (Levina & Vaast, 2005). We emphasize that in the context of our study, the three main DP actors were tightly interconnected in boundary practices. Understanding knowledge boundaries in the context of digital platforms requires scholars to view a practice field as a collection of practices performed by actors from diverse professional communities.

Finally, this study confirms the applicability of the three principles for ensuring explainability in AI-based tools derived from Adadi & Berrada's (2018) survey. Thus, our data analysis suggests that by assigning *boundary spanners* and creating and using *boundary objects* during the technology design and implementation, the ADR team was able to ensure the AI's ESG decision-making process is transparent and understandable to future users. This involved a multi-disciplinary design with interactive features allowing future users to query the AI and receive explanations in business and legal language. The ADR team's *boundary practices* involving the four D-steps process facilitated a multidimensional analysis of the data that went beyond financial data to include qualitative assessments, such as the impact of ESG initiatives on stakeholders or the environment. As a result, this approach enabled a more complete picture of the ESG performance of a platform user. By using the fourth mechanism (*boundary discourse*), the ADR team brought to light a critical issue related to the third XAI principle (amendments are paramount): the AI-based tool must have the capability for continuous learning and updates to the AI model, allowing for real-time amendments based on new data (client changes) or government regulations. This functionality would ensure the AI tool remains accurate and relevant.

Using the four EKBS mechanisms, the three main DP actors were able to build an AI tool that would generate reliable ESG reports and build trust with users through clarity and adaptability.

6. Conclusion and future research

Based on our study of applying the knowledge boundary-spanning perspective within the context of designing an XAI tool for ESG reporting, this paper contributes to the breadth of the scientific literature on ESG, digital platforms, and boundary-spanning knowledge. It has helped deepen our understanding of how DP actors develop and share knowledge by collaboratively exchanging information across initial knowledge boundaries. The study shows how the four EKBS mechanisms positively affect the transparency of the XAI solution by defining and developing boundary objects jointly.

A second contribution is made to the field of XAI. Using the theoretical lens of EKBS mechanisms in a specific context, we addressed Waardenburg et al.'s (2022) call for more research to analyze the impact of knowledge brokerage work on organizations due to the increasing opaqueness of AI-powered technologies.

Concerning practitioners, this study answers Hein et al.'s (2020) call for a better understanding of digital platform actors' practices during value co-creation. Our analysis suggests that it is essential that the complementors efficiently collaborate with the other DP actors, as the required design knowledge is fragmented across various platform actors. We recommend that DP actors' upper management facilitate and encourage their employees' collaborative behavior when sharing knowledge with other DP actors. For instance, employee incentives can be implemented to stimulate knowledge exchange positively. The results of this study will guide managers in evaluating efficient knowledge boundary-spanning mechanisms. Their assessment will allow them to optimize these mechanisms among the platform actors engaging in co-creation initiatives (Cozzolino et al., 2021).

Our study of an AI-powered ESG reporting tool design in a digital platform context underscores the importance of recognizing boundary spanners as more than just problem-solvers of knowledge boundaries in future research. They also significantly impact the process of solving AI opacity. Also, to identify knowledge boundaries within digital platforms, scholars need to perceive a practice field as a compilation of practices carried out by platform actors from a wide range of professional communities. Future research should take into consideration these aspects.

7. References

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