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# Uncovering the dark side of AI-based decision-making: A case study in a B2B context

Emmanouil Papagiannidis [a,*], Patrick Mikalef [a,d], Kieran Conboy [b], Rogier Van de Wetering [c]

[a] Norwegian University of Science and Technology, Trondheim, Norway
[b] National University of Ireland, Galway, Ireland
[c] Open University of the Netherlands, Heerlen, Netherlands
[d] SINTEF Digital, Trondheim, Norway

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ABSTRACT

Over the last decade, many organizations worldwide have been assimilating Artificial Intelligence (AI) technologies to increase their productivity and attain a competitive advantage. As with any technology, intelligence systems come with potential downsides. Despite the efforts to mitigate any negative consequences of AI, businesses and employees continue to confront the dilemmas of adopting AI, so it is essential to explore in detail the rising concerns around such technologies. In this paper, we used a single case study to investigate the dark aspects of AI in a Norwegian energy trading firm. We gathered data through semi-structured interviews and secondary data. Specifically, we interviewed AI managers, traders and developers who have worked on deploying and using AI tools over the last three years. Our aim is to identify the dark side of AI use in trading, how AI trading bots affect the relationship between traders and AI developers and how the firm adjusts to this new reality. The findings indicate that negative or unintended consequences of AI can be grouped into three clusters related to (1) the nature of the work; (2) conflicts and effects; and (3) responsibility. The paper concludes with future research and practical implications that can help organiziations mitigate the negative aspects of AI use.

## 1. Introduction

Artificial Intelligence products have the potential to vastly improve our professional and personal lives. Firms seek to make the most of AI opportunities, but with new opportunities come new challenges and risks, constituting a dark side of AI. Challenges include privacy concerns, data security, and ethical dilemmas such as staff replacement and AI fairness (Wirtz, Weyerer, & Sturm, 2020). There is little understanding of the AI challenges confronting the public or private sector, and there is no consensus on how to address them in the future (Sun, Li, & Yu, 2022). Even though AI research has started focusing on these concerns, few studies have dealt with them in depth. Understanding these challenges is important because, while the development of AI may be one of the most outstanding achievements in human history, it can be a double-edged sword. Prominent opinion leaders have voiced their concerns about this matter. According to Elon Musk and Stephen Hawking, AI may be beneficial in the future, but it may pose a threat to humanity; for instance, AI might lead to massive job losses or be vastly deployed in warfare (CBNC, 2017, 2021). It may drive people to the sidelines or even create unanticipated damage; hence, we have to consider what AI means for our society and how to mitigate its risks in advance. For example, AI might be exploited by unauthorized users, or the AI itself might cause substantial financial losses in an instant; thus, the dark side of AI must be investigated further.

In previous studies (Akter, Wamba, Mariani, & Hani, 2021; Li, Liu, Mao, Qu, & Chen, 2023), researchers began exploring the potential negative consequences of AI and how they can be mitigated by incorporating AI into business analytics (BA) capabilities, specifically focusing on data, governance, and training resources. However, there is a limited amount of research available on AI in the context of B2B interactions and its practicality in such scenarios. Rana, Chatterjee, Dwivedi, and Akter (2021) have noted the scarcity of studies examining the impact of data, system quality, and end-user training on competitiveness, both directly and indirectly, when utilizing AI-BA capabilities and

* Corresponding author.
*E-mail addresses:* emmanouil.papagiannidis@ntnu.no (E. Papagiannidis), patrick.mikalef@ntnu.no (P. Mikalef), kieran.conboy@nuigalway.ie (K. Conboy), rogier.vandewetering@ou.nl (R. Van de Wetering).

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considering the potential negative effects associated with AI. Another study conducted by Castillo, Canhoto, and Said (2021) demonstrates the growing trend of AI technology providing support or even substitution for frontline employees (FLEs), resulting in substantial investment in AI for automated customer service agents, which has led to one of the highest shares of AI investment (USD 4.5 billion worldwide in 2019 (Castillo et al., 2021)) aiming at automated customer service agents. Using conversational agents or chatbots, as well as voice-controlled digital assistants (e.g., Alexa), will fundamentally change the nature of service interfaces from being predominantly user-driven to being more autonomous and technologically driven, even in B2B. However, the authors pointed out that value can also be collaboratively co-destroyed during the interaction process (Castillo et al., 2021). It is possible that the autonomy of AI could result in suboptimal outcomes if the technology is adopted in unintended ways or if FLEs act upon biased data.

The negative effects do not stop there. They might affect innovation or the potentional to create superior value as mentioned by Gligor, Pillai, and Golgeci (2021) who argue that when relationship bonds are reduced, they can lead to adverse B2B outcomes; thus, it is essential to examine the negative aspects (dark side) of such relationships. Rai (2020) expresses his concern about the power asymmetries in a B2B context and he proposes research on explainable AI, while Behera and Bala (2023) suggest future research on organizations' ethical decision-making because when decision-making is destructive, it can lead to dysfunctional and undesirable behaviours. Gligor and Esmark (2015) also conclude that future research is required on how managers should establish policies, avoid negative effects and provide guidance to employees to help them create and maintain positive relationships. Based on the above, we argue that a gap exists on the dark side of AI in a B2B context. We build on an in-depth case study of a company that operates in the energy sector and has been utilizing AI solutions to improve energy trading. This company engages in B2B operations by acting as a liaison between energy producers and industrial customers.

Based on the above discussion, the study's research objectives are as follows. First, we aim to identify the negative aspects of AI usage in a B2B context. As a large proportion of organizations that are deploying AI within a B2B context, it is important to understand the potential negative or unintenteded consequences that may emerge. Second, adopting an inward view, we aim to understand how the deployment of AI influences the relationships between different key stakeholders within the organizational boundaries. As AI has introduced significant changes in the structuring and organizing of the company, it is important to understand how the relationships between groups of employees have shifted. Lastly, we examine the adaptation of specific employee categories, like traders, to the emerging landscape and its impact on their job perceptions and objectives, aiming to understand the dynamics between traders and AI developers influenced by AI and to assess the adjustment of AI traders in this novel context and we give future research directions based on the themes we came up with.

Based on our findings, we are able to shed light on managers' actions, traders' reactions, and the relationships between AI developers and traders. Our findings indicate that from an organizational perspective, a cultural shift towards AI use and AI training were among the new procedures and policies managers implemented to minimize complaints and fears about AI replacement and potential errors while managers tried to maximize profits. We also found that traders adapt to their new roles and responsibilities by becoming hybrids between traders and AI supervisors. Traders had mixed feelings about using an AI system that replaced a great deal of their work, while AI developers felt pressure to show real results and assist traders in their new role. Finally, AI developers worked hard to maintain good relationships throughout departments since they did not want their colleagues to blame them for losing part of their work.

The paper is structured as follows: Section 2 presents the theoretical background and discusses the application of AI in B2B and its potential negative aspects. Section 3 outlines the data collection and analysis methodologies employed. In Section 4, the findings from the data analysis are presented. Finally, Section 5 concludes the study with a discussion of the results, their interpretation, evaluation, and the limitations of the research.

## 2. Theoretical background

Our inquiry into AI begins with a definition of intelligence in the human context, which is defined as a person's ability to learn, cope with new situations, grasp and handle complicated concepts, and impact one's surroundings through knowledge (Demlehner & Laumer, 2020) or as the ability to perceive and interpret information, transform that information into knowledge, and then apply that knowledge to goal-directed activities (Paschen, Wilson, & Ferreira, 2020). Consequently, perceiving one's environment, problem solving, reasoning, learning, memory, and acting to achieve goals are only a few of the tasks that contribute to good intelligence adaptation. AI can be defined as a system capable of interpreting external data, learning from such data, and using it to achieve specific goals and tasks through flexible adaption (Enholm, Papagiannidis, Mikalef, & Krogstie, 2021). Real-life instances include the implementation of automation bots to alleviate workloads, the utilization of AI for content creation in marketing, and the application of AI to personalize experiences and satisfy individual customer needs. The B2B marketing ecosystems have witnessed the impact of AI automation and AI products, which offer diverse applications in industry (Stone et al., 2020). For example, B2B marketing companies consider AI predictions of customer purchase behaviour to be one of the most significant parts of increasing revenues (Moradi & Dass, 2022; Paschen et al., 2020).

With AI omnipresent in everything from smartphones to household finances to law and justice systems (ethical AI robots), both the public and businesses need to understand that although AI technologies indisputably offer a lot of advantages, disadvantages exist too (Vanderelst & Winfield, 2018). One disadvantage of AI-based technologies in a business environment is the requirement to involve clients in the customer service process, which increases complexity and, eventually, increases the chance of failure. Customers may become irritated and frustrated after spending a lot of time and effort during an interaction when co-created services fail to meet customer expectations, since AI chatbots lack the human intervention that plays a significant role in configuring costumers' needs and maximizing their satisfaction (Grönroos & Voima, 2013). To extend this, based on the work of Plé and Cáceres (2010), value decreases when differences exist in resources, practices, or AI agents' activities and services. Camilleri and Neuhofer (2017) discovered numerous value formations in their work about the tourism industry. To be more precise, they discovered that value could be co-created and co-recovered, and co-reduced and co-destroyed in a sharing economy context. In addition, recent research by Grundner and Neuhofer (2021) has highlighted the potential drawbacks of AI, encompassing areas such as job displacement, privacy risks, machine ethics, security concerns, and negative developments in superintelligence systems.

Other concerns or drawbacks are customer data privacy and security, a possible decline in social interactions among end users during their experiences, and technological limitations, which may dissatisfy both customers and employees. There may even be implications associated with different business settings and their capacity to establish trust and guarantee that each transaction is tamper-proof (Risius & Spohrer, 2017) as research suggests that trust builds close relationships among B2B participants that are mutually beneficial (Gligor & Holcomb, 2013). B2B relationships that suffer from diminished relationship bonds lead to a lack of innovation or inferior value creation (Gligor & Esmark, 2015). By analyzing big data, for example, firms can better understand their B2B partners and anticipate their needs and behaviours (Hallikainen, Savimäki, & Laukkanen, 2020) but it lets firms rely less on information obtained from their partners and eventually they might neglect them. That implies that if a firm loses sight of the importance of managing B2B relationships, it may experience erosion in the quality of its relationships, which can eventually lead to adverse outcomes (Gligor et al., 2021).

### 2.1. AI use in B2B marketing

AI use and adoption in B2B marketing is driven by two primary motivators (Keegan, Canhoto, & Yen, 2022). The first motivator is the fact that AI is capable of handling large datasets and identifying new patterns in data, which can be used to generate new insights (Cortez & Johnston, 2017), increase efficiency (Bag, Gupta, Kumar, & Sivarajah, 2021) and enhance decision making (Borges, Laurindo, Spínola, Gonçalves, & Mattos, 2021). This illustrates how AI technology improves marketing campaigns' effectiveness, improving the firm's performance (Liu, 2020). For instance, AI is transforming B2B marketing by solving issues in the labour intensity of data collection, management and analysis by creating better customer insights and enhancing and personalizing customer experience (Kim, Kim, Kwak, & Lee, 2022). The second motivator is the alleged cost reductions that AI technologies may bring (Keegan, Canhoto, & Yen, 2022) and the fact that AI is meant to be quicker and less prone to errors than humans (Davenport, Guha, Grewal, & Bressgott, 2020). Even the most basic AI system, however, needs a substantial upfront investment, a lot of computing power, access to several datasets, and regular upgrades. It is vital to emphasize that industrial AI is currently being developed in a conventional B2B setting and it is a transitory endeavour. As part of the design, development, and implementation of such technological solutions, businesses need to interact with customer companies and hire, temporarily at least, consulting firms and IT suppliers (Li, Peng, Xing, Zhang, & Zhang, 2021). As a consequence, partners and stakeholders, from many parties with varying interests and requirements, collaborate to produce value.

In order to produce value through collaboration, B2B marketing operations often involve agencies, which are specialized third-party marketing firms responsible for adapting a company's marketing message to target other companies (Huang & Rust, 2018). These agencies possess extensive knowledge about effectively reaching decision-makers for high-priced products and services, while B2B marketing ecosystems have seen major changes in the last decade due to the introduction of new technologies and process automation (Saura, Ribeiro-Soriano, & Palacios-Marqués, 2021). Among these changes, the utilization of AI techniques and software has emerged as one of the most notable advancements, aiming to increase efficiency and optimization and streamline processes through the implementation of intelligent agents or systems (Saura et al., 2021). What is more, B2B marketing teams recognize the importance of meeting their customers' evolving needs and integrating customization into the sales process to add value. For that reason, many businesses rely on mass customization for marketing purposes to increase product variety, and through that customer satisfaction, without increasing costs (Kamis, Koufaris, & Stern, 2008). To accomplish this, they leverage AI systems in advanced manufacturing with the primary goal of economic growth, leading to technological advancements and greater competitiveness in both local and international markets (Chen, 2017). To take advantage of mass customization though, manufacturing processes should embrace digital production and adopt AI systems (Moradi & Dass, 2022).

### 2.2. Industrial AI in B2B

Past research (Ives, Palese, & Rodriguez, 2016) indicates that AI has led to more profound adjustments and transformations to industrial organizations than earlier digital and technological innovations. Industrial AI is referred to as a broad spectrum of enterprise activities utilizing machine and deep learning (Li et al., 2021). In general, it refers to AI technology utilized to solve issues related to complex industrial operations, collaborations, and marketing activities. For example, networks have to swiftly respond to abnormalities and adjust to shifting traffic in order to sustain excellent operations (Kromkowski et al., 2019). AI is being used by telecommunications companies to monitor and enhance their networks and give the best performance to their consumers (Liang, Li, Long, Kui, & Zomaya, 2019). Another example would be in the sector of oil, gas, and energy due to safety and environmental concerns. Energy firms are now able to boost their efficiency without raising prices thanks to AI advancements (Ahl et al., 2020). This includes applications such as image processing for identifying maintenance requirements and predictive models for energy demands (Pradhan, Ghose, & Shabbiruddin, 2020).

Furthermore, a recent analysis by MIT (2018) highlights the crucial role of AI technology in enhancing business and professional service outcomes. The combination of AI and big data may assist B2B organizations in discovering and using vital information and expertise leading to a competitive advantage (Li et al., 2021; Paschen, Paschen, Pala, & Kietzmann, 2021). Furthermore, B2B marketers should focus on both consumers and people who make purchasing choices because both customers and those who make the purchases play a significant role in B2B marketing. It is envisaged that adding AI processes would result in even greater marketing efficiency through personalization (Abrell, Pihlajamaa, Kanto, Vom Brocke, & Uebernickel, 2016; Li et al., 2021) because it is critical to understand supplier and customer firms' requirements to properly create and apply industrial AI in B2B marketing (Wang, Ma, Zhang, Gao, & Wu, 2018). AI can aid marketers in gathering important information from consumers, retaining existing customers, and increasing customer satisfaction (Meire, Ballings, & Van den Poel, 2017), while assisting B2B managers to acquire more accurate customer-related innovation for retaining existing clients and exploring new opportunities to attract new customers (Han et al., 2021).

What is more, AI is rapidly being used to improve B2B market performance by speeding up decision-making processes. While this phenomenon has been widely embraced in the B2B sector, little academic research has been conducted on it in the context of industrial marketplaces (Dwivedi & Wang, 2022). That means there is a research gap that could be filled and offer illumination about customers' or competitors' habits and decisions, helping firms to improve their products and services. The majority of AI research focuses on consumer marketing at the moment, but industrial data is rarely evaluated to solve challenges such as organizational behaviour, product innovation, supply chain management, and B2B customer relationship management (Davenport et al., 2020). Besides the B2B marketing ecosystem changes, estimating the net client lifetime value (Chan & Ip, 2011) is considered critical, especially for digital marketing B2B companies. One of the most tried and tested B2B marketing tactics is personal selling, because it focuses on face-to-face networking and contacts to close purchases. This is the least scalable approach to promoting your firm to other businesses, but it has the highest conversion rate. AI, in this matter, helps firms make better decisions and create more effective content since firms may conduct targeted marketing operations, resulting in increased ROI, due to the benefits of understanding the audience better.

Simultaneously, firms attempt to maximize profit and other quantitative indicators like inventory investment and storage capacity (Chen & Chen, 2008). Data mining techniques are known to have influenced the development of intelligent systems that help the marketing strategy process (Martínez-López & Casillas, 2013). The objective is to aid managers in dealing with ambiguity and uncertainty while providing sensible marketing strategy guidance (Li, 2000). As a result of these AI encounters, B2B marketing businesses may learn from them and adjust their views and strategy accordingly (Cruz, 2009). Consequently, in the last decade, AI applications have been introduced for trading purposes in B2B marketing businesses. Businesses that leverage data to make better, faster, and more accurate trade decisions have a competitive advantage. Organizational digital networks generate a significant volume of data and have immense value for enterprises. For instance, important commercial events, natural disasters, athletic events, political crises, or just popular topics tend to increase messaging activity in networks by creating large amounts of social media data. These types of network activities are crucial for trading in B2B marketing environments since the increase in communication might be a sign of a broader problem, and it can be documented and researched to identify meaningful trends and patterns (Candi, Roberts, Marion, & Barczak, 2018). To be more specific, data stored in structured and unstructured databases, when combined with other real-time data streams (feeds from social media or sensors), may assist management and stakeholders in understanding the severity and intensity of an unfolding crisis.

Such data is usually stored or produced from outside sources. External data may be classified into two types. The first category consists of data that is directly linked to organizations, such as online social media content and mobile devices. The volume of data collected from professional and personal contacts (such as social media and cellphone data) is concerning since AI can discover personalized patterns, which threatens individual privacy. The second type of data is not directly related to an organization but can impact its performance. Collecting socio-cultural data, for example, can assist in enhancing corporate operations by making judgments that are more in line with contemporary cultural developments (Farrokhi, Shirazi, Hajli, & Tajvidi, 2020); thus, customer knowledge, user knowledge, and external market information are all key components of the knowledge management process and are accountable for the development of B2B marketing knowledge (Abubakar, Elrehail, Alatailat, & Elçi, 2019) contributing to the accumulation of big data.

Big data proves valuable in extracting critical information from structured and unstructured data inputs, such as web browsing behaviour, demographic characteristics, and purchase trends, and delivering relevant consumer knowledge for rational decision-making. With big data, B2B marketing firms could build models that generate new content and target the right audience with the right content. Customers will be happier since they will find what they need according to their needs. That means user knowledge is required for the creation of new products and method innovation and improvement (Bag et al., 2021). B2B marketing firms need to have a thorough awareness of the external market to stay ahead of the competition. By analyzing unstructured data such as news, social media content, and specialized external sources, AI may help B2B marketers improve analytic and decision-making abilities, and promote creativity (Paschen, Kietzmann, & Kietzmann, 2019). Hence, knowledge management and decision-making styles are critical for corporate success in the digital age (Bag et al., 2021). As a result, B2B organizations can utilize AI to turn enormous amounts of data into knowledge and, ultimately, expertise to develop efficient sales plans and tactics.

### 2.3. AI use in B2B marketing and its dark side

Limited research has been conducted to better understand the processes behind the dark side of B2B relationships and find solutions to minimize their negative effects (Sharma, Kingshott, Leung, & Malik, 2022). From an organizational standpoint, a company's reputation and overall profit are likely to be impacted by the launch of AI-enabled goods. The effect of the impact, positive or negative, is determined based on the success of the system. For instance, the effectiveness of AI-enabled chatbots affects how satisfied customers are (Ashfaq, Yun, Yu, & Loureiro, 2020). Chatbots that are unable to offer the requested information would have a negative impact on customer satisfaction, meaning that customers will distrust chatbots if they do not perform as well as they are expected to; thus, customers will not trust the sellers or the businesses who use AI as a result (Yen & Chiang, 2021). Furthermore, because AI is still a relatively new technology, firms frequently miss the opportunity to address the question of how AI plans will affect the human workforce. The most common fear of AI is the fact that people might lose their current positions and be unemployed due to the technological advances in AI (Li & Huang, 2020). The argument has merit since AI can do massive tasks in parallel to reduce costs and improve performance, especially for B2B that operate a type of AI-CRM (Chatterjee, Rana, Tamilmani, & Sharma, 2021). Because of that, employees fear being replaced and cannot realize how to coexist with AI, leading them to reject the idea of embracing AI in their everyday work.

From a social standpoint, AI has negative repercussions, ranging from data security concerns to ethical dilemmas (Boyd & Wilson, 2017). The issues involve AI legislation, regulations, bias, and fairness. Mikalef, Conboy, Lundström, and Popovič (2022) connect the responsible AI's aspects with the dark side of AI. One of the most common aspects is fairness and bias, which could have a huge social impact; therefore, these potential issues provide difficulties for AI governance at the social level. Consequently, many studies on fairness and bias concentrate on various choices, such as HR recruiting, budget distribution, or a set of medical testing (Mikalef et al., 2022). This focus could be justified due to the fact that a business cannot afford to ruin its position in the market since the risk of using AI could be high in some cases. AI risk assessment needs to be part of a larger business risk management framework that incorporates regulatory, financial, credit, and information technology challenges, because AI risk assessment procedures will not be ad hoc if an organizational risk management framework is implemented throughout the whole firm, i.e., there will be a continuous plan enforced with management-approved regulations (Barta & Görcsi, 2021). This signifies that data governance and safety measurements could not be ignored since these can prevent the negative consequences of the dark side of AI (Cheng, Su, Luo, Benitez, & Cai, 2021; Mikalef et al., 2022).

Another aspect of the dark side relates specifically to AI trading. Professional investors can trade financial assets in secret and anonymously by utilizing dark liquidity pools (or dark pools). Dark pools enable investors to conceal their market moves from rival traders by not releasing pre-trade information such as pricing, volumes, and the number of open orders. However, dark pools may potentially jeopardize financial markets' informational efficiency and the fair pricing of securities by preventing pre-trade information from being available to all market participants (Lagna & Lenglet, 2020). This dichotomy, which characterizes dark pools, raises an important question about how dark liquidity providers can persuade investors that trading in the dark is secure. In addition, there are legal concerns when dealing with AI. These concerns intersect with ethical considerations as there are many who expressed their views on the ethical aspect of AI. Using the proprietary trading sector as an example, emerging threats to the safe use of existing legal concepts of market abuse in dealing with misconduct by more autonomous AI trading bots should be examined. Autonomous AI trading has the potential to exhibit unparalleled flexibility and develop capabilities that human specialists can only aspire to. Because of self-learning, AI traders may operate in unexpected ways though, for both good and evil. Various ethical and legal issues emerge when dealing with accountability issues for algorithmic misbehaviour. AI's misbehaviour, for example, might someday undercut current market abuse restrictions (Azzutti, Ringe, & Stiehl, 2022). As a result, it is difficult to determine who is truly responsible and allocate responsibility for decisions that could be taken automatically by the AI or in combination with a human agent.

## 3. Methodology

Through case studies, complex issues in their real-life contexts can be explored thoroughly and in a multifaceted way (Rashid, Rashid, Warraich, Sabir, & Waseem, 2019). Many fields, such as business, law, and social sciences, recognize the value of the case study approach. Moreover, case analysis can be very helpful for gaining a more in-depth understanding of an issue, event or phenomenon in its natural setting. As a research strategy, a case study has traditionally been viewed as lacking rigour and objectivity compared to other kinds of social research (Gibbert, Ruigrok, & Wicki, 2008). This is a major reason for carefully justifying the process of designing and implementing a research study. Despite this skepticism about case studies, they are widely used because they can offer insights that might not otherwise be available (Yin, 1981). Moreover, case studies are frequently used to develop more structured instruments that make surveys and experiments possible in the preliminary, exploratory stages of a research project. Case studies provide useful information for contemporary events when the relevant behaviour cannot be manipulated. As a rule, case study research draws its evidence from diverse sources, including documents, artefacts, interviews, and observations. Rashid et al. (2019) suggest interviews for refining theories or understanding phenomena. By analyzing these data, users can gain new insights that are useful for explaining similar situations (Oates, 2005).

A qualitative methodology is chosen for our case study because it allows for flexibility in our case study and encourages discussion, which can be used to comprehend and explain the research goal (Michael, 1997), as it includes key respondents' experiences, beliefs, and attitudes through semi-structured interviews (Wynn Jr & Williams, 2012). Consequently, for the purposes of this work we used interviews combined with secondary data, including reports and internal documents, in order to supplement our data and validate our findings. We analyzed the comments and observations from different transcripts to discover common themes and patterns representing the dark side of AI trading. Another reason for using axial coding (Charmaz, 2014) is to group the comments and observations, which allowed for better interpretations due to the employees' ability to refer to the same concept using similar terminology based on their technical knowledge, experience, and position in the company. To ensure high confidence levels, the researchers examined reports, public information, and presentations related to this research that focused on the dark side of AI trading.

### 3.1. Case context and data collection

For this particular study, a Norwegian company working in the power industry has been chosen. The company is a midsize enterprise (around 500 employees) and has been in operation for 65 years. There are three main criteria that make this company suitable for this case study. Firstly, according to the Global Economic Forum's 2019 Global Competitiveness Report organizations, Scandinavian countries have a high level of ICT adoption. Secondly, the majority of individuals have strong digital skills, making them well-equipped for digital transformation. Thirdly, the company's vision and plan for developing, expanding and using AI into its B2B marketing practices in order to maintain a competitive advantage over its competitors. To be more specific, AI is used for buying and selling energy, and the company advertises these AI driven activities. Furthermore, the company uses AI to place itself in the market as a strategic partner, while at the same time the company uses AI for ensuring efficiency and low energy prices.

As part of an interview design, a total of fourteen interviews were conducted. Each participant was questioned for an average of 45 min, allowing them to convey their understanding in their own words and based on their own ideas on specific subjects. To comprehensively explore the dark side of AI trading, input was sought from both the trading and AI departments. The involvement of both departments was crucial to gain a comprehensive understanding and obtain insights into their perspectives regarding the dark side of AI trading. For this reason, the guideline questions were divided into three sections. The first part dealt with how they used to do their trading activities without AI, including the aspects of time management and the effort they had to put in to accomplish the initial business goals. The second part focused on the use of AI in trading and how it affected them personally and as a department, while we were trying to identify the various aspects of the interaction between human and machine. The last part targeted the negative aspects that might occur because of the use of AI in trading. Mostly, we investigate the fears and concerns of the employees and the expectations they had from the use of AI in their everyday work. What is more, during the interviews, we try to find any tensions between departments because of the development of AI, to be more specific, between AI developers and AI traders. Table 1 presents an overview of the participants and their respective roles within the organization.

In our case, traders do not necessarily adhere to the strict definition of a trader, thus it is important to note their activities and contribution to the company. To be more precise, while some AI traders have a background in computer science and finances, others do not. The company's strategy was to follow a quantitative approach from the beginning and this was reflected in the hiring process, where they prefer candidates with knowledge in computer science and finances. Traders' everyday activities primarily involve selling power, forecasting energy consumption, and keeping an eye on AI decisions. They also assist, or at least have assisted in the past, with the development of the AI trading system as a side task because their skills and knowledge were needed to evaluate AI and calibrate the data utilized for developing AI. Additionally, traders offered the AI team insightful comments on the outcomes of the AI while suggesting features and methods for testing the capabilities of the AI system.

### 3.2. Data analysis

We analyze content from the interviews employing a narrative analysis process because the experiences and stories shared by employees are used to answer the research questions. Our analysis is inductive in nature, as we gather our data (interviews, reports, etc.) and we came up with the general conclusions based on these data. The transcripts that were generated were imported into the software NVivo. During the analysis, we utilize an axial coding process as it involves relating data together to uncover codes, categories, and subcategories encapsulated in the voices of participants (Michael, 1997). Essentially, axial coding is a method of constructing links between data and it is used to enhance the depth and structure of existing categories. According to Charmaz (2006), axial coding aims to reassemble data and is a step that follows open coding. In our case, there are four groups of nodes corresponding to societal, organizational, interpersonal and individual entities (Ragins & Sundstrom, 1989). We also draw upon the work of Linstead, Maréchal, and Griffin (2014), who describe a longitudinal resource development model of power in organizations and the dark side of organizational behaviour, including the concept of organizational misbehaviour. To elaborate further, the leadership and expertise that individuals bring to a position within an organization are the emphasis on the individual level. The interpersonal analysis focuses on the connections between people in light of their roles within the organization, while the analysis of organizational nodes focuses on selection and promotion methods. The social level focuses on the development of roles and expectations throughout society as a whole. The analysis (Table 2) can be perceived as a system with four nodes in which each node interacts with the others, creating interconnectedness. Actions taken at any node have the potential to impact and be influenced by events at other nodes. Table 2 presents the observations we generated, the themes

**Table 1**
Respondents' stats.

| Respondent ID | Role | Years in company |
|---|---|---|
| R1 | Quality control AI manager | 5 |
| R2 | ML Engineer | 4 |
| R3 | Trade AI Manager | 5 |
| R4 | Chief AI Officer | 5 |
| R5 | ML Engineer | 3 |
| R6 | ML Engineer | 4 |
| R7 | ML Engineer | 4 |
| R8 | AI Trader | 3 |
| R9 | Data Scientist | 4 |
| R10 | Trade AI Manager | 5 |
| R11 | Data Scientist | 4 |
| R12 | AI Trader | 3 |
| R13 | AI Trader | 3 |
| R14 | Data Scientist | 16 |

**Table 2**
Themes, observations, and nodes for the dark side of AI trading.

| Themes | Observations | Nodes |
|---|---|---|
| Nature of work | Deskilling | Individual |
| | AI false expectations | Organizational |
| | Unemployment | Social & environmental |
| | Mobilize human capital | Organizational |
| | Losing interest in work | Individual |
| | Hacking attempts | Organizational / Social & environmental |
| Responsibility | Lack of AI decision explainability | Organizational |
| | Absence of AI accountability | Organizational / Interpersonal |
| | Manipulating the market | Social & environmental |
| Conflicts and effects | Portfolio risks | Individual |
| | Enforce patterns / overconsumption | Social & environmental |
| | Conflict of interest between managers and traders | Interpersonal |
| | Sell overseas / lack of energy | Social & environmental |
| | Conflicts among AI developers and traders | Interpersonal |
| | Conflicts among AI traders and non AI traders | Interpersonal |

formed by grouping these observations, along with the corresponding nodes.

## 4. Findings

The interviewees discussed the negative aspects of AI with respect to trading. In particular, they provided their views about the use of AI in their daily work and what the future holds for them as a result of the continued evolution of AI capabilities. The findings provided a range of contrasting views in terms of the existing and potential benefits but are wary about the potential consequences for their careers if AI becomes mainstream.

### *4.1. Nature of work*

To begin with, employees had high expectations of AI technologies but like any technology or software there were many times when things could have worked better during production time.

> "When it goes to production, things will go wrong, mostly because some data is missing or incorrect… (that is why) we always have mechanisms, like fallbacks and manual mechanisms to correct things…so the system did not produce the value that we expected." (R1)

AI might fail in different ways, such as adding business value or giving unexpected results.

> "Many organizations face the problem of getting things into production…they do some experiments and develop some prototypes but AI is not adopted and used…(personally) I was expecting that AI would be more profitable." (R1)

> "We tried to gather different projects that we thought AI would give some value to us. Then we started with the easier ones and the ones that we believe would give financial gain, but not all of them were successful." (R2)

Similarly respondent 3 stated*:*

> "We have done some tests on whether we can improve inflow forecasting to hydropower…but the tests that we have done so far gave negative results on the horizons we wanted." (R3)

Since the company decided to develop the software, they had the opportunity to maximize AI outputs as they did not use a generic AI software that provides outputs for unspecific goals. That was a double edged sword as the small AI team could make fatal mistakes because AI models failed to show adaptation when unexpected weather conditions applied.

> "We optimize AI for our company, which I am quite sure is the reason why we were the 'best'. We worked closely with the domain experts, who could help us evaluate our systems in the best possible way. Recently (though) we failed…we forecast for wind parks…but we did not understand how poorly the model worked…So it took time until we realized that something is very wrong here and we have a very high cost of it." (R4)

> "We observe things the system is not aware of. Like the icing conditions on the wind farm and if there is any change in the way the company is operating the windmills. For example, the company have implemented a new software…and the AI models did not know that. Meaning that the models did not learn from the new data." (R14)

Due to intraday trading, i.e. selling and buying on the same trading day, traders do less manual trading and instead tend to rely on high speed AI agents. Consequently, traders lose their competence, and deskilling will be a challenge in the upcoming years since the traders will do less and less trading, transforming the nature of work.

> "You cannot have people doing this manually because the good bits, they just vanish before you see them, maybe before even they get to your screen. So you need algo-traders." (R4)

Respondents R3 and R13 reinforced that statement:

> "We are on the dashboard, we have tried to focus on some key values…So that is sort of daily monitoring." (R3)

> "We have 24/7 operators that are sitting at the production central…(monitoring) processes or predictions." (R13)

As a result, traders do not necessarily become better by learning through AI.

> "I think maybe it is almost the other way around; they see behaviours that maybe they did not expect. They analyse it a little bit, and they use them to improve the algorithm itself, instead of themselves becoming better traders." (R8)

Meanwhile, the company aimed to make the transition from manual to automatic trading smoothly. Traders are still in use as their expertise is required to develop these systems since AI developers are unlikely to be experts in the field. Therefore, the board decided to use AI to do the heavy lifting and manual trading is still on to counter the feeling of being replaced. AI brings this tension to a point where, in the best-case scenario, employees are transferred to another position within the company or, in the worst-case scenario, lose their jobs and have to find new ones in a market being taken over by technology.

> "You could expect because we automate…people will become jobless…We need to automate and then you should automate in the best possible manner. And that is about doing it."

(R4)

However, that will not be the case in the near future. Most trade interactions today occur within a split second, so keeping up with the pace is essential. Currently, transactions occur almost every hour in the energy market, but this will likely change drastically soon.

> "We will switch from our hourly production times to quarterly. So that way, every 15 minutes, there is going to be products that you can trade on…It is not easy to monitor and manage, and do all of these things, because you need people that have high education, and experience as well."
>
> (R8)

Respondent 10 stated:

> "In my mind, we should do it as much automatically as possible. So the operators are not using that much time taking manual decisions, and of course, I would prefer that we use AI for the most part."
>
> (R10)

Respondent 13 expressed his concerns regarding the potential downsizing of positions as a result of AI:

> "I believe some jobs might be changing based on how AI is being used. It might reduce some of the positions due to being more efficient, but at the same time, it might need to be watched a bit. So it will be a change for someone."
>
> (R13)

It is worth noting that a trader who had previously worked in a similar role in another firm, in the same industry, mentioned that AI technology was not well received there, and most traders resisted changing. Their resistance was due to facts or patterns they observed in the market that AI models did not consider highly important; thus, traders were very skeptical, if not against the use of a system that did not incorporate what they believed was important.

> "When we argued with other traders about which trade they should perform, they might say 'Oh, yeah, but even though the expected price is higher than the market price, we should not buy now because the price has gone down the last five days'. So they argue that the trend of the market was very important, whereas our backtests did not support this. So although we were closer to the price due to our distribution model, they had arguments against it based on more short-term things that they observe in the market."
>
> (R12)

Their primary concern was that AI would certainly replace their work, and eventually, they would lose their jobs since AI could do exactly what they do now, if not better. The issue was addressed through workshop sessions. Employees were trained and educated on AI throughout the entire development process, allowing them to understand, at least, how AI works, how traders will use it, and why it was adopted. Last but not least, the AI team built models for other companies. The obvious benefit is revenue, but there might be some problems. For example, if the models fail to predict accurately even for a short period of time, energy prices will rise. The effect may be more severe in northern European countries with more prolonged and colder winters.

> "Short notices on production emergency requirements and incorrect estimations of supply and demand will lead to bad reputation and high prices for consumers."
>
> (R12)

Therefore, companies need to utilize AI to replace manual trading, and hence the role of human traders will be reduced or marginalized. In this case, the company shifted traders to another department and set up a monitoring room where traders monitor patterns and detect any anomalies that may occur. This provided an opportunity for traders to explore the market and discover new patterns because they did not have to conduct as much trading as they had in the past while developing new talents.

> "There will have to be much more back and forth between the trading desk and various developers to ensure that we really have good enough monitoring tools and good enough systems and pipelines that are robust. I think trade will shift more to monitoring tasks, and also coming up with strategies and more control tasks because they would obviously be better at something like that, compared to someone like me."
>
> (R8)

The main benefit of AI is that it reduces overload and makes it possible to scale up in areas where human capabilities cannot grow without the participation of new employees. Because AI's scalability is reliable and supports rapid growth, managers may choose to let go of some employees or not hire new ones in the wake of AI automation.

> "It is much easier to scale up so that you can trade on several portfolios."
>
> (R8)

Hence it is likely that traders will end up doing something that they are not interested in or they have not signed up for in the first place and this might lead them to lose interest in their job. Furthermore, due to the nature of the work cybersecurity issues might arise. Respondent 11 mentioned that he had been aware of similar companies whose AI systems had been hacked, causing financial and reputational loss to the company, its clients and the surrounding social environment.

> "You have to ensure that systems are secured because they have many activators and control over the value chain. Security and AI have to go together. Otherwise, the risk is high. Last year, two companies (in this sector), this is publicly known, were hacked, but I do not know the consequences in monetary value."
>
> (R11)

Nevertheless, traders in the company try to use AI to develop new strategies and tactics that are impossible to think of without using AI. Back-testing is applied, and traders came up with new insights into how they could operate under different scenarios.

### 4.2. *Responsibility*

As far as the responsibility part is concerned, many disagree in terms of who is responsible for the AI outcome and use. The concerns arise because it is hard to identify if the AI developers are the ones to blame since they build the software, or the traders who eventually use the AI, although in this case, they are monitoring mostly AI. The lack of explainability tools may contribute to that as it is hard to deal with concerns surrounding transparency and bias.

> "In the energy business, legal complication starts when we are trading with AI. Questions arise, for example, who is responsible or how should we put a new trading algorithm into operation. You have to make sure that you do not place any bids that are bigger than the ones you can take."
>
> (R3)

Respondent 8 added more on this topic:

> "There are going to be humans involved, which means there are going to be a lot of things that are very difficult to understand for a machine. Someone might implement a way to trick the machine in some way or trick the algorithm into gradually lowering or increasing its price to get a good sale or a good transaction out of it. That is something that would be much easier for a trader to detect, because they could see the 'tells'."

(R8)

Companies might be held responsible for price speculations as AI might affect prices and lead to a dramatic increase, meaning that in energy markets speculations are not allowed and there are legal consequences. Furthermore, the company did not have clear distinct roles, which contributed to the question of who was held responsible in case of something going wrong.

> “We have been doing this with no distinct roles. But there are, of course, distinct positions within the company that work on different things. So they will have access to different parts of some database. But it is dependent on the problem that is solved and who deals with it.”
>
> (R6)

To mitigate some of the issues, the company decided to promote robustness and reliability through infrastructure and by standardizing processes.

> “In the beginning, there was not an infrastructure which promoted robustness and reliability in the whole process…we have these error detection methods now, which do it automatically.”
>
> (R7)

On the same matter, even managers have different views, which highlights the fact that there are blurred boundaries on where responsibility lies. This raises the issue of who is held accountable in cases where there are important deviations from forecasted values.

> “Who is responsible? That is almost a good question when it comes to the AI, but I guess that it should be the head of the Energy Management department who supervises the trading.”
>
> (R10)

> “So there is a responsibility when you use AI. You have to have some kind of explainability so that you can actually explain why this trade was done…but then again, who should be held accountable for AI’s actions remains a good question.”
>
> (R9)

Nevertheless, employees do not find this a major problem since trading in their sector has to follow strict regulations, and there is a great deal of documentation on how AI should behave. All the limits should make the algorithms simple enough, meaning that, ideally, most traders can understand how the processes work and how the decision making is done.

> “You need to define some limits. The algorithm ideally has to be simple enough but not naive, it cannot be too complicated.”
>
> (R8)

Obviously, if the algorithms were too naïve, the employees would challenge the outcomes and adoption issues may occur. In case of unexpected events, AI might produce undesirable outcomes, especially in unknown scenarios; thus, the human controller is required to identify and outmanoeuvre the issue. In order to do that the trader should have critical thinking and be able to judge if the AI outcomes are reliable, robust and profitable in the long run.

The responsibility part is a real concern if the legal aspects that the government has enforced are taken into consideration.

> “But I am worried that our algorithm will place orders, for instance, in a way that creates a pattern on the orders. Then you might make a fake impression that there is a lot of buyers in the market, while there is only one algorithm placing all of these orders and that is not legal…someone could implement it in a way to trick the machine or trick the algorithm to gradually lower or increase its price to get a good profit.”
>
> (R12)

Hence, the employees raise the question of who is truly responsible for such undesirable outcomes. Violating these rules could mean a lot of legal trouble on the horizon and it is a dark side of AI trading that employees are not willing to face. Considering the upcoming energy crisis, which seems to be a huge problem in the near future, it would be difficult to decide who is accountable, at least for the economic effects on society.

### *4.3. Conflicts and effects*

One of the main effects that traders identified in terms of AI outputs was trust due to results in comparison with other traditional methods.

> “We are exploring how we could use AI methods to solve hydropower scheduling problems, especially when it is important to represent uncertainty. But that is on a research level. I am a little bit skeptical, though. I think it will take many decades to use AI in advanced decision making because models cannot compete with the classical optimization tools that we use now.”
>
> (R3)

> “We get questions of why and how it comes up with the results, which is maybe one thing that can sometimes be a bit difficult to explain because most of the time, it can make sense, if the data looks a specific way. But sometimes the results do not really make sense.”
>
> (R2)

At the same time, employees should be able to provide predictions even if AI data is not updated. That means the quality of outputs might not be as expected. That makes the company decide the development of tools that promote trust in AI.

> “Sometimes you have to do forecasting even if you have missing data, using old data to fill them. It depends on the application how we deal with the missing data. But we need to handle this, we cannot say that we cannot predict. So, maybe the old data are a little bit off, (meaning that) the data we want to use might not be right.”
>
> (R5)

> “What is done is that usually a person is in control and he is given options so he can see the choices and he can evaluate (the outcome) and decide if he should use whatever this computer produced for him. This is done as a tool to build trust and confidence in the solution because that is something that is extremely important for us, at least to make sure that the operators feel heard and taken into consideration. Also, it is important to have meetings where we discuss what we are doing and what we should be doing in the future.”
>
> (R8)

Another issue that arises is the communication among departments. Traders have to understand new terms and effectively explain what they believe is the problem to AI developers so that they can take all the necessary steps to resolve potential problems. In comparison to other dark sides of AI trading, that minor problem could cause a lot of misunderstanding and confusion and cause a lot of discomfort to traders, who would feel unable to pass on their message effectively.

> “Whenever we talk to experts, we cannot just talk in terms of what a feature does in the model, what are the statistical errors, what models we are using etc. We need to use vocabulary that they understand.”
>
> (R7)

> "There are very different terms that traders use. They use classical training terms and I was not familiar with those terms. So it took me a while to get used to it…For them it was difficult too, because it was difficult to talk about machine learning terms with them because I could not explain to them properly."
>
> (R9)

Nevertheless, some traders resisted accepting AI outputs. Respondent 12 described as follows other traders' perceptions:

> "However, the fundamental models and the way that prices are actually formed might not support all traders' decisions. You have many traders focused on different areas. The importance of these things (i.e. what traders believe is important) might be, for them, very high, but for the actual price formation in the market, it might not be like that at all. So my impression is that they focus on this, ignoring the models, and they just try to justify their view."
>
> (R12)

Another effect is the way employees thought about AI. Especially in the beginning AI was perceived as a magical way of solving all kinds of problems.

> "They think AI is magical. They think that if we have some data, and use AI, it will magically solve the problem…Someone comes with an idea, and you have a conversation to find out what we can actually do."
>
> (R3)

> "I think people have an overly positive expectation that AI will always come up with profitable technical trading strategies."
>
> (R12)

As noted above, respondent twelve had been part of another company who were making their trade manually, at least in the past. Traders there were quite skeptical and there was a lot of conflict among employees, who were open to the idea of involving new technologies in their work. That was the case when some traders adopted some forecasting models for energy consumption, which triggered a lot of conflict. This behaviour may be a product of how the traders feel about themselves in terms of competence and their understanding of quantitative systems.

> "Sometimes when the market was volatile, it went against us. Everyone else was telling us that you should not believe the algorithms now. And they were telling us this all the time…do they feel safe? Well, it depends on their competence, regarding quantitative systems, what underlies these systems etc."
>
> (R12)

In some cases, the traders felt that they had to take extreme actions to either prove their quality as a trader or make a vast amount of money based on their trade decisions. Their personal income is affected by the amount of money they make every year, and a huge bonus may be earned based on that. Hence, it makes sense for them to take huge risks even if that could lead to losing their job, as the money they could earn is more than enough to make the risk worthwhile, if not desirable.

> "We would like to take high risk. That means one out of five years, we will lose all our money but that is ok."
>
> (R12)

Conflicts might arise among traders and managers too. Managers need results and a system that is robust and reliable. An automated system can be robust and reliable since it performs with the same quality and speed daily. However, traders do not want to see all parts of their work being automated since they will lose the most important and interesting part of their job, which is trading assets.

> "As a manager of course I would prefer that we are using AI for the most part. But of course, since you are trading with physical assets, we need to ensure that AI is making the right trades."
>
> (R3)

What is more, consumption might be affected based on energy prices. For example, companies might choose to sell overseas instead of in the local market because the energy price was higher in these countries. Hence, short-term profitability can shape the nature of consumption, supply and demand, as energy companies can not generate an infinite amount of energy. Some evidence can be found in countries like Germany, where Nordic companies decided to sell their energy to Germany due to the fact that prices were higher there.

> "A trader might be very interested in how the German prices are related to the Nordic prices because if the German energy price is very high compared to the Nordics, then it is a sign that the Nordics can export power because energy consumption is always flowing the direction of the price in the power market… and you have all of these market manipulation rules that you have to follow, so if you have an AI placing orders, then you need to be very careful that the way AI is placing orders is not manipulating the prices and hence the consumption."
>
> (R12)

It is worth noting that the firm has moved the decision-making mostly to AI to minimize high risk decisions and in order to be more robust and persistent in decision making. Nevertheless, the managers understood that setting up an AI team and developing AI products is not enough because it is equally challenging to adopt AI in the trade department, without losing the confidence and loyalty of the employees. Another crucial side of AI in trading is the false expectations that the employees develop. It is common to ask for features and capabilities that are not realistic. Traders might ask for a magical solution that will solve huge problems using some data. At the same time, developers should remember that overwhelming traders with information is not ideal, because it could cause discomfort using AI as a trader.

## 5. Discussion

This study explores the dark side of AI trading and how it affects the employees. Specifically, we gathered data from interviews and organized our observations into three themes: (1) the nature of work, where we investigate how it affects the traders in their work, (2) responsibility, where we investigate who is considered to be responsible for AI decisions and (3) conflicts and effects, where we investigate which conflicts arise between AI developers and traders or the social effects that might occur. The purpose is to underline the dark sides of AI and what the consequences are that underpin them. To be more specific, we found that traders had to go through a process of evolving and adding different values to the business through their expertise. Notably, traders express significant fear of being replaced by AI technology, particularly as it assumes a prominent role in their vital trading functions. Furthermore, responsibility plays a huge role as someone should be accountable for AI decisions and explainability tools should be implemented as they will add a safety net for decision-makers. It is equally important to understand that there might be social effects, such as shaping clients' energy consumption behaviours.

The ability to obtain large amounts of high-quality data and manage that data effectively is crucial for AI. However, it can be challenging to extract worth from B2B data. B2B firms frequently lose out on actionable insights due to the absence of meaningful data and the fact that the data that is acquired is frequently irrelevant and poorly handled, which can result in the development of unsuccessful business strategies (Chatterjee et al., 2021). In order to effectively apply AI in B2B, it is crucial to address the issue of data orchestration, meaning acquiring, cleaning, matching, enriching, and making data accessible across technology systems (Sun, Hall, & Cegielski, 2020). When B2B firms lack the necessary data, they may be able to solve their problem by using insight from AI. Other drawbacks, albeit less pervasive, should be considered. For instance, customers may have increasing demands, such as the desire for customization and competitive pricing, which can extend the purchasing process for businesses. Additionally, a lot of businesses are continuously investing in AI to stay competitive in the market (Chen, Jiang, Jia, & Liu, 2022). Although many firms embrace the AI path, employing AI to drive B2B sales is still in its infancy and has not yet had a big impact, similarly to our case.

A few studies have looked into how AI may affect B2B sales management. AI that predicts future events based on recent data has the potential to automatically add underlying prejudices, which may encourage unfairness. With the demand for enhanced client experiences reaching unprecedented levels, a rise in operational efficiency, and a more intense competitive landscape, it is only logical for B2B vendors to pursue AI technologies. However, any AI system has to provide benefits that outweigh the cost of handling data and assembling a specialized team (Rahman, Hossain, & Fattah, 2021). If not, you work for AI; not AI for you. Using AI may be challenging in a variety of ways. Firms should make sure that they have a solid use case for the project and the necessary funding. Consider alternatives such as automated workflows. For the reasons stated above, B2B firms need to carefully evaluate how to handle and resolve any ethical quandaries that may arise while implementing AI-based B2B marketing solutions.

Lastly, B2B success can be hampered by a number of factors, including leadership and lack of organizational readiness. In our case study this was not the case but it might be true for other firms who do not have the proper organizational structure (Di Vaio, Hassan, & Alavoine, 2022). While some of these obstacles are clear, others that typically obstruct achievement are more difficult to identify. B2B sales may be substantially more complex since there are more moving parts, more decision makers, longer sales cycles with more touch points, and more potential for mistakes. B2B enterprises usually thrive on long-term relationships, which means that it can be difficult for smaller B2B firms to establish a name and clientele among individuals accustomed to doing business with certain suppliers without using an advanced AI system that would probably be very costly to have. Table 3 summarises the current state and contribution of this paper.

**Table 3**
Summary of current state and contribution of this study.

| Current B2B state | Paper contribution |
|---|---|
| Researchers explored the drawbacks of AI and sought to address them by incorporating AI into BA capabilities. They specifically focused on data management, governance, and training resources to effectively tackle these concerns (Akter et al., 2021; Li et al., 2023). | This study examined employee adaptation in B2B departments and their changing perceptions and goals. Our study delved into the dynamics between traders and AI developers influenced by AI, exploring how AI traders adjust in this context. |
| The need for more comprehensive studies on the influence of data, system quality, and end-user training on competitiveness, both directly and indirectly, in the context of utilizing AI-BA capabilities has been investigated (Rana et al., 2021). | This study provides insights into managers' actions, traders' reactions, and the dynamics between AI developers and traders. Managers implemented new procedures and policies to address concerns and maximize profits, including a cultural shift towards AI adoption and providing AI training. |
| Addressing accountability problems related to algorithmic misbehaviour, numerous ethical and legal concerns arise (Boyd & Wilson, 2017) | This study shows how models often failed to learn from new data despite having access to abundant data, which can be attributed to the specific nature of the intended prediction. Moreover, establishing a proper organizational structure is crucial for successful AI adoption in B2B firms, enabling seamless integration and utilization of AI technologies. In the B2B context, obtaining large volumes of high-quality data and effectively managing it are essential for AI implementation. However, extracting valuable insights from data remains a challenge for many B2B firms due to data relevance and management issues. |
| Determining true responsibility and allocating accountability for decisions made either solely by AI or in collaboration with a human agent poses a significant challenge (Mikalef et al., 2022). | Traders, although no longer directly involved, were still relied upon as domain experts, raising concerns about responsibility and accountability. The company prioritized the use of explainable AI over higher-margin options that carried potential unknown risks. Additionally, compliance was emphasized in areas where government regulations were not explicitly mandated. |
| The reduction of relationship bonds can result in unfavorable outcomes for B2B interactions (Gligor et al., 2021). | This study demonstrated the socio-economic effects. The company's actions influenced clients' behaviour regarding energy consumption, as energy prices varied based on the time of day. |

### 5.1. Research implications

There are two distinct categories in which AI dark side effects can be classified. The first category encompasses harm inflicted upon the organization itself, while the second category pertains to harm inflicted upon others (Linstead et al., 2014). Our study highlights that many organizational aspects of a firm may change, including procedures that did not exist before, such as monitoring AI decisions. Investigating how to mobilize human capital will be vital for firms that do not want to damage their public image due to firing employees. Nevertheless, managers should deal with this internal issue and find a solution that is satisfying for traders since the most important part of their job is taken by AI. Equally important for research are other dark sides of AI in trading, such as negative implications on the individual (harm done to others) or the social level (Ibáñez & Olmeda, 2021). For example, AI fear, deskilling, and unemployment are concerning aspects that firms should not underestimate. Therefore, it is stated that, although adopting AI is vital, establishing the necessary procedures and mechanisms for building and aligning AI applications with business objectives is also critical (Bag et al., 2021; Saura et al., 2021). One of the most difficult parts of AI is that it is a technology that requires ongoing modification and change as new data and conditions emerge. As a result, there is a fleetingness that emphasizes recognizing the negative elements of AI in trading in order to ensure that the business continues to function as intended and that all organizational changes are in accordance with the firm's goals. In addition, firms should take into consideration the dark sides of AI in trading when planning, designing and building AI strategies and products, as AI can add value co-creation but co-destruction too, in aspects that range from job loss to privacy concerns, machine ethics, security issues and negative developments of superintelligence (Petrescu, Krishen, Kachen, & Gironda, 2022). Therefore, it is vital for organizations to effectively govern AI in a sense that promotes business goals, since AI governance should close the gap that exists between accountability and ethics in technological advancement (Papagiannidis, Enholm, Dremel, Mikalef, & Krogstie, 2022). For example, the difficulties encountered throughout the AI deployment process are obvious at various stages and influence diverse job duties, meaning that when it comes to difficult management tasks, AI solutions may give a selection of responses, as well as the likelihood of each of these choices (Papagiannidis et al., 2022).

### 5.2. Research agenda

There have been few studies examining the interpretation and prediction of behaviour in B2B contexts and the use of AI to govern organizational workflow, including employee and corporate procedures. For instance, Kushwaha, Kumar, and Kar (2021) developed a model that examined customer experience and trust, shedding light on their influence on the overall reputation of systems and brands. However, they did not specifically address the direct effects of AI in a B2B context, leaving an avenue for future research in that particular domain. While Davenport et al. (2020) discussed the broader impact of AI in the future, their exploration did not delve into the specific implications of AI in B2B environments. Their findings serve as a foundation for further research in this specific field. Similarly, Farrokhi et al. (2020) devised an AI model for anomaly detection aimed at averting external crisis events that could harm a firm's reputation. However, their study did not provide insights into the establishment of a centralized AI system tailored specifically for B2B environments, thereby leaving room for further investigation. In an similar direction, Grewal, Guha, Satornino, and Schweiger (2021) explored both the positive and negative aspects of AI in B2B and B2C contexts, with a predominant focus on the positive impacts on B2C firms. While they did address concerns regarding the black box nature of AI and potential opportunistic behaviour, further research is necessary to examine the social-economic effects of AI in B2B settings. Furthermore, Graef, Klier, Kluge, and Zolitschka (2021) discussed the concept of human-machine collaboration, emphasizing the significance of a feedback-based approach to provide accurate and reliable solutions. However, they did not delve into the specific practices required for the successful adoption of AI in such collaborative scenarios. Troisi, Maione, Grimaldi, and Loia (2020) emphasized the need for a framework that transforms data into actionable knowledge, fostering continuous learning, creativity, and improvement. They introduced the concept of a hacking mindset to achieve marketing objectives in B2B. Expanding their work to include practical implementation strategies and investigating AI-driven analytics could enhance their proposed framework. While Rai (2020) explored the concept of interpretable models and the conversion of black-box models to glass-box models, their overview was broad and did not focus on specific sectors like B2B. Additionally, they did not delve into critical decision-making processes in depth.

We propose a variety of ways in which researchers could investigate the dark side effects of AI in a B2B context for the future research agenda. Research could be directed towards the positive and negative effects of AI in business-to-business and the consequences that AI could have on a company's reputation and market positioning. Consequently, it is necessary to fully understand which effects AI might cause and how to deal with them, as well as the dark side effects of AI not only in a business but also in society as a whole. It is important to note that having an AI system does not guarantee success. To understand and utilize an AI product, a firm must incorporate an AI system into its culture and educate its employees, because vulnerabilities usually appear with the introduction of new technologies and AI systems are no exception to this rule. An AI hack can cause great financial loss to a B2B firm as a B2B firm usually has a limited number of clients, and losing one could be devastating. Furthermore, understanding and trusting your AI system is crucial for B2B, and there are a few technologies designed with B2B in mind that support bias removal and transparency. As a final note, it is equally important to investigate the ways to centralize a B2B ecosystem around AI, because B2B environments are very different from B2C ones. Table 4 provides a summary of the research questions that we propose to the readers, as well as references for further investigation and guidance.

**Table 4**
Future research agenda.

| Themes | Research question | References for guidance |
|---|---|---|
| Nature of work | In which ways does AI affect B2B reputation and how should AI anxiety be addressed? | (Kushwaha et al., 2021) |
| | In a B2B environment, how does AI impact employee expectations of AI? | (Davenport et al., 2020) |
| | How should AI be adopted and used in a B2B culture? | (Keegan, Dennehy, & Naudé, 2022) |
| | How can an AI system be properly centralized in a B2B environment in order to detect anomalies in AI decisions? | (Farrokhi et al., 2020) |
| Conflicts and effects | What are the dark side social and economic effects on society due to the use of AI in B2B? | (Grewal et al., 2021) |
| | What are the best ways to mitigate conflicts when adapting a human-machine AI collaboration, and what practices should be created? | (Graef et al., 2021) |
| Responsibility | How is it feasible to secure a B2B AI system from its data and model outputs being hacked? | (Troisi et al., 2020) |
| | How can AI transparency tools be developed for a B2B firm while mitigating fatal AI model mistakes? | (Rai, 2020) |

### 5.3. Practical implications

Regarding the practical implications, AI developers should not overlook the importance of explainability tools for addressing AI decisions. This is crucial as it allows the accountable employees, in this case, the traders, to acquire a better sense of accountability and feel safer when using AI for decision making (Paschen et al., 2019). In this way, managers can ensure safety for their employees and the processes or mechanisms they introduce and against legal regulations that might demand an explanation of how decisions are taken. What is more, firms need appropriate infrastructure to centralize their advanced systems (Al-Surmi, Bashiri, & Koliousis, 2022). AI, in particular, should be founded and developed to decrease inequality and promote social empowerment while preserving individual autonomy and enhancing advantages that are shared equitably by all (Puntoni, Reczek, Giesler, & Botti, 2021). AI must be explainable since it is a major tool for establishing public trust and understanding of the technology (Keegan, Dennehy, & Naudé, 2022). By doing this, monitoring AI is much easier, and it allows for reallocating employees from the position that AI takes over; thus, employees do not lose their jobs. Lastly, firms should develop tools for testing AI decisions to identify new patterns that would lead to a deeper understanding of data and information (Davenport et al., 2020). By doing so, employees would come up with new ideas that may lead to new strategies and tactics boosting productivity and innovation. Backtesting is common when traders want to test a theory using various hypotheses. Therefore, managers may prioritize such processes, allowing their traders to be more enlightened about their data and how they can be in the loop of actively improving AI trading bots through their expertise (Mikalef, Conboy, & Krogstie, 2021); thus, traders can contribute by innovating ideas that will potentially boost the competence of the algorithms and as a result the competence of the company.

### 5.4. Limitations and future research

This paper has looked into the negative aspects of AI in trading. A few limitations exist to this study. Firstly, the information was gathered through interviews with only one organization; as a result, our data may be biased or offer an inadequate picture of the problems surrounding relevant procedures. Secondly, while we performed multiple interviews with important individuals inside the organization, our data was gathered at a specific point in time and may not accurately reflect the full range of activities. Lastly, the company had used AI for only five years and in general had a positive experience due to the slow, steady and careful development of AI to prevent risks; therefore, the results may be affected by that factor. As a result, generalization may be a problem that should be considered. A future study might acquire additional empirical data through interviews and postulate the concept of the dark sides of AI in trading from a positivist viewpoint, which could be evaluated with empirical evidence on the antecedents and consequences. It would be useful for the field to understand how companies reallocate human resources to meet organizational goals and how they regulate AI resources to improve performance while keeping in mind the negative consequences for workers.

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## Data availability

The data that has been used is confidential.

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