Sustainability through Normalization: How Sustainability is Enabled and Constrained by Data in Sustainability Initiatives

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Abstract— Recent discussions portray AI as a way of addressing the grand challenge of sustainability, as organizations across the globe are looking for ways to redesign their business based on sustainability principles. However, despite AI's potential for addressing sustainability challenges, recent research demonstrates the negative consequences that AI may impose on sustainability. Accordingly, the ways in which AI enables and constrains sustainability initiatives remain uncharted. To address this, this paper draws from a case study in the Swedish forestry sector to present research on algorithmic brokering of data work to organizational practice in a way that resonates with sustainability ideals. We first investigate how data are produced and managed to enhance forestry practices through ML. Second, we imply the principles of normalization theory to explore how sustainability initiatives enables and is enabled by algorithmic brokering.

Keywords—data, sustainability, normalization process theory, algorithmic brokering

I. Introduction

In today's algorithmic era, human-computer symbiosis has supported the cooperative partnership between humans and machines such as artificial intelligence (AI) and has the potential to address some of the most challenging issues facing society (Jain et al., 2021). But while IS researchers have discussed the many opportunities associated with AI (e.g., Berente et al. 2021; Gregory and Muntermann 2014; Holmström, 2022; Rai et al. 2019), there is still a lack of integrated discussion on how sustainability is enabled and constrained by ML (see Nishant et al., 2020; Galaz et al., 2021; Crawford, 2021 for exceptions).

Sustainability has become an increasingly visible construct of investigation in the social sciences over the last few decades (Melville, 2010; Malhotra et al., 2013). Recently, it has been argued that AI can be leveraged to address the grand challenge of sustainability (see e.g., Van Wynsberghe, 2021; Schwart et al., 2020). However, to leverage the promise that AI may hold in relation to sustainability, we need to do a better job in conceptualizing the challenges associated with the task. The sustainability challenges include design of AI systems, the deployment and interpretation of AI system results, the way that organizations use, manage and governing data in a sustainable manner, and the design of ML algorithms, deployment AI to reinforce positive behavioral responses to follow sustainability goals, and the interpretation of the AI-systems results (Galaz, et al., 2021; Nishant et al., 2020; Jarvenpaa and Essén, 2023). Regarding the latter, Galaz et al., (2021) elaborate on how developers of AI systems in the context of digital agriculture were unable to translate complex geospatial data to concrete sustainability actions. As such, while organizations across the globe are looking for ways to redesign organizations based on sustainability principles alongside new AI systems (Enholm et al., 2022; Galaz et al., 2021), the use of new AI in organizational settings paradoxically often involve negative consequences for sustainability (see Crawford, 2021; Strubell, 2019; Van Wynsberghe, 2021). Despite the significant operationalization of the concept of sustainability in relation to AI, a problem is that the concept of sustainable AI has been used regularly but also inconsistently (Van Wynsberghe, 2021).

This paper presents research on algorithmic brokering (Alaimo and Kallinikos, 2021; Alaimo and Kallinikos, 2022) in a way that resonates with sustainability ideals. Algorithmic brokering in this context refers to how AI systems rarely can be adapted as is, but need to be interpreted, filtered, and translated to fit specific contexts (Waardenburg et al., 2021). Accordingly, the role of algorithmic brokers implies the knowledge transfer, translation, and interpretation of logic and value of the AI systems to different groups in the organization (Kellogg, 2020; Waardenburg et al., 2020; Waardenburg et al., 2021). This research is based on longitudinal single case study interpretive case study (Walsham, 1995) of the use of data and evolution of data work practices in the forestry sector. Specifically, we study how practitioners with different roles tasked with brokering between data work practices and algorithmics. We first investigate how data are produced and managed to enhancing forestry practices through AI. Research has studied the way that professionals often bridge information (Currie and White, 2012) and technology gaps (Hargadon and Sutton, 1997) to ensure dissemination of relevant information in a work context (see Hargadon and Sutton, 1997). Therefore, in this study we build on the abovementioned research to explore the dynamics of algorithmic brokering. Specifically, we have formulated the following research questions: *What roles do domain experts play in brokering and managing data* *in sustainability initiatives drawing on ML? How is sustainability enabled and/or constrained in such processes?*

To answer these questions, we draw on normalization process theory (NPT) (May and Finch, 2009) to zoom in and provide insight into how and why the algorithmic brokering practice occurs. Specifically, we leverage NPT to conceptualize how employees in forestry engage in algorithmic brokering. Hence, this research contributes to a growing stream of literature focusing on the organizational and societal impacts of data and AI (see Zuboff, 2019; Crawford, 2021). By doing so, this study offers an understanding of the effects of algorithmic brokering and how data can be managed for fostering sustainability initiatives in organizations. This work also contributes to the public policy debate on the regulations of data and AI. Given the complexities associated with new AI, policy makers often need to reexamine and balance regulations, considering the benefits from AI while also monitoring the ways in which sustainability initiatives may be enabled and/or constrained. Lastly, we contribute to the emerging literature of algorithmic brokers (see Kellogg et al., 2020; Waardenburg et al., 2021) by elaborating on the nature of this new organizational role along with the practices and strategies that enable or constrain sustainability initiatives.

II. Research Site: "The grand challenge" of sustainability in the ERA of AI and data

Sustainability has been considering a grand challenge for academia and practitioners (Becker et al., 2015). Pursuing research on the topic, the investigative context for the paper is a forestry organization in Sweden. The forestry sector is an important source of the Swedish economy, also playing an important role on the global forestry. Thus, it is important to ensure continuation of its international competitiveness, sustainability, and productivity (Scholz et al., 2018). Paradoxically, however, the role of Sustainable AI along and the data work practices within forestry remains uncharted.

Holmen Forest (henceforth Holmen) is a part of Holmen Group, and one of the biggest forest companies in Sweden. Covering 1.3 million hectares from the north to south part of Sweden, Holmen's produces wood for the Swedish sawmills, paper, and paperboard mills. In addition, the company purchases and sells wood from Swedish private landowners (approximately 5.000 private landowners each year), forest owner associations, and sawmills. In this setting, we explore the role of data work in the organization's operations (c.f. Waardenburg et al., 2020). Over the last decades, the transformation of the forestry industry has accelerated due to the use of AI technologies. Specifically, precision forestry has led to a transformation for forest managers, enabling new opportunities for tighter control of operations with improved data collection and optimization of the decision-making processes (Choudhry and O´Kelly, 2022; Lui et al., 2021). Following this transformation, and with the aim to address the challenge of sustainability and the opportunities of AI, Holmen started exploring how data and AI can be used and managed for optimizing productivity but also contributing to sustainable goals. For instance, the company is using satellite data, introduced a ML algorithm for enacting predictive analysis identifying potential tree damages in the forest. In this work, we zoom in the practices of algorithmic brokering to also investigate the roles of the practitioners in the managing of data work.

Specifically, we explore how a ML algorithm is used for assessing biodiversity and evaluating the conservation value and biological diversity of forest strands based on their eligibility and suitability to remain as "high conservation value" or "return to the production phase" (Natural Value Assessment Responsible and Silviculture Manager). The objective with the ML algorithm is to optimize the effectivity and time of the forest practices while also ensuring and focusing on the sustainability goals.

III. Theoretical Framework

Normalization allows us to focus "*the work that actors do as they engage with some ensemble of activities, and by which means it becomes routinely embedded in the matrices of already existing, socially patterned, knowledge and practices*" (May & Finch, 2009, p. 540). Therefore, normalization theory provides a novel theoretical lens to uncover what roles play in brokering and managing the algorithms in forestry practice. In doing so, it guides us to examine how sustainability is enabled and/or constrained sustainability. Specifically, normalization process theory (NPT) presents a derivative sociological theory on the implementation, embedding and integration of new technologies and innovations (May & Finch, 2009) which include ML algorithms in practice. NPT has provided significant contributions around in other research contexts (McEvoy et al. 2014; Nordmark et al. 2016; May et al. 2018; Carroll et al., 2023) which makes this a suitable theory to investigate ML algorithms in forestry.

NPT identifies factors that promote and inhibit the routine incorporation of complex interventions into everyday practice (May et al., 2009; Murray et al., 2010) making it applicable to examine how new technology-driven work practices can be managed such as ML algorithms in forestry. Through the NPT perspective, we set out to explain how data are managed, focusing not only the implementation of ML algorithms in forestry but beyond this to the point where change becomes so embedded into routine practice that it 'disappears' (i.e., it is normalized) and part of the sustainability fabric of our forestry practices. Specifically, NPT considers the social organization of the work (e.g., forestry practice), of making practices routine elements of everyday life (e.g., wood production and delivery), and of sustaining embedded practices in their social context (e.g., integration of ML algorithms in forestry to guide and enable decision-making) (May, 2006). NPT allows us to examine assumptions around what roles forestry professionals play in brokering and managing the algorithms in practice. Lastly, NPT has clear applicability to ML algorithms in forestry sector to examine the normalization of sustainability initiatives because of forestry practitioners' broker and manage ML algorithms through the following theoretical constructs (Figure 1):

1. **Coherence**: refers to the process of sensemaking that individuals and organizations undergo to promote or inhibit the routine embedding of a practice.
2. **Cognitive Participation**: examines how stakeholders engage in the newly adopted practice.
3. **Collective Action**: focuses on the work that individuals and teams have to do to change practice by enacting the new practice.
4. **Reflexive Monitoring**: describes the value realization inherent in the informal and formal appraisal of a new technology-driven work practices and the reported process improvements. This can also provide new insights into the impact of a new practice on forging new organizing structures, social norms, group processes, and conventions due to new technology-driven work practices.

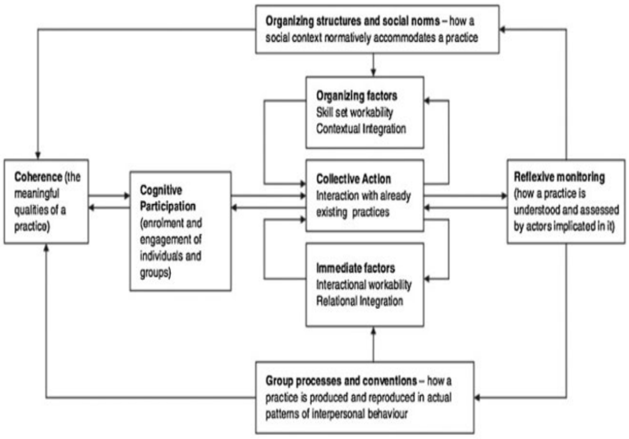

Figure 1. Model of Normalization Process Theory (May & Finch, 2009)

IV. RESEARCH METHODOLOGY

A. *Overview of data collection*

Grounded in our study of a forestry organization in Sweden, we explored how employees pursue brokering between data work practices and ML. We employed a longitudinal single- site design starting from April 2021 to June 2023(Gerring, 2007). In this work, the grounded theory is used as an approach for data collection and analysis (Glaser and Strauss, 1967).

The data collection revealed employees´ practices, intentions and experiences while working with data. We interviewed employees holding different positions in all the three regions of Holmen, from data scientists to CEO and marketing assistants. During the first wave of data collection process that took place from April 2021 to September 2022, we immersed into the case study and engaged in the intensive in-depth semi-structure interviews (Charmaz, 2006). In this primary exploratory phase, 13 interviews were conducted to unveil the company´s forestry and business practices and the transforming role of digital technologies. However, during the data collection period, we were struck by the frequent references on data as a building block for improving prediction and sustainability objectives (insights from Innovation Leader and Nature Value Assessment Responsible). As such, we engaged in a second wave of interviews that led to 45 interviews, this time focusing on data work practices, their emergence, and their importance on framing the sustainability objectives of the company (Urquhart, 2013).

We expand our interview guide, accordingly, to capture the new emerging nuances (Charmaz, 2006), following the premises of *theoretical sampling*. Therefore, we ensured that data collection and analysis occur in an inseparable way (Birks et al., 2013) to also gain the analytical grounds on what data and insights needs to be investigated after (Urquhart 2013). The interviews, in this phase, last from 45 min to almost 60 minutes and were audio recorded and transcribed. Following Glaser (1978) suggestion about the importance of versatile and rich data and that "everything is data" different "slices *of data*" are included. The transcribed interview material results in around 600 pages of qualitative data that was coded and analyzed after in over 550 pages of qualitative data that was coded and analyzed as soon as possible and almost after each interview.

Furthermore, beyond the interview, the data collection of primary data includes a 98-hour observation of formal and informal meetings that led to around 220 pages of field notes (Table 1), The "shadowing technique" was used during the observation sessions as a venue to understand how data work practices and the accounts of practices are produced (Czarniawska, 2007). The interviews and observation sessions are still in progress.

Data Sources	Descriptive explanation and rationale
Primary data: • First wave of interviews (April 2021-October 2022) *(n=13 semi-structured interviews)* Duration: From 40 min to 60 min	• During the first wave, we explore and gather insights on the company´s operations, business and forestry practices, and digital technologies used to support their objectives and values.
• Second wave of interviews (November 2022- June 2023) *(n= 35 semi-structured interviews)* Duration: From 45 min to 60 min	• During the second wave of interviews, we emphasized understanding data practices, and the role and impact of ML algorithms on shaping sustainability objectives.
Additional Primary data: Fieldwork notes. Notes were taken during field visits (98 hours) at Holmen in the north and central regions including "shadowing observation" during formal meetings about topics such as emerging timber delivery issues and informal conversations during lunch and coffee breaks with different employees. We did also participate to converastions and events that focuced on sustainability.	• Delving into the research context, allowed us to understand the work of actors as the engage with the activities, and how a sustainability initiative is becoming routinely embedded in data and ML practices.
Secondary data: Archival data We reviewed and analyzed publicly available material: annual reports (from 1999-2022) to gain a comprehensive picture of company´s diverse operations, and sustainability objectives and values; company´s blog where monthly an employee shares for a week details about work practices and systems used; other documentary and interal materials such as Power Point presentations (e.g., a 5 years plan for improving forest data for forest planners). Lastly, we analyzed around 45 articles focusing on data forest-related practices (Gabrys, 2020), and digital technologies (Noordermeer et al., 2021; Guimarães et al.,2020) widely used within the forestry sector.	• Archival data and reports provided valuable insights, and contibute to data triangulation and cross-validation of sustainability initiatives and values.

Table 1: Visual representation of the data sources and analysis

Lastly, for comprehending the importance and the role of data and AI on the forestry, we analyzed around 45 articles (e.g., Zoo et al., 2019; Gabrys, 2020), annual reports and additional material. The variety of material allowed us to triangulate the data derived from interviews and additional material.

B. Data Analysis

Our coding process starts with open coding, selective coding to theoretical coding (Glaser, 1978). Staring from *open coding*, we engaged in coding data in every possible way (Ibid). We generated multiple categories that reveal aspects of data work and ML. Then, during the *selective coding* process, we focus on subsequent analysis and the open codes were sorted into selective codes. Throughout, the coding process, we follow the key principles of grounded theory methodology. Therefore, we approach the emerging data and the literature in iterative fashion by constantly comparing and coding data and reviewing the literature (Glaser and Strauss, 1967; Birks et al., 2013). Lastly, during the theoretical coding, we conceptualize "how the sustentive codes relate to each other" (Urquhart, 2013, p.107), being cautions of not force-fitting theoretical codes to the data just because they seem adequate (Glaser, 2005). Therefore, we are engaged in a practice of having a "repertoire" of multiple theoretical codes that will eventually inspire us to theorize. Some of the existing categories seem to be suitable for our theoretical coding at this point of analysis (Urquhart, 2013),

V. EMPIRICAL FINDINGS

In this section, we briefly elaborate the empirical results of our research. Our data demonstrate four dominant data work practices constitute the practice of algorithmic brokering. We extrapolate that algorithmic practices can enable and constrain sustainability initiatives and objectives in our investigative context.

Data sourcing as a practice of enacting coherence

The first data work practice revealed in our findings is *data sourcing*. Data sourcing explains the situated making of data engendered by the participants working in the forest in their attempt to achieve sustainability and business objectives through ML. The sense-making process involves data understanding and sustainability awareness. As such, the practices are also encompassing the subsequent interaction between the participants and the data infrastructure. During these activities, the participants engaged in activities of data provenance and foster data creation.

The sourcing process encompasses data derived for multiples sources (such as satellite, geospatial and laser-scanning data) in order to enrich and design forest maps that outline the forest areas satellite data, production/ harvester data, laser-scanning and geospatial data. The data provide, for instance, insights into *"how moist is the ground, the elevation of the ground, the location that is suitable for leaf grow"* (Production manager). In the practice of creating data, practitioners (such as forest planners, wood buyers and natural value assessment specialists) are visiting actively forest strands. Data creation *is in the making* while the practitioners investigate meticulously the forest strands, evaluating "how low or high" the biological importance of the area. During this practice, the domain experts/ practitioners answer a long questionnaire that determines the value of the specific forest area (figure 2).

Figure 2: The picture demonstrates a Natural Value Assessment Specialist in action. The red color showcases, the most vital questions, namely the ones that ultimately decide if a forest stand has a high value to be preserved or can go to production.

Data cleaning and data augmentation as a means of organizing factors

The practice of data cleaning and augmentation occur with the mutual collaboration and communication between data scientists or responsible of the IT development with domain experts in the natural value segment. As such, data scientists filter and analyze potential direction for optimizing the model with the aim to improve sustainability. To delve into, how data scientists procure these practices, we are currently observing interactions and discussions between the responsible of ML design and the domain experts.

Algorithmic design as a practice of cognitive participation

The making of the algorithm is far from being a simple and linear process. Contrariwise, our data showcase that algorithmic design is an iterative and complicated process, during which data scientists and practitioners need to continuously collaborate to "make sense". We realized that practitioners and data scientists (the ones responsible to materialize the wishes of practitioners on the algorithm) negotiated the positive and negative edges, taking always into consideration "to whom is important and why" and "how it could be more useful for the practitioners". In this case, practitioners explicate also to data scientists the importance of their task. Interestingly, we deduce that the design of algorithm is a *collaborative action* between data scientists and domain experts (see also Parmiggiani et al., 2022), that also demands a level of creativity in solutions. For this collaboration to work, the practitioners need to explicate their wishes on how the algorithm should reach the optimal level to help them achieve biodiversity and comply to the general sustainability guidelines. In this negotiation process, data scientists also realize the importance of domain experts on transferring their domain knowledge and informing them. As nicely stated with an appreciated tone by one of the data scientists: "*We are privileged to have domain experts that go to the forest and helps us with their insights to improve our model"*.

Still, however, as the process is complicated, there were many instances during the observation when participants demonstrate their wish with a grain of disappointment, declaring that "*I want more, but sometimes that it is more complicated that I think it would be*" (Field notes).

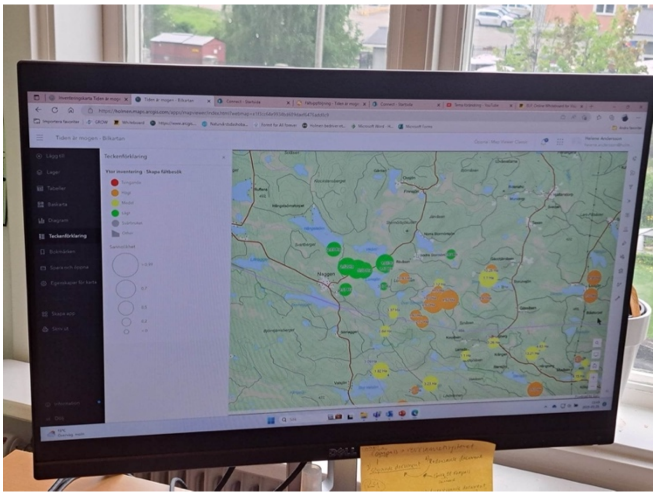

Figure 3: This map demonstrates the areas that potentially will go to production or will deemed as a "high natural conservational value.

Algorithmic enactment as a collective action of shaping work

Accordingly, the *algorithmic enactment* is an also collective action and a management process in the making, shaped through the negotiation and knowledge transfer (Kaplan et al.,2017). This practice signifies a change into data work where the participants crystallize new data work practices through the use and interaction with the ML model. It also entails the "acceptance" of the model and its importance from the practitioners (beyond the Natural Value Assessment team). In this case, the team interprets the results and the objectives of ML algorithm across organization, informing and shaping new ways of work with and on the data at the field. Simultaneously, it succeeds to disseminate the cumulative knowledge of the biodiversity objectives and data work across the organization.

VI. DISCUSSION: TOWARDS A SUSTAINABILITY REFLEXIVITY MONITORING

With this research in progress, we contribute to research agenda on sustainability (Nishant et al., 2019), data work practices and ML (Alaimo and Kallinikos, 2022; Alaimo and Kallinikos, 2021). We design our research based on the premises of grounded theory (Glaser and Strauss, 1967; Glaser, 1967), and we apply the lens of Normalization Process Theory (May,2006) to demonstrate the process through which the sustainability initiatives became a practice of reflexive monitoring. The reflexive sustainability monitoring practices acts as the consolidation of sustainability initiatives, where practitioners realize the value of the algorithm and actively use to effectivities their data and work practices. Reflecting back to the formulated research questions of what roles do practitioners play in brokering and managing data in sustainability initiatives drawing on ML and how is sustainability enabled and/or constrained in such processes, we argue first for the need to reveal the creative and collocative work that algorithmic brokering requires (c.f. Parmiggiani et al., 2022). Then, we realize that sustainability initiatives entail practices that both can enable and constrain the consolidation of sustainability objectives. In what follows, we elaborate on the tentative theoretical and practical contributions of our work.

Implication for research and practice

We aim to demonstrate, first, how algorithmic brokers serve as enablers that help to bridge the gap between algorithms and forestry practice by acting as conduits for the transfer of resources (Waardenburg et al., 2021). Engaging in brokering activities requires the ability to translate knowledge and information from one domain to another (Kaplan et al., 2017). Second, we found how brokers can connect ML predictions with forestry practice by engaging in algorithmic brokering activities (see figure 3)

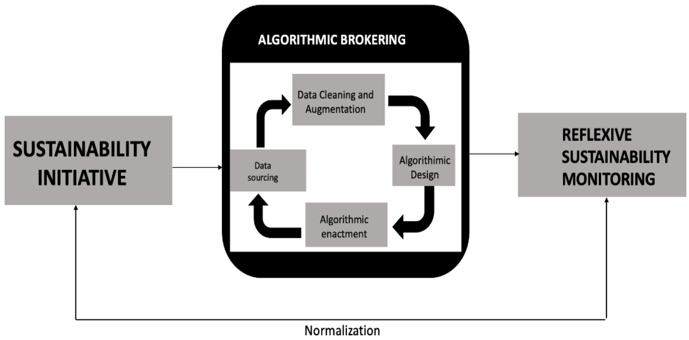

Figure 3: The dynamics of data, algorithmic brokering and ML for sustainability normalization.

In the model, sustainability initiative enables and is enabled by algorithmic brokering. We define algorithmic brokering as a strategic and iterative organizational practice constituted by interconnected and codependent activities. We also highlight that algorithmic brokering is a collective action and thus adding to nascent discussion on the emergence and importance of algorithmic brokering (see Waardenburg et al., 2021). By considering and depicting, algorithmic brokering as a collective action, we argue that the interpretation of results requires different responsibilities, but also knowledge transfer (c.f. Currie et al., 2012). Interestingly, the role of algorithmic brokers is always in the making, shaping the responsibility to interpret the results and stress the importance of biodiversity to rest of the team and across the organization. These activities of brokering encompass data augmentation, algorithmic and practice effectivization, and increase in terms of usage. We also identify that the relationship between algorithmic brokering, sustainability and ML algorithms is bidirectional. Thus, the practice of algorithmic brokering enables ML, and ML outcomes feed back to the algorithmic brokering practice. This process reconfigures the knowledge and strategies that enable or constrain sustainability initiatives.

Third, our study is insightful in relation to the emerging research agenda on sustainability (Nishant et al., 2019) by providing empirical and conceptual knowledge of how sustainability ideas are transformed as they are enacted by means of data. Specifically, our empirical results demonstrate how sustainability is both enabled and constrained.

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