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Disclosures about algorithmic decision making in the corporate reports of Western European companies

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ABSTRACT

Over the last decade, the use of different artificial intelligence (AI) tools has increased. To shed some light on the emerging trend of AI disclosure, the aim of this paper is to analyse the current practices of major Western European companies regarding the automated decision-making (ADM) disclosure in their annual or sustainability reports. This paper proposes a methodology based on bigrams that enables the automatic extraction of the information on ADM that companies disclose. The sample consisted of 962 annual/sustainability reports, published in 2018 and 2019, of 337 companies listed on 13 Western European countries' stock markets. Our findings show that ADM disclosure is still at an early stage and that the first adopters are mostly companies operating in the financial sector.

1. Introduction

Over the last two decades, organizations all around the world have initiated and evolved non-financial disclosure to complete their financial statements with the aim of shedding more light on the general impacts of their activities. Immense stakeholder pressure has pushed companies to be more transparent about their environmental, social and governance performance due to possible negative impacts on the environment and society. This has further led to the development of quite generally accepted non-financial reporting standards, such as the Global Reporting Initiative (GRI), EMAS, ISO 26000, SA 80,000 and so on, which provide guidance for companies on how to report their non-financial performance together with their key performance indicators (KPIs). Alongside these standards, legislation has been put in place in some countries as environmental, social and governance issues might imply certain threats to the society as a whole.

Over the last decade, the use of different artificial intelligence (AI) tools has increased. Companies and organizations from different industries have been seeking to develop and apply AI in their processes to improve their efficiency, reduce costs or personalize products and services. Nevertheless, the rapid evolution of new technologies has also raised certain concerns regarding human rights, data security, privacy or ethical issues. In particular, disruptive artificial intelligence tools with a high level of automation, massive data

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collection and manipulation and possible inherent biases are reasons for the wider society to worry.

Algorithms of all kinds have been and are continuously being created. Evidence exists for biased algorithms and their impact on individuals and society. Thus, the rapid proliferation of AI-empowered tools in our daily lives in recent years has caused legitimate worries in society, which advocates the ethical and responsible development and implementation of such tools. Thus, there is an urgent call for more transparency in this matter. Therefore, our study aims to shed some light on companies' disclosure practices related to AI.

Special attention should be paid to highly autonomous AI tools – algorithmic decision systems (ADS), also known as algorithmic decision making (ADM), which are based on the analysis of large amounts of data to infer correlations or to derive information to make decisions. Such applications imply, per se, potential practical and ethical concerns as the decision making is left to machines.

The use of ADM systems is increasing in EU countries (AlgorithmWatch, 2019), which implies that humans will be less and less involved in decision-making processes (Hoofnagle et al., 2019). Companies incorporating ADM into their day-to-day activities and operating in the EU market should comply with the EU regulations related to the use of AI, in particular Article 22(2)(b) of the GDPR, which addresses the case of automated decision making, providing specific exemptions and relevant safeguards (Malgieri, 2019). The GDPR subjects ADM to new transparency, ethics and accuracy requirements; however, it makes a clear policy preference for human-in-the-loop systems (Hoofnagle et al., 2019).

As these technologies continue to evolve rapidly, an increasing number of new as well as established companies are using them to build applications that reliably perform activities that were previously undertaken by humans. Therefore, it is just a natural evolution that stakeholders are now putting pressure on companies to be more transparent about the use of artificial intelligence, in particular different aspects of ADM as a part of non-financial disclosure. Indeed, some companies have already started to respond to this request by voluntarily disclosing such information in their annual or non-financial report. However, the fact that this is quite a novelty implies a lack of standardization in such a disclosure. To standardize the way of reporting on AI applications, first, a consensus has to be achieved on what and how to report and which key elements should be disclosed to satisfy the information needs of different stakeholders.

To shed some light on the emerging trend of AI disclosure, the aim of this paper is to analyse the current practices of major Western European companies regarding the automated decision-making (ADM) disclosure in their annual or sustainability reports. This paper proposes a methodology based on bigrams that enables the automatic extraction of the information on ADM that companies disclose. The sample consisted of the annual/sustainability reports of companies listed on the stock markets of 13 Western European countries from both 2018 and 2019. A total of 962 PDF documents were downloaded from companies' websites. Our findings show that only a small number of companies reported on ADM in their non-financial or annual reports. The early adopters of this new form of non-financial disclosure are mostly companies operating in the financial sector.

2. Literature background

2.1. Previous studies

Sutton et al. (2016) analysed the artificial intelligence research in accounting over the past 30 years, pointing out that the application of AI techniques by businesses continues to be robust, and call for more research on AI in accounting domains.

The first studies focusing on the scope of information technologies' responsibility date to the early 1990s, when ethics in the information age started to be discussed (Mason, 1986; Moor, 1985). Ethics in emerging IT was the main object of a number of studies in the following years as well (Brey, 2012; Bynum, 2001; Chatterjee et al., 2015; Floridi, 2010; Sarathy and Robertson, 2003).

Due to the rapid evolution of IT and the use of artificial intelligence in business and public administration, serious concerns arose regarding AI ethics, which was the main topic investigated by several authors (Angwin et al., 2016; Bonsón et al., 2021a; Cath, 2018; Cheng, 2020; Fjeld et al., 2020; Floridi, 2019; Greene et al., 2019; Hagendorff, 2020; Hickok, 2021; Jobin et al., 2019; Robbins, 2019; Vidgen et al., 2020). Alongside the fast development of new IT tools and the penetration of AI, a number of studies focused on privacy concerns and data protection (Ashworth and Free, 2006; Beke et al., 2018; Culnan and Bies, 2003; Kehr et al., 2015; Yigitbasioglu, 2015).

The concept of corporate digital responsibility (CDR) started to appear in the literature very recently, and a few studies related to this topic have been published. However, the scope of those studies is rather narrow. Liyanaarachchi et al. (2020) explored the CDR related to data management in the banking sector. Isensee et al. (2020) studied the relationship between organizational structure, sustainability and digitalization in SMEs. The first study with a wider CDR scope was the one Lobschat et al. (2021), who introduced a framework of CDR culture. While several professionals have discussed the concept of CDR and there is an increased awareness of this topic, in the academic literature, there is still a lack of conceptualization and no previous studies on CDR disclosure.

2.2. Corporate digital responsibility (CDR)

Lobschat et al. (2021) made a parallel between human behaviour and its compliance with certain ethical norms and digital technology, arguing that the development of new technology that assists in human decision making or makes decisions autonomously should be governed by the same rules. With this argument, they pointed out that the usage of new technologies is not solely a technological challenge but implies certain responsibilities, which we can refer to as corporate digital responsibility (CDR). The Institute of Consumer Policy defined CDR as: "companies' responsibility for the consequences of their business processes, products and services for employees, suppliers, customers, society as a whole and the environment encompassing: 1) data and algorithmic decision making, 2) participation and reduction of inequality, 3) digital education, 4) future of work, and 5) digitalization in service of an ecologic transformation" (Conpolicy, 2021).

Lobschat et al. (2021) introduced a comprehensive framework of CDR culture. According to them, in compliance with CDR, organizations should demonstrate how responsibly they operate in the digital age. In their conceptualization of CDR, they focused on ethical aspects that are inherent to the digital context while also drawing links between corporate social responsibility (CSR) and CDR.

2.2.1. Conceptualization of CDR: a new layer of CSR?

Indeed, CDR shares some principles with CSR, which covers economic, legal and ethical concerns related to environmental and social issues (Schwartz and Carroll, 2003). Nevertheless, Lobschat et al. (2021) considered CDR to be slightly separated from CSR due to its particularities related to digital technologies, such as the moral challenges related to the malleability (often unintended) of digital technologies (Soltani, 2019) and the high level of proliferation of digital technologies in our daily lives.

Other studies (Deloitte, 2019; Gärtner and Heinrich, 2018; PWC, 2020) have considered CDR to be a new layer of CSR. The empirical evidence obtained in this study confirms this approach as we observed that early adopters of CDR disclosure provide this information in their CSR reports. Thus, organizations perceive CDR as a complementary aspect of CSR. Similarly, Pauer, an expert in CDR and digital ethics at PWC (2020), argued that the CDR approach and sustainability go hand in hand and pointed out the importance of boosting stakeholders' trust in digitalization. Nicolai Andersen, chief innovation officer at Deloitte (2019), talked about redesigning corporate responsibility by extending its scope to CDR.

Over the last decades, organizations have managed their responsibility to the environment and society at large through CSR. Nevertheless, the digital revolution has brought new responsibilities, which should be treated with the highest strategic priority (Deloitte, 2019). Gärtner and Heinrich (2018) pointed out the immense impact of digitalization due to the exponential advancement of technology. He argued that, as digitalization redefines almost all aspects of our lives, such as the economy, society and even our values and beliefs, it is of the utmost importance to adjust the way in which organizations approach their responsibility.

2.3. Theoretical background

As CDR can be considered a new layer of CSR (Deloitte, 2019; Gärtner and Heinrich, 2018; PWC, 2020) and the empirical evidence confirms that early adopters of CDR disclosure provide this information in their CSR reports, the question arises what drivers of such approach are. By other words, how the motivation of organizations to voluntarily disclose information about AI systems in general, or ADM in particular, could be explained.

While AI might have a pivotal role in future sustainable development, it also has some social and ethical implications for companies and their stakeholders. Previous studies on corporate disclosure frequently use Voluntary Disclosure Theory (VDT); Signalling Theory (ST); and Legitimacy Theory (LT) to explain voluntary non-financial reporting (Dye, 2001). VDT and ST are economic-based theories (Lu and Wang, 2021). Thus, the center of their attention is mainly the financial community such as potential investors and company's shareholders. LT is considered a socio-political theory focusing on the dialogue between the organization and the society (Gray et al., 1995). This multi-theoretical approach has been applied on this study as the combination of these three theories might help provide a comprehensive interpretation of voluntary AI disclosure.

2.3.1. Economic-based theories

According to Dye (2001), VDT has its roots in the game theory and implies that companies voluntary disclose mainly favorable information and avoid disclosing unfavorable facts. Although this theory has been initially applied to financial information, recently, it has been expanded to non-financial disclosure too as both financial and non-financial information is used by analysts to gain a reliable picture of companies' performance and annual and sustainability reports are the main tools for the decision-making process of investors and other agents in the financial market (Araújo Júnior et al., 2014; Zhou et al., 2017). Hence, according to VDT, the main objective is to overcome a minimum mandatory level of disclosure to reduce the information asymmetry. Nevertheless, the tendency is to highlight favorable information to obtain positive effects in terms of economic impact and to appeal to investors. A connection between VDT and AI disclosure has been introduced by Bonsón et al. (2021). Indeed, VDT seems to provide interesting insights regarding the interpretation of AI voluntary disclosure. According to this theory, companies are motivated to disclose positive information about the development, application and use of AI in general, or ADM in particular, as this disclosure can help investors to gain a clearer picture in terms of company's investments in smart technologies and digitalization.

Another economic-based theory used in this study is ST, whose main concept is reducing information asymmetry between organization (signaller) and outsiders/stakeholders (receivers) (Connelly et al., 2010; Cotter et al., 2011; Spence, 2002). Although initially the receivers were mainly investors and shareholders, nowadays, the concept of receivers has been expanded to all stakeholder groups (An et al., 2011; Connelly et al., 2010; Lu and Wang, 2021). Regarding the signal, a tool by which the information asymmetry is being reduced, previous studies point out three main categories of signals: intent, camouflage, and need (Albertini, 2019; Connelly et al., 2010). Intent signals relate to a signaller's future strategies. This signal is being used to indicate company's future actions with the aim to attract the investors' attention. Camouflage signals are messages (information) designed to divert receiver's attention away from company's potential weaknesses. Need signals are used to appeal to investors to affect their resource allocation decisions.

According to Lu and Wang (2021), following the ST, companies try to highlight their positive aspects which are hidden to external subjects and by increasing transparency to reduce the information asymmetry between the company and its stakeholders. Thus, signalling should lead stakeholders to reassess the company's value and make decisions that would have positive impact on the company (An et al., 2011).

In compliance with ST, companies want to inform about unobservable company's characteristics such as increased efficiency, value creation, or sustainability related to AI applications. They also want to signal excellence over competitors in terms of R&D in new technologies and digitalization to attract potential investors. Regarding appealing to other stakeholders, by being more transparent and shedding some light on it, they also aim to increase the trustworthiness of their products and processes.

2.3.2. Socio-political theory

Some experts point out that CDR approach and sustainability go hand in hand with the aim to boost stakeholders' trust in digitalization (PWC, 2020). As several studies suggest that legitimacy theory may provide a satisfactory explanation of voluntary non-financial reporting in general (Bonsón and Bednárová, 2013; Branco and Rodrigues, 2006; Campbell et al., 2003; Deegan et al., 2002; Ellerup Nielsen and Thomsen, 2018; Gray et al., 1995; Hahn and Kühnen, 2013; Solikhah, 2017); considering the parallel between the two, legitimacy theory seems to offer a reasonable explanation for voluntary AI or ADM disclosure (Bonsón et al., 2021a).

Suchman (1995) defines corporate legitimacy as a general assumption that the actions of a company are in compliance with norms, values and beliefs of a society. Legitimacy theory suggests that an organization has to gain the acceptance granted by a society to be able to conduct the business successfully (Deegan et al., 2002). Therefore, the company has to legitimate their practices and prove that they are in compliance with stakeholders‘ expectations. Companies adopt different strategies to legitimate their activities, transparency being one of them. According to Bonsón and Bednárová (2013), organizations can gain social approval for their actions by engaging in higher transparency. Nevertheless, to obtain legitimacy, companies have to continuously adjust their disclosure practices regarding the issues that matter to a society in a particular moment of time and through the increased transparency and communication prove that their actions are socially acceptable.

In terms of AI or ADM disclosure, this could mean that information about AI projects; AI systems applied; algorithms used or ADM incorporated into decision making is communicated to satisfy the current information needs of different stakeholders in order to gain their trust (Osburg, 2017; Thorun, 2018). This way a company can align corporate behaviour with stakeholders‘ expectations, gain their acceptance and obtain legitimation. Over the years, a number of factors were used to test legitimacy theory (Bonsón and Bednárová, 2015) and many studies pointed out the sector as one of the most important explanatory factors (Amran and Devi, 2008; Gray et al., 1995; Ratanajongkol et al., 2006). Hoffman and Ross (1999) states that sector creates some kind of institutional context in which companies benchmark each other in order to gain social acceptance. Thus, some sectors might be more sensitive in terms of consumers‘ trust in corporate digital practices than others. Hence, such companies might feel obliged (forced by stakeholders‘ pressure) to report more on AI systems incorporated into a company‘s processes.

2.4. Algorithmic (automated) decision making (ADM)

The first definitions related to what we today call automated decision making systems (ADM systems) have their origins in the late 1950s or early 1960s (Power et al., 2019). One of the first attempts to conceptualize ADMs was when Cyert and March (1963) developed a computer model for business decision-making in a firm, concluding that it had a good predictive power, referring to it as a decision system. A decision system can be defined as a set of interacting people, methods, procedures, programs, and routines for making decisions or supporting decision processes (Power et al., 2019).

Power et al. (2019) point out that the study of decision systems as organizational phenomena has been diverse and different synonyms have been used over the years. Their study provides a comprehensive summary of research and definitions related to decision systems over the last 60 years.

Simon (1960), as well as Gorry and Scott-Morton (1971), distinguish two subtypes of computerized decision systems, including (1) automated decision systems, and (2) decision support systems. In Gerrity (1970), used the term "man–machine decision system" (MMDS), which he defined as the interaction of three main components: man, machine and a decision task. More recently, synonyms such as decision automation system (DAS) and automated decision system (ADS), as well as automated decision making (ADM) systems, have appeared in the literature.

Costa (2021) describes ADM systems as systems that sense online data, apply algorithmic logic, and make decisions – all with minimal amounts of human intervention, which can help companies reduce labour costs, leverage scarce expertise, improve quality, enforce policies and respond to customers. From the legal point of view, Sangdon (2017) defines ADM as the general ability to make decisions based on the generated profiles without human actors, which entails the use of personal data, and he points out the importance of personal data protection.

ADMs can be applied in different sectors including, but not limited to, the public sector (Cobbe and Singh, 2020; Suksi, 2020), manufacturing (Grishina, 2012), education (Mougiakou et al., 2018), healthcare (Harris and Davenport, 2005) telecommunications (Seufert et al., 2016), retail and financial services (Power et al., 2019), etc., and they might have a wide array of areas of applications, from automated pricing decisions and loan approvals (Power et al., 2019), to automated driving (Gerwien et al., 2021).

As automating decisions becomes more feasible, organizations should consider different aspects (organizational, technological, and legal) when considering which decisions should be made by people and which can be computerized.

Cobbe and Singh (2020) point out the importance of reviewability as an approach to improving the accountability of ADM that involves machine learning systems. They argue that it is important to break down the ADM process into its technical and human (organizational) components to gain a complete understanding of a whole process and allow for its review.

Thus, being able to fully understand and review the process and algorithmic logic of a particular ADM, transparency from the company's side is necessary. Therefore, our study aims to investigate the extent to which companies using ADM disclose it.

In a summary, Algorithmic decision systems (ADSs), also known as algorithmic decision making (ADM), are based on the analysis of large amounts of data to infer correlations or to derive information to make decisions. Humans are error prone and biased, but systems can be biased too, so it is important to know who built them, how they were developed and how they are ultimately used. To avoid bias in the algorithm, it should be fed with a representative data set, the right model should be chosen and the algorithm should be continuously reviewed and monitored. Therefore, transparency regarding these aspects might not only increase the trust in ADM but also serve as proof of a company's commitment to corporate digital responsibility (CDR).

ADM processes are fed with data that might be biased. If there is a bias in the data that the ADM is trained with, this bias would be reinforced and amplified, which would ultimately lead to unfair or discriminatory decisions.

Thus, the results yielded by ADM can be discriminatory without decision makers being motivated to discriminate. For example, there might be some variables, such as gender or race, that normally cannot be taken into consideration when making a decision but are often statistically associated with seemingly inoffensive characteristics, such as height or postal code. As ADM works with huge sets of correlated data, it can lead to indirect discrimination. Therefore, individuals should have some basic rights, such as transparency, when a biased decision has been made based on ADM.

2.5. Research questions

CDR seems to be a new layer of CSR. This implies changes in corporate disclosure in the coming years. Early adopters of CDR reporting, normally large corporations, under pressure from stakeholders, might start to realize the importance of their digital responsibility and try to legitimate their digital practices via voluntary disclosure. Transparency in this matter increases the level of trust of society (Osburg, 2017) and of consumers (Thorun, 2018) in digitalization and offers a platform for companies to inform the wider public about how they leverage digital technology for the greater good in society (Shingles et al., 2016).

In our research, we focused on a particular aspect of CDR (data and algorithmic decision making); within this subcategory, we focused on ADM due to the high risk that the application of this technology implies, which therefore seems to be the most relevant to stakeholders. As there is still a lack of guidelines on how to report on CDR in general, the main aim of our study was to analyse the current ADM reporting practices of large Western European companies. To shed some light on the current practices, the following research questions were formulated:

RQ1. Are Western European companies disclosing information about the use of ADM in their annual/sustainability reports?
RQ2. What is the content of those disclosures?
RQ3. What are the factors associated with ADM disclosure?

3. Methods

3.1. Sample and methods

The sample consisted of the annual/sustainability reports of 337 companies listed on 13 Western European countries' stock markets in 2018 and 2019. A total of 962 PDF documents were downloaded from companies' websites (Table 1).

The reports were processed as shown in Fig. 1, which also displays a flowchart providing an overview of the text-mining operations conducted with the open-source R statistical advanced software (R Core Team, 2018), detailing every step and R package function used. The extraction of the text was performed through the "*extract_text()*" function of the "tabulizer" R package (Leeper, 2018), which converts the text of an entire PDF file or specified pages into a single character vector (1×1). This is necessary due to the small semantic structure of the PDF format. Once the text is extracted, it is separated independently into sentences with the functions already incorporated into R "*unlist()*" and "*strsplit()*". The "*strsplit()*" function splits the elements of a character vector into a substring list according to a parameter. This list must be converted into a vector through the "*unlist()*" function, which produces a vector that contains all the atomic components that occur in it. In this way, a vector (number of rows $\times$ 1) ready for analysis is extracted. Before the analysis with the dictionary, the symbols should be deleted, some words should be replaced and capital letters must be converted into

Table 1
Number of documents analysed from Western European countries.

Country	Index	2018	2019	Total
Austria	*ATX 20*	32	33	65
Belgium	*BEL 20*	22	23	45
Denmark	*OMXC 25*	45	46	91
Finland	*OMXH 25*	39	38	77
France	*CAC 40*	41	41	82
Germany	*DAX 30*	49	52	101
Greece	*FTSE 20*	23	22	45
Ireland	*ISEQ 20*	19	22	41
Italy	*invit40*	67	68	135
Netherlands	*AEX 25*	27	31	58
Portugal	*PSI 20*	23	23	46
Spain	*IBEX 35*	43	44	87
Sweden	*OMXS 30*	44	45	89
		474	488	962

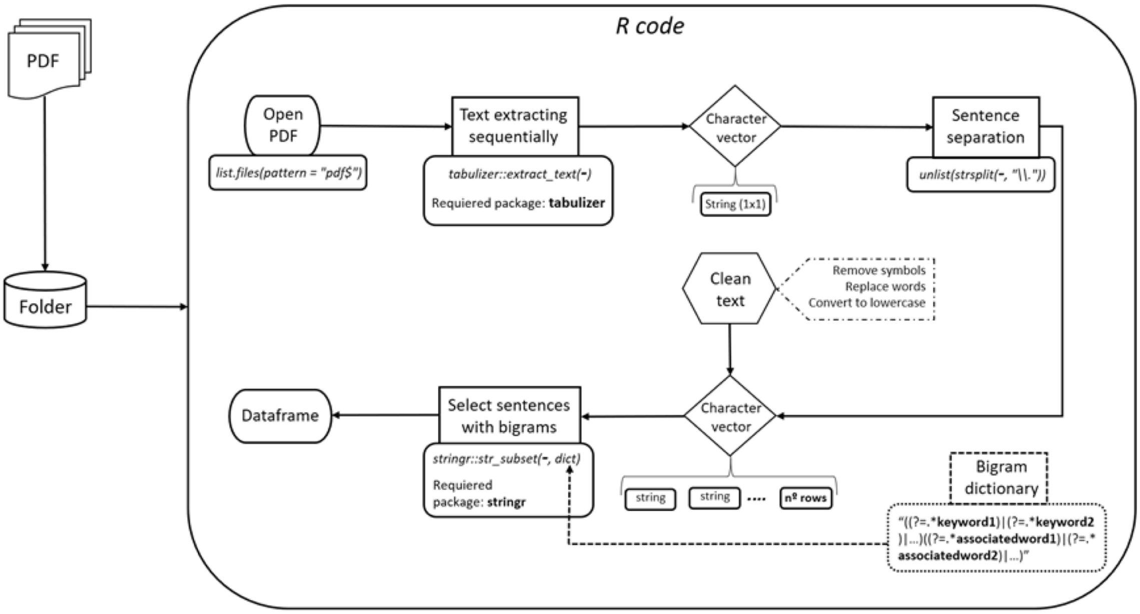

Fig. 1. Flowchart of PDF text mining.

lower case.

All the reports were later analysed automatically using the "*str_subset*" function of the "*stringr*" R package (Wickham, 2019), which keep strings matching a pattern. This pattern is a dictionary formed by a combination of two ngrams (bigrams), which are divided into keywords and associated words (Table 2). Based on this function, some of the words from each group must appear in the sentence together regardless of their order. The dictionary is an own creation, where the words that compose it were chosen after the reading of several reports. Once the dictionary is applied, the sentences are automatically extracted and must be filtered manually. Thus, each extracted sentence is read, and it is decided whether or not it is related to ADM. This approach combines automatic techniques for massive extraction and manual techniques for monitoring the precision of the extraction.

In addition to the keywords selected to be part of the dictionary, other potential keywords were raised during the pre-reading phase of several reports that when related to the associated word "decision" could identify ADM disclosures. The words that were proposed were: "models", "data science" or "classifier". However, after testing the analysis including those keywords, it turned out that sentences that actually disclosed the use of an ADM were not obtained. Those concepts are not strictly related to the ADM. The process extracted a lot of sentences with irrelevant and confusing information. That is why these keywords have been excluded from the dictionary that we have used in the extraction of sentences regarding ADM.

The analysed companies in our sample operate in 11 different sectors. Table 3 shows the distribution of companies by sector, and Table 4 provides details of the dependent and independent variables used in this study.

3.2. Variables

To try to answer RQ3, "What are the factors associated with ADM disclosure?" we used the following independent variables: the geographical area of the country where the company is listed, the sector in which the company operates, the company size and its sustainability leadership position. These variables were selected from the previous literature on companies' non-financial information disclosures (Baird and Zelin, 2000; Bonsón et al., 2021b; Clatworthy and Jones, 2003; Gao et al., 2016; Kohut and Segars, 1992). Therefore, we addressed classic elements of study in this matter.

3.2.1. Geographical area

The practice of disclosing different topics in business reports can vary from region to region as the different cultural and social

Table 2
Dictionary.

Keywords		Associated words	
algorithm	(s) (ic)	Decision	(s)
artificial intelligence			
automat	(ed) (able) (ability) (ic)		
machine learning			

Table 3
Distribution of companies by sector.

Energy	7.93 %
Materials	10.67 %
Industrial	18.60 %
Consumer discretionary	9.76 %
Consumer staples	6.10 %
Healthcare	7.93 %
Financial	20.73 %
Information technology	4.57 %
Communication services	5.79 %
Utilities	3.05 %
Real estate	4.88 %

Table 4
Variables' definition and measurement.

Variable	Full Name	Shortened Name	Description	Source
Dependent	DM report	ADM	Dummy variable (if the company has reported at least one relevant mention of ADM = 1; other = 0)	PDF mining as shown in Fig. 1
Independent	Geographical area	GeoArea	Dummy variable (northern country = 1; southern country = 0)	Country location
	Sector	Sect	Dummy variable (financial sector = 1; other = 0)	Global Industry Classification Standard (GICS)
	Company size	Size	Natural logarithm of the total assets of the company in 2019	Investing.com
	Sustainability leadership	SustaiLead	Dummy variable (leader in ESG ranking = 1; other = 0)	MSCI

considerations of a country are a driving factor that influences the presentation of reports (Golob and Bartlett, 2007). Both the characteristics and the cultural trends draw the role of companies (Welford, 2005). Organizations' strategies are strongly influenced by their institutional characteristics and by the legacy reflected by the culture of a specific country or region (Doh and Guay, 2006). In short, several authors have argued that the region or country of a company influences its social behaviour (Hassan et al., 2013; Mikkilä and Toppinen, 2008; Sotorrío and Sánchez, 2008; Thanetsunthorn, 2015). Welford (2005) presented data showing that, in general, there is a higher level of corporate social responsibility reporting in Northern Europe than in Southern Europe, perhaps suggesting a historical trend towards greater transparency in the north and links with the development of the economic system.

Based on economic forecasts for 2030, the impact of AI on the GDP varies between regions; in Europe, the impact will be greater in the south than in the north, 11.5 % and 9.9 %, respectively (PWC, 2017). Accordingly, for this study, we addressed the dissemination of ADM in two different geographical areas: the first includes countries in northwestern Europe, such as Belgium, Finland, Germany, Ireland, the Netherlands and Sweden, while the second contains several countries in southwestern Europe, like France, Greece, Italy, Portugal and Spain.

3.2.2. Sector

Another of the classic elements that are addressed in this kind of reporting is the company's sector. The literature has shown some consistent evidence of a significant relationship between industry and disclosure (Bonsón and Bednárová, 2013; Bonsón et al., 2021a,b; Brammer and Pavelin, 2006; Hahn and Kühnen, 2013; Hassan et al., 2013). The corporate disclosure strategies adopted by companies in a particular sector differ significantly from those in others (Aljifri, 2008; Cooke, 1992; Javaid Lone et al., 2016), with the companies operating in the financial sector those which disclose more non-financial information to demonstrate to their stakeholders that maximizing income is not their sole purpose (Giannarakis, 2014).

A recent report Eager et al. (2020) by the European Parliament revealed that some of the leading economic sectors in terms of AI adoption are financial services, automotive and assembly, and high-tech and telecommunications, but the industries that are leading the development of AI capabilities tend to focus more on developing capabilities in house, as is the case of high-tech or financial services.

In our study, we considered the eleven sectors defined by the Global Industry Classification Standard (GICS), which we segmented into two groups. The first group contains companies that operate in the financial and insurance service sectors. The second group consists of all the others.

3.2.3. Company size

Company size is commonly used as an important and fundamental company characteristic in empirical studies. Dang et al. (2018) showed that different proxies are used to measure company size, such as the number of employees or net assets, but the most popular measures in corporate finance are the total assets, total sales and market value of equity. Based on their research, of these three measures, we used the total assets as a measurement for two reasons: (1) it is the most used firm size proxy in papers, 56.23 % compared with the 22.99 % and 18.39 % of total sales and market capitalization, respectively; and (2) it seems to be a more relevant measure of investment policy (Comment and Schwert, 1995; Graham et al., 2012; Harford et al., 2008).

The interest in studying company size is that this element has a positive effect on the adoption, scope and quality of reports and is linked to corporate visibility (Bonsón et al., 2021a). Numerous studies (Bonsón and Bednárová, 2013; Bonsón and Flores, 2011; Brammer and Pavelin, 2006; Clarkson et al., 2011) have supported the idea that, in general, large companies are more likely to disclose more non-financial information and have a greater social impact since, for small companies, not being exposed to a huge number of stakeholders, the need to explain their business conduct and convey credible information is substantial.

In this context, ADM information disclosure can be considered to be more likely to occur in companies with more resources, considering that large companies must guarantee their legitimacy by pointing out their ADM efforts in their corporate reports. However, the original value of the total assets is not used – only 3 % of studies use it – since most studies in empirical corporate finance use the natural logarithm form of firm size measures to mitigate the substantial skewness of these data (Dang et al., 2018).

3.2.4. Sustainability leadership

Finally, another determinant that is considered to be important is sustainability performance. Numerous studies have found that companies with better results in sustainability tend to disclose more non-financial information (Dhaliwal et al., 2012; Hummel and Schlick, 2016; Ng and Rezaee, 2015; Rezaee and Tuo, 2017). In our study, we use the MSCI's environmental, social and corporate governance (ESG) ranking. In this way, we classify companies as leaders (rating = AAA–AA) or not (all other ratings and unrated companies).

Table 4 below summarizes the variables used in this study and their measurements.

To check the relationships between the variables, the generalized linear model (logit regression) was applied.

$$\{logit(ADM) = \beta 0 + \beta 1 GeoArea + \beta 2 Sect + \beta 3 Size + \beta 4 SustaiLead\}$$

4. Findings

4.1. RQ1. Are Western Europe companies disclosing information about the use of ADMs in their annual/sustainability reports?

After the content analysis of 962 documents, 33 mentions of ADM in companies' reports were identified. These mentions were associated with 22 companies, of which 18 operate in the financial sector. The mentions appeared in 28 documents. Out of 33 mentions, 21 came from the annual and other 12 from the sustainability reports. Regarding the years of publication, 18 mentions were extracted from the reports in 2018 and 15 in 2019. These ADM mentions are equivalent to only 3.85 % in relation to the total number of mentions of decision-making.

Thus, the answer to our RQ1 is that only a small number of Western European companies disclose information about the use of ADM in their annual/sustainability reports. These companies were from the financial or internet and telecommunications sectors.

As an additional finding, the relationship weight that each keyword in the dictionary had (Table 2) in reference to the ADM is presented. Table 5 shows the frequency of each keyword or group of them in the sentences about ADM. Out of 33 sentences in which the associated word "decision" appears, we have identified 51.52 % that appear exclusively with the keyword "algorithm". The next most frequent term was "artificial intelligence", which appears in 18.18 % of extracted sentences. The rest appear with more than one associated word. For example, 9.09 % appear either in the combination of "algorithm" and "artificial intelligence" or "algorithm" and "machine learning"; 6.06 % appear in the combination of "algorithm" and "automat". Finally, the combinations of three keywords appear in 3.03 %, with "algorithm", "automat" and "machine learning", or with "algorithm", "artificial intelligence" and "machine learning".

4.2. RQ2. What is the content of those disclosures?

To shed some light on the content of the disclosures, Tables 6 and 7 provide extracts from annual/sustainability reports related to ADM. Our findings show that the majority of ADM disclosures were related to credit risk assessment (CRA) or ADM responsibility. Regarding the ADM responsibility, we found that there was no mention of any standards followed. In total, there were five mentions of

Table 5
Frequency of keywords in ADM sentences.

Keywords	Frequency
Algorithm	51.52 %
artificial intelligence	18.18 %
algorithm-artificial intelligence	9.09 %
algorithm-machine learning	9.09 %
algorithm-automat	6.06 %
algorithm-automat-machine learning	3.03 %
algorithm-artificial intelligence-machine learning	3.03 %

ADM responsibility disclosure, all of which were rather general. Just one company reported that it had formally defined guidelines for responsible AI (Table 7). In addition, there were two mentions categorized as “medical algorithms and diagnostic” from a company operating in the healthcare–pharmaceutical industry and four mentions labelled as “others”, which were reported by companies from the consumer staples sector, explaining how AI is used in electronic devices such as smartphones, home robots and so on.

4.3. RQ3. What are the factors associated with ADM disclosure?

Regarding our RQ3, our findings show that there is a relationship between the ADM reporting and the sector in which a company operates (Table 8). Thus, companies operating in the financial sector are more likely to disclose information about ADM in their annual/sustainability reports. There was no significant relationship between the ADM disclosure and any other factor, such as geographical area, sustainability leadership or size of the company.

5. Discussion and conclusions

As CDR seems to be a new layer of CSR, we might anticipate certain changes in corporate disclosure in the coming years. Following the pattern of CSR disclosure evolution, first we might expect early adopters, normally large corporations, to disclose CDR aspects voluntarily to legitimate their digital practices. This is likely to continue with the seeking of a global consensus on what to disclose and how, which would be followed by legislation. Nevertheless, while the legislation on CSR disclosure took more than two decades to be implemented, with CDR, we face greater urgency to address the associated risks due to the exponential advancements of technology due to which the damage might take decades to repair, particularly in relation to ADM.

Our findings show that ADM disclosure is rather scarce and still at the preliminary stage. Most decisions made that have been disclosed are not made automatically. Only 22 Western European companies disclosed information related to ADM in their annual/sustainability reports in the years investigated. In total, there were 33 mentions. This type of information appears more in the annual reports than in the sustainability reports and was distributed in a similar way between the two years contemplating 2018 and 2019.

To extract the ADM sentences, a dictionary was applied with an associated word and four keywords. It was found that only two of them (algorithm and artificial intelligence) are sufficient to identify the sentences related to ADM.

The main categories of ADM disclosure that were identified in our study were ADM for credit risk assessment (CRA), ADM responsibility, medical algorithms and diagnostics, and other. The latter was related to the electronic sector disclosing the AI technology used in devices such as smartphones, smartwatches or home robots. The most frequent disclosure was related to CRA by companies operating in banking and financial services and ADM responsibility. Nevertheless, despite the fact that ADM for CRA was the most frequent reporting category, the disclosure itself was rather general and lacked details on which processes are fully automated and which are just assisted by the AI. This phenomenon might be explained by both signalling theory and voluntary disclosure theory. According to signalling theory, companies attempt to decrease the information asymmetry and appeal to their stakeholders by being more transparent about the use of AI technology. Nevertheless, they only reveal favorable or very general information without more details on how ADMs operate, which could be explained by voluntary disclosure theory.

The second most frequently reported category was ADM responsibility. However, the way in which this category was reported showed weaknesses as well. We observed different approaches to this type of disclosure. Some companies were simply expressing general concerns regarding unacceptable effects of the decisions made by AI or regarding a future scenario in which decisions will be taken only on the basis of an algorithm. Other companies were more specific regarding ADM’s responsibility towards issues such as

Table 6
Disclosure category: ADM for credit risk assessment (CRA).

Sector	Disclosure extract
Banking and Financial Services	For certain selected retail portfolios, scorecards and automated strategies (together referred to as ‘score enabled decisions’) are deployed to automate and to support credit decisions and credit management. For procedures in favour of private customers, small businesses and small economic operators, decision- making engines (scopri, transact) are used to support the financing of the proposed transaction, which define a summary valuation with increasing riskiness. Various lending requirements are stipulated, including (but not limited to) client rating, maximum loan amounts and maximum tenors, and are adapted to regional conditions and/or circumstances of the borrower (i.e., for customer loans a maximum loan amount taking into account customer net income). Given the largely homogeneous nature of this portfolio, counterparty creditworthiness and ratings are predominately derived by utilizing an automated decision engine. For individual customers and SMEs with low turnover large volumes of credit transactions can be managed more easily with the use of automatic decision models for classifying the customer / transaction binomial. Similarly, for our personal customers, we continued to expand the use of automated credit decision tools so that customers seeking home finance or a consumer loan are now able to get loan approval on the spot. However, no credit application may be processed in the Bank without the recommendation of the branch manager who is responsible for the credit, with the exception of credit decisions made via automatic modelling. Automatic models used in such decisions require the approval of the Group Chief Executive. The Bank has established two new exclusive partnerships for 2018 (FORD & PLAISIO), with a few more expected to commence in 2019. Online automated decision engines have substantially improved service levels and new microloans are delivered swiftly to the customer. With regard to the bank’s credit policy rules, group organization contributed to the design of a mechanism for the automatic system of checks and balances regarding the customer’s transactional behaviour, that promotes sound decisions regarding credit card renewals.

Table 7
Disclosure category: ADM responsibility.

Sector	Disclosure extract
Banking and Financial Services	**prevention of unacceptable effects** we monitor **the impact of the decisions made by artificial intelligence algorithms** to prevent undesirable effects being created or aggravated. By way of example: AI algorithms could be used in healthcare, which might have repercussions for treatment and insurance cover. In our view, it is un-acceptable if a higher risk for a serious illness results for the person concerned due to decisions made by an AI algorithm. Financial service providers belong to a small group of companies who have the obligation to say "no" if we are convinced that it is the right thing to do for our customers: "please do not buy this; may I explain to you why I think you should not take this loan, but I believe in you". By "refusing to lend", we may avoid future risk costs, but we will certainly not earn any profits. but regardless of whether a loan is granted or not – how do our customers benefit if we believe in them, but if, in the future, such **decisions will be taken** only **on the basis of some algorithms** without recognising the individual? and as regards loans that even in the future may not be granted by artificial intelligence – what are our beliefs good for if regulatory standards do not allow us to grant loans without collateral and / or guarantees? we will have to find really good answers to all these questions in the course of the next few years. **to inform persons** concerned about the fact that their personal data is being processed and (a)…, ……. (l) if applicable the existence of **automated decision-making**, including **profiling**
Consumer Internet	payu has formally defined a responsible lending **guideline** to govern its approach in this vital area, including elements **of responsible artificial intelligence** and the **avoidance of bias and discrimination** within automated and data-driven credit decision models.
Telecommunications	in addition, we have volunteered to participate in **the digital rights** ranking pilot to test its revised methodology integrating indicators on targeted advertising and algorithmic decision-making systems in view of the next ranking in 2021.

Table 8
Generalized linear model (logit regression).

Independent variable		Dependent variable			
		ADM report			
	Estimate	Std error	t value	Sig.	
(Intercept)	−0.066896	0.075758	−0.883	0.378	
Geographical area	0.006244	0.029801	0.210	0.834	
Sector	0.212907	0.035113	6.063	3.71e-09	***
Company size	0.009589	0.007948	1.207	0.228	
Sustainability leadership	−0.022022	0.027427	−0.803	0.423	

*** Significant at $p < 0.001$ (2-tailed).

avoidance of bias and discrimination, digital rights or transparency when ADM is being used for personal data processing and client profiling.

While analysing the factors, we took into account classic elements of research in this matter, which allowed us to reach consistent conclusions about ADM disclosure. We found that companies operating in the banking and financial sector are more likely to disclose information about ADM. This can be explained by a legitimacy theory, as the banking and financial sector can be considered critical in this context because they deal with the highly sensitive and private data of users and the automated decision might have an important financial impact on them. Therefore, this sector is subjected to bigger scrutiny by stakeholders and companies operating in it feel obliged to be transparent about their digital practices to gain customers' trust. On the other hand, the size of the company, the country and sustainability leadership were not associated with ADM disclosure.

5.1. Addressing standardization needs

However, this topic being quite a novelty, there is a lack of standardization in such disclosures. Indeed, no company reported its compliance with certain standards regarding ADM usage. To standardize the method of reporting on ADM, first, a consensus has to be achieved on what to report and how, what the key elements should be and what information should be disclosed to satisfy the information needs of different stakeholders. As our findings suggest, at the moment, we are at the preliminary stage of ADM disclosure; therefore, such tools are still lacking. Thus, one of the implications of our research is to point out the lack of standardization in ADM disclosure and the urgency to act in this matter.

The main aim of the new standards for AI disclosure should not be to impose a greater burden on companies in preparing their non-financial reports or to demonize the usage of AI, which can indeed be highly beneficial, but there are certain fundamental rights of individuals that should be guaranteed. Hence, it is important to act quickly as the negative impacts of irresponsible AI usage might take decades to correct. Given that AI technology in a modern and interconnected world is a global problem, a global consensus based on a multistakeholder approach should be pursued. Only in this way can we, as a society, guarantee the respect of fundamental rights such as freedoms, privacy, data protection and non-discrimination while using AI technology and benefiting from it.

To contribute to the evolution of a standardized framework for AI reporting to which ADM disclosure belongs, we elaborated a list of basic elements that might be relevant to such disclosure. Those could be classified into three categories: governance model and system control; ethics and integrity; and strategy.

Regarding the governance model and system control, organizations should be transparent about how AI is governed. Hence, the following information should be provided: the governance structure; who is being held responsible; consultations with critical stakeholders about AI usage; an overview of the key AI topics; and the main areas of concern.

Some companies might rely on international principles regarding the ethical use of AI, such as the IEEE, UE, OECD and so on, while others might design their own principles or code of ethics related to AI usage. On this point, organizations should provide some information about the mechanism for advice and concerns about ethics regarding the responsible use of AI.

Concerning the strategy, perhaps the most relevant part of this section is how AI-related risks are identified and managed. Companies can also report on ongoing training activities related to the responsible usage of AI and any projects focused on Sustainable Development Goals (SDG), in which AI plays a crucial role.

5.2. Contributions and limitations of the study

First, we analysed the current practices of AI reporting among large Western European companies focusing on ADM disclosure. Second, we pointed out the importance of standardization in this area. Third, we proposed a set of general elements that should be disclosed to structure the information about corporate digital responsibility (CDR), improve the transparency, mitigate the risks and prove real responsibility in the usage of AI and ADM.

Before closing, a number of limitations should be acknowledged and future research outlined. In our study, we considered only large Western European companies; thus, the sample might be extended or compared with one from another region. It should also be noted that only two years are considered in the analysis. Thus, analysing a longer period might bring some interesting insights into the evolution of ADM disclosure. Similarly, more factors influencing the propensity to disclose ADM could be tested. Another limitation that should be highlighted is related to the methodology. When extracting the sentences automatically, we may have missed some companies that do disclose about ADM, but without using any of the specific words from our dictionary. Regarding the content analysis, in future research, a wider scope of CDR disclosure could be analysed.

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