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Measuring machinewashing under the corporate digital responsibility theory: A proposal for a methodological path

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Abstract

Recently, a number of scholars have warned against the risk of a new form of deliberately deceptive communication companies use to assure stakeholders of their good intentions in the adoption and development of digital technologies and advanced information systems based on artificial intelligence. This corporate behaviour, defined as machinewashing, in an attempt to empower engagement processes in the stakeholders' network and satisfy stakeholder expectations with regard to the ethical implications of the use of artificial intelligence, has, in the final instance, the prevailing purpose of achieving better levels of corporate performance and reputation. However, thus far, scholars have not provided any empirical studies on the existence of corporate machinewashing strategies, and there is a significant lack of clarity as to how to measure machinewashing. Utilising the corporate digital responsibility theory, this paper offers an original methodological contribution to the nascent research field dedicated to machinewashing behaviour. Particularly, this paper provides considerations for detecting machinewashing through an analysis based on the comparison between the information capacity of the reporting and the information reliability level as a proxy for machinewashing strategies and, thus, for the real impact of digitalisation strategies on stakeholders. To this end, we conducted an exploratory content analysis of the reports of 10 Italian-listed companies from 10 different industries. Overall, looking at the gap between what companies say about the impact of digitalisation from an ethical perspective, and what really happens, our results define a possible path for identifying machinewashing, the fields where it happens and the practices that companies use in order to realise these strategies.

KEYWORDS

corporate digital responsibility, digital ethics, exploratory content analysis, machinewashing, stakeholder engagement

1 | INTRODUCTION

In recent years, some concerns began to emerge about the digital transformation's negative effects and, particularly, about the negative effects of the use of artificial intelligence (AI) (Haenlein et al., 2022; Haenlein & Kaplan, 2020). A few examples of the digital transformation's adverse effects are the use of robots replacing human labour, fatal accidents caused by self-driving vehicles,

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issues related to privacy and discrimination against people (Wirtz et al., 2023), as well as the use of social media algorithms potentially distorting the results of political elections.

As a result, the recent acceleration in the development of digital technologies (e.g. big data, AI, the Internet of Things, machine learning) has stimulated a debate on ethical digitisation or digital ethics when it comes to the way in which advanced technologies impact society and the economy.

Despite the significant impact of such AI use-related distortions in terms of prejudices and stereotypes of the public opinion, the business community, governments and academic research still argue only on a theoretical level. In fact, the only proposals that exist are those on conceptual frameworks and key principles, aimed at driving the ethical development of AI for current and future technologies. There is, however, a lack of clarity and a lot of differences when it comes to the practical implementation of digital ethics (Ashok et al., 2022; Kelley, 2022), and there is also an incoherent theoretical perspective (Haenlein et al., 2022).

Telkamp and Anderson (2022), for example, state the need to evaluate the ethical issues of AI according to three dimensions of analysis: the purposes AI is used for, the data used to create and maintain the AI and the decisions the AI makes. Based on the moral foundations theory, the authors conclude that a person perceives the AI use as ethical according to the three dimensions of analysis, in so far as such use reflects the moral fundamentals of that person, which are highly subjective and variable depending on the context.

The transition from the fourth to the fifth industrial revolution enlightens the emerging awareness of the negative impacts that digitalisation may produce for society and for human beings (Elliott et al., 2021; Wirtz et al., 2023). In the corporate context, the ethical issues connected with AI use[1] grow. This is because of the attempt to make technology centred on mankind, or in any case at man's disposal, and to promote a socially inclusive development (Kartajaya et al., 2021). Many efforts have been made to convey the idea that AI use has undoubted benefits and no bad intentions. For example, companies can use digital technologies such as social platforms for improving stakeholder engagement, sharing information and experiences (Okazaki et al., 2020; Viglia et al., 2018). Along with the development of information and communication technology (ICT) solutions, digital technologies and collaborative platforms, companies increasingly experiment with value-creation processes in digital environments. This represents an opportunity for managers to engage their stakeholder networks, especially considering that AI systems remain black boxes for most stakeholders as a result of the language, terms or jargon used (Seele & Schultz, 2022).

However, managers may also use digital technologies badly or unethically, thus destroying value in stakeholders' network engagement processes. Indeed, along with the aforementioned unintentional effects of digital transformation, a new form (or the lack) of communication, deliberately deceptive, has emerged, with the objective for companies to reassure stakeholders of their good intentions, from an ethical point of view, in the development of digital technologies and advanced information systems using AI.

In other words, there could exist a form of greenwashing applied to the digital sector (also known as machinewashing or humanwashing) where the public relations activities create the impression of a positive change, which does not correspond to a verifiable reality (Obradovich et al., 2019). As Schultz and Seele (2023) state, greenwashing-related issues predicted some crucial challenges due to the 'technological storm' that Industry 4.0 has generated, and due to the emerging need for questioning the 'ethical' or 'responsible' use of AI. The latter issues led to the fifth industrial revolution that is known as Industry 5.0.

Machinewashing is defined as a business strategy for the ethical use of AI and algorithm-based systems, based on misleading behaviour affecting reporting (omitted or misleading information provided by words and images) and/or action (the underlying algorithm of AI) directed at various critical stakeholders to gain their acceptance. The definition can also include symbolic actions involving multi-stakeholder partnerships or aimed at exerting pressure to avoid a more stringent regulation (Seele & Schultz, 2022). Moreover, for machinewashing to occur, it is also necessary for a company to have the intention to deceive stakeholders and to take advantage at the expense of society. Therefore, in the case of machinewashing, companies try to appear more digitally ethical than they actually are. They achieve this by creating a gap between ethical policies/guidelines/codes (which we call digital talk) and real practices (which we call digital walk), between ends and means (decoupling), in order to deceive stakeholders about the true capabilities of advanced technologies and in order to deceive public opinion about the anthropomorphism of intelligent machines (Scorici et al., 2022). Specifically, machinewashing is characterised by the use of statements that are vague, distorted, inaccurate or exaggerated, symbolic and therefore without a substantial meaning, even through the use of charts, images and AI certification.

Particularly, the relevance of the topic is linked to different factors, as argued by Seele and Schultz (2022). First of all, unlike the social and environmental practices of greenwashing, machinewashing appears to be more intangible, theoretical and less visible due to the high complexity and opacity of AI systems (also determined by the proprietary rights underlying the use of such technologies). Moreover, machinewashing is characterised by the use of technical jargon comprehensible to only a few experts and it is a dynamic phenomenon, constantly evolving due to the high variability and real adaptability of AI systems. In addition, machinewashing is not characterised by the presence of generally accepted principles, guidelines and standards, nor by the existence of activists and organisations of the society that can focus attention on such a phenomenon (Seele & Schultz, 2022).

As mentioned, the theoretical research on the AI use-related ethical issues within the business context is still at an early stage, while there is no empirical research. This is undoubtedly due to both the novelty of the topic and the objective difficulties in measuring machinewashing, some of which already exist for measuring greenwashing,[2] while other difficulties are specific and potentially greater.

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Since, to the best of our knowledge, there are to date no empirical studies in academic and practical research on this particular topic, our pioneering work provides a first methodology for the assessment of the existence of machinewashing, under the theoretical lens of the corporate digital responsibility theory.

Machinewashing is a disclosure strategy that aims to conceal the real ethical position that companies assume while they manage their digital transformation. Machinewashing is therefore defined as a 'deceptive strategy' (Schultz & Seele, 2023, p. 105). In fact, a disclosure regarding digital responsibility (Elliott et al., 2021) is used as a signal (Mahoney et al., 2013) of a company's ethical approach to these issues. Such a disclosure makes stakeholders aware that the company's behaviour is congruent with their expectations. Nowadays, there is still no full regulation regarding the ethical perspective of digitalisation for companies, and there is also no full regulation regarding their reporting on digital transformation.

Our paper aims to observe the machinewashing phenomenon from a quantitative measurable perspective, within a business economics approach, to be associated with an emergent theoretical definition of these strategies.

As stated, considering that machinewashing is a disclosure-based strategy, we use reporting as a tool to operationalise and measure the strategy itself and we focus on the following research questions: *Is it possible to operationalise and measure machinewashing by analysing companies' reporting? How can machinewashing be measured in terms of intensity, impact on ethical/sustainable issues and types of deceptions towards stakeholders?*

In order to answer the above research questions, we investigated a sample of ten Italian-listed companies belonging to ten different industries. In fact, despite being closely connected with high-tech companies, machinewashing should not be confined to this sector only. We examined the ten companies' corporate reporting through an exploratory content analysis. An exploratory study is typically performed when the investigated phenomenon's characteristics and relationships are unclear and the researcher aims to explain and define the nature of a new problem for which further studies can be conducted.

Particularly, our exploratory study allowed the proposal of a methodological path to identify machinewashing behaviours and define some specificities. Results show that our approach can provide both a multi-dimensional perspective and a synthetic representation of the phenomenon, through a weighted machinewashing index (MW_{index}). Overall, the machinewashing identification, its frequency and extent emerge from the comparison between digital talk and digital walk. Moreover, our analysis suggests that the traditional content analysis that is focused only on the assessment of digital talk would not be fully explicative of the machinewashing strategies carried out by companies.

Our research shows some results that are focused on the method's effectiveness, rather than on the evidence we observed for each of the ten companies in terms of machinewashing attitude. In fact, our most relevant result shows that MW_{index} is helpful in detecting machinewashing strategies, measuring their extent and representing their specificities. The results of our study could help companies focus on providing reliable and understandable performance information to stakeholders to avoid misleading them using vague and blurry communication, particularly when communicating the benefits of digitalisation.

This paper presents some fundamental contributions. From a theoretical point of view, it extends the recent literature on corporate digital responsibility (e.g. Elliott et al., 2021; Herden et al., 2021; Lobschat et al., 2021) by including, within the corporate digital responsibility framework, the evidence of digitally irresponsible behaviours such as machinewashing. In addition, to the best of our knowledge, this is the first study on machinewashing from both a methodological and empirical perspective. Particularly, this paper proposes an original methodological path based on an exploratory content analysis of both the information capacity of the reporting and the information reliability (IR) level as a proxy for machinewashing strategies. This methodological path leads to the operationalisation of the concept of machinewashing and to the definition of an instrument for measuring the extent of the machinewashing. Starting from the analysis of what companies report, we aim to propose a useful way for assessing the corporate digital responsibility's (Elliott et al., 2021) consistency or, otherwise, it's merely symbolic nature. The measuring method may be particularly useful for realising analyses of big samples, with both researchers and regulators, who want to scrutinise the phenomenon of machinewashing, being able to carry out the above-mentioned analyses.

Interestingly, we use ESG (environmental, social and governance) as a proxy for the corporate ethical commitment. At the same time, this paper also responds to the call for empirical research on machinewashing, through qualitative methodologies based on the corporate reporting analysis (Scorici et al., 2022).

Moreover, by comparing listed companies from different industries, our empirical analysis contributes to doing comparable further research. In other words, our methodological proposal may be easily replicable in other research contexts, thus providing the groundwork that leads to future studies. Lastly, since our study is based on companies from all industries (as well as the technology industry), we offer a non-trivial perspective of the machinewashing phenomenon beyond its ordinary context of evidence.

Our study has some practical implications for managers and policymakers. For managers who need to increase their digital competitiveness by means of improving their digital performance, our study offers some practical implications of relevance. Disclosing digital information is critical because of the increasing attention stakeholders pay to that information. However, managers need to carefully evaluate the implications before proceeding with digital transformation and its disclosure. We provide an instrument that allows managers to evaluate the company's reputational risk, as they can detect how disclosure on digitalisation may reveal some conflicts within the company, contributing to the improvement of the governance mechanisms. Thus, managers should provide scientific and technological guarantee for the effective internal control of inconsistent digital information disclosure. At the same time, managers should minimise machinewashing behaviour by adopting a third-party team containing industry experts to audit the information disclosed by the company and reduce public scepticism about the disclosed information.

Policymakers should consider the need for stricter regulations to ensure transparency and accuracy in the presentation of digital information. Particularly, governmental policymakers should establish a set of scientific, reasonable and feasible tools for companies to unify the understanding about firm's machinewashing, in a way to strengthen the daily supervision of corporate digital behaviour. Implementing standards for digital information disclosure could contribute to a more transparent market. Therefore, our study points to the crucial role that regulation can play in setting boundaries for digital claims. Regulatory frameworks can raise the bar for digital commitments, compelling companies to be more cautious with their digital efforts. Similarly, international regulatory bodies should collaborate and enforce more stringent and universally applicable standards to counter machinewashing.

The remainder of the paper is organised as follows. The next section describes the positioning of this work within the machinewashing conceptual framework, and it also describes the theoretical lens adopted. Section 3 explains the methodological proposal for measuring and detecting machinewashing strategies. Section 4 shows the results of the exploratory content analysis. Section 5 discusses the main findings, and the final section shows implications, contributions, concluding remarks, limitations and further research avenues.

2 | THE CONCEPTUAL FRAMEWORK FOR DETECTING MACHINEWASHING

Seele and Schultz (2022) provide a general conceptual framework of machinewashing practices in terms of antecedents and outcomes. Compared to Seele and Schultz's framework, this paper focuses only on external effects and in particular on stakeholder relations. From a theoretical perspective, machinewashing strategies may include a plethora of alternative theories at a macro-, meso- and micro-level (Seele & Schultz, 2022). In light of our research questions, we focus on a meso-level investigation, that is on business organisations. For this reason, we refer to the corporate social responsibility theory,[3] which we consider in terms of corporate digital responsibility. As Lobschat et al. (2021) stated, corporate digital responsibility includes all the values and rules that direct firms' decision-making processes when it comes to digital issues. In other words, in the case of digital transformation there is an ethical perspective, that is an opportunity to consider an ethically sustainable approach linked to the usage of AI and more advanced technologies (Wirtz et al., 2023). From this, it is possible to consider some firms' actions aimed at promoting ethical management of digitalisation and taking into account the needs related to stakeholders' inclusion. For example, Mueller (2022) argues that corporations' corporate digital responsibility efforts should be aimed at identifying and recognising the pertinent stakeholders that need to be considered, which may not be traditional social actors only, but also artificial/technological actors (e.g. algorithms or software agents), in a setting where human and technological actors collaborate. Managers should therefore interact with the stakeholders, considering not only one-to-one relationships, as the company's behaviour with a particular stakeholder could affect the expectations and the perceptions of other stakeholders that are linked to them (e.g. Sciarelli & Tani, 2013) via human or technological relationships.

Furthermore, issues related to corporate digital responsibility may vary in relation to the specific stage of digitalisation development and in relation to the specific technology under analysis. As to these aspects, some risks may arise from digital irresponsibility (Wirtz et al., 2023). The corporate digital responsibility lens therefore seems to be an appropriate point of view for analysing not only the threats to the ethical conduct of companies involved in the digital transformation but also unethical strategies grounded in misleading disclosure, such as machinewashing.

At the same time, corporate digital responsibility, just like corporate social responsibility, is also inspired by the commitment towards social and ecological matters and, in more extensive terms, the commitment towards the ESG profiles. Ultimately, the corporate digital responsibility framework may be associated with corporate social responsibility and the stakeholder theory. This is because corporate digital responsibility-related values and norms share some principles and goals with corporate social responsibility, or an organisation's commitment (and accountability) towards social and ecological causes in general. Corporate digital responsibility is therefore also strictly related to ESG issues. For example, Wade (2020) defined corporate digital responsibility as a set of practices and behaviours that help an organisation use data and digital technologies in a way that is socially, economically, technologically and environmentally responsible. As Aitken et al. (2020) stated, for companies, the adoption of technology implies the establishment of a social licence that is grounded in the public engagement. This is necessary in order to define credible and trusty relations and to develop digitalisation in a way that is compliant with the values of the social environment.

In that context, our study aims to explore a method for understanding whether the companies disclose the ethical and sustainable application of digital technologies to realise machinewashing strategies. We aim to analyse how these strategies are realised, and we also aim to quantify the extent of the misleading approach towards stakeholders. The perspective of analysis of stakeholders is useful for a firm's legitimacy and reputation (Saetra, 2021), which can be promoted by business strategies carried out through disclosure. In order to explore such impacts, we study the ESG aspects of the use of digital technologies, only considering the areas of stakeholders' commitment with an ethical-sustainable impact. Indeed, the ESG factors play a central role in aiding stakeholders in understanding and assessing the ethical-sustainable aspects of the business (Cappucci, 2018; Clementino & Perkins, 2021).

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On the other hand, prior research (e.g. Fleischman et al., 2019) emphasises that the achievement of performance and its disclosure can encourage businesses to turn the ethical issues into logics and strategies connected to the search for legitimacy towards stakeholders, moving away from the real ethical issues (Ims et al., 2014; Moore & Gino, 2015). For this, some scholars (e.g. Clementino & Perkins, 2021) suggest to critically consider the disclosure inherent in ESG, since, while it can determine corporate ethical behaviour (Jackson et al., 2020), it could also distort stakeholder perceptions (Graf et al., 2019).

What we stated above enables us to highlight the underlying concept of our research, that is machinewashing. In its theoretical dimension, machinewashing is a deliberate strategy grounded in the use of unreliable disclosure, particularly regarding AI and digitalisation in general (Seele & Schultz, 2022), in order to deceive stakeholders. This strategy attributes a predominant role to communication over actions. Machinewashing may be derived from signals of unreliability of information that corporates report (i.e. vagueness, selective disclosure, misleading or false information, etc.) (Seele & Schultz, 2022). In fact, companies may use this strategy to improve how the actors of the social environment perceive the implications of their adoption and use of digital technologies (Bowen & Aragon-Correa, 2014; Delmas & Burbano, 2011; Ferrón-Vílchez et al., 2021). This may result in a company's disclosure aiming to advance a better representation of the digital transition's effects than is actually the case with the real situation (Obradovich et al., 2019).

Owing to the novelty and particular connotation of machinewashing, it is challenging to intercept and measure it. Therefore, starting from a theoretical definition, we aim to operationalise machinewashing. We seek to achieve this by considering the analogy with greenwashing studies. The greenwashing studies provide a way for measuring greenwashing, namely as the gap between 'talk' (what companies say) and 'walk' (what companies really do) (i.e. Du, 2015; Gatti et al., 2021; Pizzetti et al., 2021; Seele & Schultz, 2022; Testa et al., 2018).

Considering this analogy, and therefore supposing the possibility that reporting about digitalisation is unreliable, machinewashing may derive from the deviation between the informative capacity and the disclosure's reliability. The informative capacity stems from the attributes of disclosure, that is the way companies communicate. Notwithstanding, some statements might not be fully reliable, because they are affected by some signals of strategic, deceptive corporate practices.

We ground our assumptions in the presence of one or more unreliability signals revealing companies' machinewashing strategies. The presence, the number and the type of the unreliability signal therefore allow to identify the theoretical concept of digital walk and to measure it. An increasing number of signals means that the information's unreliability grows, thereby rendering the disclosure unreliable. In contrast, the absence of such signals suggests that the companies' communications are consistent with their real actions.

3 | METHOD

3.1 | Measuring machinewashing: Research design and the proposal of a methodological path

Since machinewashing is a totally novel subject, there are no peculiar extant identification and measurement methodologies in prior research. For this reason, we started from the study of Seele and Schultz (2022), who view machinewashing as a possible form of greenwashing applied to the digital sector. Considering the analogies between the two phenomena (see Section 1), we developed our method based on the methodologies normally used for greenwashing studies. Among these latter, most of them do not propose a measurement of greenwashing. On the other hand, when greenwashing is quantified, the measure is founded on stakeholders' perception (e.g. Jog & Singhal, 2020; Torelli et al., 2020) and, in a more limited number of papers, it emerges from a comparison between disclosure indexes and environmental performances (i.e. Kim & Lyon, 2015; Testa et al., 2018; Zhang, 2022). In the light of the above, we considered the framework of Seele and Schultz (2022), which connects greenwashing and machinewashing and highlights some opportunities in terms of their similar measurement.

Therefore, this paper aims to offer a methodological contribution to the emerging machinewashing research field, by providing suggestions on how to detect machinewashing behaviours through the comparison between the information capacity of corporate reporting (i.e. digital talk) and IR, as a proxy for digital walk. We identify machinewashing with reference to the gap between the information capacity of the reporting and its reliability. A bigger gap highlights a misleading approach of greater intensity and therefore of machinewashing strategies implemented by a firm. To this end, we adopt an exploratory research design based on a content analysis of the reporting of a sample of ten Italian companies listed in the Italian stock market exchange.

Exploratory research designs are suitable for and applied in areas where there is no prior literature, with the objective of exploring a problem and providing valuable insights to better understand it, but without guaranteeing conclusive or definitive evidence.

Particularly, a qualitative exploratory study is suitable for this work. This is because it enables freedom in data collection, which freedom is needed for a comprehensive understanding of the phenomenon, to fulfil the research purpose (Easterby-Smith et al., 2021) and to let the methodological difficulties characterising machinewashing measurement emerge.

We selected a sample of companies (which we anonymised for confidentiality reasons) showing the largest market capitalisation in each of the 10 different industries based on the Industry Classification Benchmark level 2: Utilities – company A; Financial – company B; Consumer cyclicals – company C; Industrials – company D; Basic materials – company E; Consumer non-cyclicals – company F; Real Estate – company G; Healthcare – company H; Energy – company I; Technology – company L. By following this approach, we aim

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to gain the greatest spectrum of analysis and industry diversification in investigating machinewashing strategies.

The content analysis was performed in a two-step approach. The first step started with the common definition of the text, which is useful for both the digital talk and the disclosure reliability (Walker & Wan, 2012). The second step followed different encoding procedures of the text. Particularly, on the one hand, the digital talk was based on the content analysis generally used in accounting and disclosure quality studies too, with those studies aimed at qualitatively and quantitatively investigating the corporate reporting (Beattie & Thomson, 2007; Beretta & Bozzolan, 2008; Cinquini et al., 2012; Guthrie et al., 2004). On the other hand, the IR stemmed from the greenwashing studies (e.g. Guix et al., 2022; Seele & Schultz, 2022) and, specifically, it was applied on the basis of conceptual and methodological similarities to the machinewashing investigation. This analysis was aimed at observing the abovementioned tools' explicative capacity in order to identify machinewashing strategies and achieve evidence of their intensity. In particular, we aimed at highlighting whether and which strategies were differently implemented depending on the ethical-sustainable aspects analysed, proxied by the ESG factors.

3.2 | The content analysis for measuring digital talk and IR

The main assumption underlying the methodological designs based on the content analysis is that the disclosure level of a certain topic can represent the commitment and efforts of a certain company in such regard (Bernini et al., 2022; Mention, 2011). This leads to assumption that a better disclosure is indicative of both a greater business activity in a specific context and a higher relevance of a certain topic (stronger commitment) (Krippendorff, 1980). On this assumption, digital talk may also signal real corporate behaviour. This could be a limitation on the possibility of investigating the IR and, consequently, the machinewashing strategies. For this reason, starting from the common contents, the researchers carried out two paths of content analysis (see Appendix, Table B): a content analysis for the identification of digital talk, and another content analysis for the identification of IR.

According to the literature (e.g. Cabrita et al., 2017; Campbell et al., 2010), the information sources were represented by the annual reports and the non-financial statements.

The content analysis was carried out on the basis of a semi-objective approach, under which the contents to use and code are selected ex-ante (Beattie et al., 2004). The first step is the selection of information to submit for classification. To this end, we identified some keywords (see Appendix, Table A) to detect sentences or paragraphs in the text where topics related to digitalisation were covered. Those keywords stemmed from the literature on the definition of an interpretative scheme used to analyse the disclosure on the digitalisation paths carried out by businesses (Hossnofsky & Junge, 2019). In addition, we integrated the keywords set with the categories of enabling technologies, as defined in the 'Piano Nazionale Industria 4.0' (2017–2020) report issued by the Italian Ministry of Economic Development. The main assumption for doing so is that the institutional environment affects the way in which companies respond to the requests for and efforts of social responsibility, while taking economic advantage from the use of AI for digital technologies (Ashok et al., 2022).

From the research of the keywords, we extrapolated the individual text units as a coding basis to assess. The text unit represents the portion of the text that includes specific information and it could be identified by a section, a paragraph, a sentence or a part of it (since the same sentence can reveal information that is classifiable in different manners), a word or a table (Yi & Davey, 2010). Moreover, we selected paragraphs in order to support a more precise understanding of the meaning of the text units and a better contextualisation of them.

Consistent with the research goals, we carried out a further analysis of the text, aimed at identifying the ethical-sustainable aspects of digitalisation, obtaining the definitive information set. The information contents to be investigated were defined ex-ante on the basis of a top-down approach (Humphreys & Jen-Hui Wang, 2018); we referred to the profiles used for the definition of the ESG rating indicators (Drempetic et al., 2020; Refinitiv, 2022). Particularly, the environmental profile was classified into 'Resource use,' 'Emissions' and 'Innovation'; the social profile was classified into 'Workforce,' 'Human Rights,' 'Community' and 'Product Responsibility'; the governance profile was classified into 'Management,' 'Shareholders' and 'Corporate Social Responsibility Strategy.'

Next, a pilot analysis was required, aimed at ensuring coding uniformity among the researchers, as well as reliability of coding (Beattie & Thomson, 2007). Lastly, a human coding process was carried out, considering the complexity of the contents to be analysed.

3.3 | The digital talk measurement

Consistent with the relevant literature on content analysis (e.g. Beattie et al., 2004; Boyatzis, 1998; Weber, 1985), we follow a formalised and articulated coding process (Bernini et al., 2022) to ensure methodological validity and reliability (Beattie et al., 2004; Cinquini et al., 2012; Weber, 1985). The text units' analysis was based on a multidimensional coding related to a mix of the following information attributes (Beattie et al., 2004) (see Appendix, Table C): time orientation (historical, forward-looking, non-time-specific information); financial or non-financial; qualitative, quantitative, or mixed. In this way, each text unit was classified considering its frequency and its corresponding information capacity depending on the attitude of the attributes mix to qualify certain information as more or less reliable and verifiable. Past information is factual, forward-looking information is not verifiable or just wilful. A higher score is therefore associated with past information. At the same time, the financial information presents a higher score than the non-financial information, as the former is generally considered more accurate. Lastly,

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the mixed information is considered more explicative than the information that is only qualitative or quantitative (Beattie et al., 2004). On this basis, a different weight for each attribute mix was defined (Mention, 2011) according to the truthful and verifiable nature of the information.[4]

3.4 | The IR measurement

In order to detect the presence of one or more signals of unreliability, we re-processed the information previously coded into the three ESG dimensions. Following Seele and Schultz (2022), who identify five signals of information unreliability (see Appendix, Table D) among machinewashing practices (i.e. 'Vague and misleading claims'; 'Inaccurate claims'; 'Jargon claims'; 'Irrelevant claims', 'Exaggerations'), we assigned one or more of those signals to each text unit; such attribution was based on a pilot analysis repeated and validated by the research group.

In order to reduce the researcher's subjectivity and coding bias, we conducted an initial pilot study. We therefore defined guidelines and analysis procedures for the detection of deception types and we gave the coders the same instructions to coordinate the interpretation of the units. In addition, we met at regular intervals to discuss trends and issues that emerged during the analysis and also to supplement the guidelines and to resolve disputes over claims for which divergent opinions were reported.

In doing so, we measured the IR level, which is intuitively higher when the number of signals decreases (Appendix, Table E).

Finally, the digital talk-IR gap allows us to understand machinewashing behaviours; a bigger gap suggests a stronger misleading approach, and this means that the company adopts a machinewashing strategy. We assume that, in the case of the information's partial or total unreliability, the company disclosure could not partially or fully correspond to the actions undertaken by the company itself (digital walk).

4 | RESULTS

4.1 | Content analysis results

The information frequency and composition analysis of digital strategies' effects on the ESG profiles aims to investigate the similarities and/or discrepancies among the ten companies belonging to ten industries in order to attest the effectiveness of the tools used.

Table 1, Panel A, shows that the number of the text units varies among the sampled companies. Most of the units are reported by companies from the Utilities, Industrial and Basic Materials Sectors (A, D and E), with a prevailing disclosure of the social component. The smallest number of the text units is referred to G and L (Real Estate and Technology). For company L, the number of units that resulted from the first selection of information to submit for classification is very high. However, due to the high technological level of the company, much of its reporting obviously has to do with technology and digitalisation, but not specifically with the ethically sustainable impact. Therefore, from the first to the second selection, more units have been excluded, compared to other companies.

The explorative content analysis reveals some interesting differences regarding the ethically sustainable impact of digital technology development (Table 1, Panel B). Particularly, percentages of disclosure vary depending on the three ESG profiles, but also depending on the areas related to each profile. Moreover, all the companies deal more extensively with the social dimension, showing a prevalence of issues related to the community and workforce, while all the companies deal less extensively with the environmental and governance dimensions. Specifically, the highest percentage for the social dimension is provided by F (85%) and the lowest by D and E (49%).

In addition, A, D and E show a greater balance between the percentage values of social and environmental disclosure and a lower incidence of the governance dimension. Together with their higher number of text units generally dedicated to the ethically sustainable impacts of digitalisation, the above finding suggests that, in the presence of a wider disclosure (Table 1, Panel A), the information area dedicated to the social dimension is less concentrated in favour of the environmental one. In fact, for A, D and E the environmental dimension is less neglected than in the other cases. This may be explained by a greater sophistication of the disclosure provided, with the disclosure progressively grounded not merely in the social component, but also more devoted to the other sustainability profiles, especially the environmental profile, which in recent years has been boosted by the increase of legal requirements.

Company B, operating in the financial sector, shows the highest relative value of the disclosure regarding digitalisation's ethical impacts on governance issues: Twenty-six per cent of the text units referred to governance, compared to the 5% of the texts referring to the environmental dimension (Table 1, Panel B). We can hypothesise that, in this case, the residual weight of the environmental profile is mainly due to the business nature of B and the consequent limited involvement in activities that directly affect the environment, especially compared to other industries.

4.2 | Information capacity: Digital talk results

The analysis of the information attributes, representing the digital talk and relating to the digital strategies' impacts on the ESG profiles, aims to understand the information capacity of the disclosure (Table 2). The analysis reveals a common prevalence of qualitative information and an almost not-existent financial one. Particularly, the qualitative disclosure tends to prevail both for the non-time-specific attribute, which has the worst informative capacity (the maximum value is for A), and for the historical attribute, which is considered more reliable (the maximum value is for B). Moreover, the low frequency of the financial attribute depends on the nature of the topic

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TABLE 1 Absolute value of the text units in relation to the information contents (ethically sustainable perspective of digital technologies).

Panel A: Information areas										
	Number of text units per company									
Information	**A**	**B**	**C**	**D**	**E**	**F**	**G**	**H**	**I**	**L**
E										
Resource use	19	3	2	19	19	3	5	1	3	3
Emission	24	6	8	31	24	4	-	2	6	4
Innovation	130	2	14	136	132	1	3	2	12	5
TOT E	173	11	24	186	175	8	8	5	21	12
S										
Workforce	46	88	10	35	35	7	3	35	15	3
Human rights	18	–	–	14	13	–	–	–	4	–
Community	158	65	71	145	139	138	32	40	28	46
Product responsibility	4	–	10	5	4	7	–	–	–	–
TOT S	226	153	91	199	191	152	35	75	47	49
G										
Management	–	30	1	–	–	1	2	6	47	–
Shareholder	–	–	–	–	–	–	–	–	–	–
CRS strategy	37	28	23	22	22	18	4	5	16	3
TOT G	37	58	24	22	22	18	6	11	63	3
TOT	435	222	139	407	388	178	49	91	131	64
Panel B: Information contents										
	% text units per company									
Information	**A**	**B**	**C**	**D**	**E**	**F**	**G**	**H**	**I**	**L**
E										
% (Resource use/E)	11	27	8	10	11	40	63	20	14	25
% (Emission/E)	14	54	34	17	14	50	–	40	29	33
% (Innovation/E)	75	18	58	73	75	10	37	40	57	42
% (E/tot)	40	5	17	46	45	5	16	5	23	19
S										
% (Workforce/S)	20	57	11	18	18	5	8.50	46	32	6
% (Human rights/S)	8	–	–	7	7	–	–	–	9	–
% (Community/S)	70	42	78	73	73	90	91.50	54	59	94
% (Product responsibility/S)	2	–	11	2	2	5	–	–	–	–
% (S/tot)	52	69	66	49	49	85	72	83	52	77
G										
% (Management/S)	–	52	4	–	–	5	33	55	68	–
% (Shareholder/S)	–	–	–	–	–	–	–	–	–	–
% (CRS strategy/S)	100	18	96	100	100	95	67	45	32	100
% (G/tot)	8	26	17	5	6	10	12	12	25	4

Note: Percentages of the text units in relation to the information contents (ethically sustainable perspective of digital technologies).

we investigated, which tends to concern managerial and strategic profiles that, to date, are reported mostly through non-financial disclosure. As a consequence, we considered the mix of 'non-financial/mixed/historical' (Beattie et al., 2004; Bernini et al., 2022; Mention, 2011) as the mix with the greatest informative capacity in the context of analysis of the ethically sustainable impacts of digitalisation.

The companies that divulge the greatest number of 'non-financial/mixed/historical' units are A, B, D and E. Furthermore, the greatest number of 'non-financial/quantitative/historical' units are

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TABLE 2 Frequencies of the mix of attributes (information capacity).

	A	B	C	D	E	F	G	H	I	L
Financial/qualitative/historical	–	–	–	–	–	–	–	–	–	–
Financial/qualitative/forward-looking	–	–	–	–	–	–	–	–	1	–
Financial/qualitative/non-time specific	–	–	–	–	–	–	–	–	–	–
Non-financial/qualitative/historical	121	152	53	105	106	42	16	50	79	6
Non-financial/qualitative/forward-looking	21	22	1	25	21	6	4	8	24	6
Non-financial/qualitative/non-time specific	203	13	51	200	185	85	17	26	18	30
Financial/quantitative/historical	9	–	1	8	8	–	–	–	–	1
Financial/quantitative/forward-looking	1	–	–	1	1	–	–	–	1	–
Financial/quantitative/non-time specific	–	–	–	–	–	–	–	–	–	–
Non-financial/quantitative/historical	34	3	7	26	26	33	6	1	–	–
Non-financial/quantitative/forward-looking	3	–	–	3	3	–	1	–	–	–
Non-financial/quantitative/non-time specific	–	–	4	–	–	–	–	–	–	–
Financial/mixed/historical	3	–	–	–	–	2	–	–	–	–
Financial/mixed/forward-looking	1	–	–	1	1	–	–	–	2	–
Financial/mixed/non-time specific	–	–	–	–	–	1	–	–	–	–
Non-financial/mixed/historical	30	30	10	28	28	7	5	6	5	14
Non-financial/mixed/forward-looking	2	2	–	2	2	–	–	–	1	6
Non-financial/mixed/non-time specific	7	–	–	8	7	2	–	–	–	1
Total	435	222	139	407	388	178	49	91	131	64

Note: Value of the text units in relation to the mix of attributes representing the information capacity of each unit.

reported by A, D, E and F. As a consequence, A, D and E are the companies that report the highest frequencies of 'non-financial/historical' disclosure (mixed or quantitative).

Methodologically, the tool for investigating the information capacity has highlighted that the greater frequency and the higher information capacity are aligned, as both refer to the same companies. Hence, we infer that the method is sensitive to the peculiarities of the disclosure regarding the ethical-sustainable dimensions of the digitalisation.

4.3 | IR results

The analysis carried out aims at highlighting the following inter- and intra-company aspects:

a. the deviations between digital talk and IR (Tables 3 and 4),
b. the same deviations according to the ESG profiles (Table 5),
c. the types of unreliability signals (Table 6).

The main purpose was to understand if the proposed tool was effective for the identification of the different machinewashing degrees with reference to the ESG profiles as well.

Table 3 shows a machinewashing variability in the sample (intra-company). Such variability is evidenced by the presence of deviations in all the classes. At the same time, we note an inter-company variability. This inter-company variability results from the higher concentration of deviations in different classes and also from the presence of values that are very different within the same class.

We note that our tool for detecting machinewashing has a multidimensional potential. This is because it allows us to evidence not only the frequency of a company's misleading behaviour (IR) but also the relevance of the misleading behaviour, represented by the gap between the digital talk and the reliability of the information (Table 3). Moreover, our tool offers a synthetic representation of machinewashing. Methodologically, we refer to the studies on corporate disclosure, that measure the characteristics of reporting through the development of disclosure indexes capable of synthetising its qualitative-quantitative profiles (Beattie et al., 2004; Beretta & Bozzolan, 2008; Bernini et al., 2022; Cerbioni & Parbonetti, 2007; Cinquini et al., 2012; Mention, 2011). Therefore, we assessed the level of machinewashing through a weighted synthetic index that includes both the frequency of the misleading behaviour of a company (IR) and the relevance of the misleading behaviour (digital walk-digital talk gap).

Consistently with our first research question, in order to operationalise and measure machinewashing by analysing companies' reporting, we determined the MW_{index} by applying the following formula: $MW_{index} = \sum(\alpha_i \times n_i)$, where α_i is the weight assigned to each gap (omitted for the sake of brevity), and n_i is the frequency of unreliable text units for each divergence class. Particularly, such an index aims to represent the misleading intent of companies by considering both the number of unreliable units and the extent of the gap between what companies report and what they really do. Since we extract

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TABLE 3 Analysis of deviations.

	A		B		C		D		E	
	AF	% deviation/n. units (195)	AF	% deviation/n. units (131)	AF	% deviation/n. units (57)	AF	% deviation/n. units (15)	AF	% deviation/n. units (7)
VSD	3	2	4	3	6	11	–	–	3	43
SD	17	9	23	18	13	23	–	–	–	–
HID	5	3	12	9	13	23	4	27	2	29
ID	38	19	67	51	9	16	1	7	1	14
LID	26	13	2	2	12	21	9	60	–	–
MoD	92	47	5	4	4	7	–	–	1	14
LD	4	2	5	4	–	–	–	–	–	–
MiD	10	5	13	10	–	–	1	7	–	–
%deviation/total units	45		59		46		65		58	
	F		**G**		**H**		**I**		**L**	
	AF	**% deviation/n. units (78)**	**AF**	**% deviation/n. units (13)**	**AF**	**% deviation/n. units (27)**	**AF**	**% deviation/n. units (105)**	**AF**	**% deviation/n. units (33)**
VSD	3	4	–	–	3	11	10	10	2	6
SD	11	14	3	23	12	44	24	23	2	6
HID	12	15	2	15	4	15	3	3	5	15
ID	7	9	4	31	1	4	28	27	1	3
LID	23	29	–	–	4	15	18	17	15	45
MoD	20	26	4	31	1	4	4	4	5	15
LD	–	–	–	–	–	–	12	11	2	6
MiD	2	3	–	–	2	7	6	6	1	3
%deviation/total number of sentences	54		46		29		81		52	

Note: Classes of divergence: very strong divergence (VSD); strong divergence (SD); high-intermediate deviation (HID); intermediate deviation (ID); low-intermediate deviation (LID); moderate deviation (MoD); low deviation (LD); minimum deviation (MiD). AF is absolute frequency.

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TABLE 4 Machinewashing index.

	A	B	C	D	E	F	G	H	I	L
MW_{index}	567.5	470.5	234.75	50.75	32.5	268.75	46.75	112.5	381.75	110.25
More frequent type of unreliability	MoD	ID	HID	LID	VSD	MoD	MoD/ID	SD	ID	LID
Incidence %	22	31	21	40	43	21	Both 31	37	14	24
ESG area	E	S	S	E	E	S	S	S	G	S

and consider only the unreliable units from the codified units, the comparability of the outputs among the 10 companies is maintained (Table 4). Instead, the percentage value of unreliable units in relation to the total codified units suggests the relationship between the misleading disclosure and the intensity of the reporting on the ethical-sustainable effects of digitalisation. This information allows us to measure machinewashing in terms of intensity and impacts on ethical/sustainable issues, as indicated in our second research question.

As shown in Table 4, company A is a case worth noting. In fact, the first-step analysis of the disclosure (Table 1, Panels A and B) and the analysis devoted to the definition of digital talk highlighted virtuous behaviour. However, the analysis of the unreliable units observed in relation to the severity of the deviation classes shows non-virtuous behaviour. The digital talk-digital walk comparison therefore allows to intercept the machinewashing as well as its extent. In addition, the investigation reveals that the traditional content analysis focused only on the assessment of digital talk is not fully explicative of the machinewashing strategies carried out by companies.

In order to focus on the machinewashing sources, our analysis of distortions also considers the ESG profile. In particular, Table 5 shows that the above-mentioned machinewashing variability is confirmed according to the ESG dimensions as well, with a maximum value for the environmental profile of company E, within the very strong deviations class (VSD).

Moving to the analysis of the unreliability signals allows us to investigate types of deceptions towards stakeholders (the second research question). In fact, Table 6 shows that machinewashing is mainly realised through the reporting of 'Vague and misleading claims' and 'Inaccurate claims.' With reference to the ESG areas, we notice a prevalence of such unreliability signals in the social area. Surprisingly, companies A, D and E, which show a greater balance between the percentage values of social and environmental digital talk (Table 1, Panel B), present a prevalence of the above-mentioned unreliability signals in the environmental area. Besides, specifically for E, we have just highlighted (Table 5) the severity of the 'very strong deviations' class for the environmental profile. Lastly, company I is the only company that shows unreliability signals within the governance area.

Furthermore, particularly company C shows the presence of 'Exaggerations' as a relevant type of unreliability signal, too.

Hence, we confirm the tool's capacity to detect some peculiarities of the companies.

5 | DISCUSSION

Our study's purpose was to contribute methodologically to the nascent machinewashing research field by investigating machinewashing strategies potentially included in the corporate reporting of a sample of Italian-listed companies belonging to 10 different industries. The exploratory content analysis carried out outlines many aspects about the effectiveness of the methodological approach proposed.

In particular, observing a sample of 10 companies, we developed an exploratory application of the tool for detecting machinewashing, which ultimately gives the opportunity to operationalise the concept of machinewashing and to measure it. In doing this, we proposed a weighted synthetic index emerging from the analysis of corporate reporting. Bearing in mind the objective of our research, we consider the 10 sampled companies as an instrument to be used for developing our methodological texting. Therefore, the results of our research are focused on the method's effectiveness, rather than on the evidence we observed for each of the 10 companies after testing the machinewashing index. In fact, the results of our exploratory texting gave us the opportunity to formulate some reflections and to draw some conclusions regarding the methodological path that we propose for operationalising machinewashing. The most relevant result therefore consists in the valuation of the index's investigative potential for detecting the presence of machinewashing strategies, for measuring their extent and for representing the specificities of machinewashing strategies.

In particular, our exploratory research shows the evidence that we report in the following.

First, since the variable for digital talk and the variable for IR differ significantly, it was found that the tool allows us to identify potential machinewashing strategies through misleading disclosure. The extent of deviations also allows us to quantify the machinewashing intensity.

The coding process of disclosure allows us to understand the differentiation of the digitalisation impact with reference to the three ESG profiles and on the particular issues that these three dimensions encompass. Moreover, the method used to measure IR also allows us to extract the main types of unreliability, that is the way in which misleading actions are adopted, indicating machinewashing behaviour.

The methodological path we have proposed to investigate machinewashing strategies suggests some relevant concluding considerations regarding the usefulness of the proposed tool and the need

TABLE 5 Analysis of distortions according to ESG profiles.

	A			B			C			D			E		
	TOT E (%)	TOT S (%)	TOT G (%)	TOT E (%)	TOT S (%)	TOT G (%)	TOT E (%)	TOT S (%)	TOT G (%)	TOT E (%)	TOT S (%)	TOT G (%)	TOT E (%)	TOT S (%)	TOT G (%)
VSD	–	2	–	–	2	1	2	7	2	–	–	–	43	–	–
SD	2	6	2	–	14	4	7	14	2	–	–	–	–	–	–
HID	1	2	1	1	8	1	–	21	2	7	20	–	14	14	–
ID	5	12	2	2	31	19	–	16	–	7	–	–	–	14	–
LID	5	7	2	–	1	1	2	18	2	40	20	–	–	–	–
MoD	22	18	7	–	2	2	4	2	2	–	–	–	14	–	–
LD	2	1	–	1	3	–	–	–	–	–	–	–	–	–	–
MiD	3	2	1	2	7	1	–	–	–	7	–	–	–	–	–
	40	47	13	5	67	27	14	77	9	60	40	–	71	29	–

	F			G			H			I			L		
	TOT E (%)	TOT S (%)	TOT G (%)	TOT E (%)	TOT S (%)	TOT G (%)	TOT E (%)	TOT S (%)	TOT G (%)	TOT E (%)	TOT S (%)	TOT G (%)	TOT E (%)	TOT S (%)	TOT G (%)
VSD	1	3	–	–	–	–	4	7	–	–	6	4	–	6	–
SD	1	12	1	–	23	–	4	37	4	6	10	8	–	6	–
HID	–	15	–	8	8	–	4	11	–	–	3	–	6	9	–
ID	1	6	1	–	31	–	–	4	–	3	10	14	–	3	–
LID	3	21	6	–	–	–	–	15	–	2	4	11	15	24	6
MoD	1	19	5	–	31	–	–	4	–	1	2	1	–	15	–
LD	–	–	–	–	–	–	–	–	–	3	1	8	3	3	–
MiD	–	1	1	–	–	–	–	7	–	–	2	4	–	3	–
	8	77	15	8	92	–	11	85	4	14	36	50	24	70	6

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TABLE 6 Types of unreliability signals per deviation class (frequency).

	A	B		C	D	E
	MoD (E)	**ID (S)**		**HID (S)**	**LID (E)**	**VSD (E)**
Vague and misleading claims	22	22		12	5	2
Inaccurate claims	19	12		12	6	3
Jargon claims	–	–		2	1	1
Irrelevant claims	–	–		–	–	–
Exaggerations	1	6		10	2	3
	F	**G**		**H**	**I**	**L**
	LID (S)	**MoD (S)**	**ID (S)**	**SD (S)**	**ID (G)**	**LID (S)**
Vague and misleading claims	15	3	4	22	5	7
Inaccurate claims	14	1	–	12	5	6
Jargon claims	–	–	–	–	4	–
Irrelevant claims	1	–	–	–	1	–
Exaggerations	–	–	–	6	–	2

to go beyond the traditional analysis of disclosure. In particular, important evidence emerges by comparing the analysis conducted for companies A and D. Looking only at the frequency of the disclosure (Table 1, panels A and B) and its informative capacity (Table 2), both companies suggested virtuous behaviours. This is consistent with an important stream of literature on the content analysis of voluntary disclosure under a traditional perspective, which assumes that the degree of the disclosure can represent the commitment to a specific topic. Specifically, Krippendorff (1980, p. 21) stated that content analysis is a 'research technique for making replicable and valid inferences from data according to their context,' and Mention (2011, p. 286) affirms that 'the basic assumption underlying content analysis is that the amount of information disclosed reflects the importance of the information.' This is aligned with the essential concept of content analysis (Krippendorff, 1980), according to which the extent of reporting shows the disclosed issues' importance (Bernini et al., 2022). In other words, looking only at what companies say and at the informative capacity highlighted by the mix of information attributes, without questioning their reliability, companies A and D both appear virtuous. This concept, although valid in accounting studies, does not consider the possibility that, even in the case of an extensive amount of reporting, the companies' disclosure could be unreliable.

The contribution of this paper therefore lies in the ability to reveal the gaps between information capacity and disclosure reliability. The existence of the aforementioned discrepancies is particularly demonstrated by the analysis of company A, which has the highest MW_{index} while showing a good level of digital talk.

A further potential of our tool is related to the possibility of detecting the ESG areas in which the machinewashing strategies are perpetrated (Table 5). This makes it possible to perceive the ESG area in which the misleading behaviour occurs. This may contribute to understanding not only the machinewashing sources, but also, more generally, how companies behave in the management of digital transformation, and, specifically, how they manage their ethically sustainable impacts on the stakeholders – all this in light of the conceptual framework underlying this paper, with the framework based on corporate digital responsibility (Wade, 2020), which is related to both the ethical use of AI and to reputational risk (Wirtz et al., 2023). At the same time, our theoretical background recalls the legitimacy theory perspective (Deegan et al., 2002), on which basis disclosure may help improve the company's reputation (Lyon & Montgomery, 2015). Moreover, disclosure may foster the possibility of reacting to the stakeholders' pressure and meeting their expectations (Freeman, 1994; Patten, 2002; Uyar et al., 2020). This allows companies to gain legitimacy and improve their reputation.

6 | CONTRIBUTIONS, IMPLICATIONS AND MAIN CONCLUSIONS

Recent acceleration in digital technology development has been undoubtedly favoured by both internal and external factors. As to internal factors, in a dynamic context where no industry can avoid the growth-innovation relationship, the use of more advanced digital technologies (AI, big data, IoT, etc.) becomes a crucial driver for increasing company competitiveness. External factors are related to the incentives (such as the fiscal incentives) for digital transformation, following the principles for the fourth industrial revolution.

However, while we fully recognise the relevance of 'Piano Industria 4.0' by the Italian Ministry of Economic Development, it is currently considered appropriate to overcome that vision based only on technical and economic issues and to include environmental and social factors in a more holistic approach according to the framework for the fifth industrial revolution. The latter is aimed at placing innovation beyond the search for higher levels of corporate performance, encompassing the idea of harmonious human–machine

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collaborations, with a specific focus on the well-being of the multiple stakeholders.

Our work contributes to the above research lines by calling for authorities' attention to be focused on the need of AI regulation in ethical terms (e.g. Aitken et al., 2020; Crawford & Calo, 2016; Haenlein & Kaplan, 2020; Kopalle et al., 2022; Taddeo & Floridi, 2018). Particularly, literature is focused on the topic related to voluntary and mandatory disclosure, the centrality of which is connected with the mentioned characteristics of opacity and complexity of technologies. In fact, as Schultz and Seele (2023) state, the effort towards a more transparent and standardised disclosure on digital issues is a crucial step for institutionalising AI ethics.

Finally, the inappropriate clarity of reporting seems to promote machinewashing behaviours.

Machinewashing issue has been investigated mainly from a theoretical point of view (Seele & Schultz, 2022). Our paper contributes to the research stream on machinewashing by proposing an instrument that may help scholars aiming to operationalise the machinewashing concept. In fact, our methodological design indicates that it is indeed possible to operationalise and measure machinewashing strategies. Furthermore, this also suggests that a specific analysis of corporate reporting may be a tool to detect such strategies, to measure their intensity and to identify the drivers' companies may use to deceive stakeholders. A specific analysis of corporate reporting may therefore be a tool to emphasise the ethical-sustainable impacts of digitalisation. Particularly, it allows researchers to understand which ESG dimensions the machinewashing strategies mostly involve and which unreliability signal they mostly report.

For these reasons, the methodology we propose may be applied and developed to test the research questions pertaining to the investigated phenomenon of machinewashing along a business economics perspective. Specifically, we aim to contribute to empirical studies, using variables resulting from the operationalisation of machinewashing and from the measurement of the machinewashing strategies' intensity. Moreover, this may be particularly useful for conducting studies on big samples, with both researchers and regulators carrying out those studies in order to scrutinise the phenomenon of machinewashing.

An additional relevant managerial and practical implication consists in the definition of an instrument that managers, shareholders, regulators and other external stakeholders may use to evaluate the consistency of disclosure and the company's accountability regarding the effects of the digital transformation. MW_{index} may also represent a tool that allows managers to evaluate the company's reputational risk. As the corporate digital responsibility perspective enlightens, reputational risks are embedded in the digitalisation development when ethical concerns are not effectively or substantively pursued (Wirtz et al., 2023). Moreover, the investigation of the IR and of the more frequent unreliability signals may help managers and owners understand the level of transparency and the level of standardisation of companies' disclosure (Schultz & Seele, 2023); the above-mentioned investigation may also help managers and owners detect how disclosure on digitalisation may reveal some conflicts within the company, contributing to the improvement of the governance mechanisms. Finally, MW_{index} is a useful tool for analysts who evaluate companies' ethically sustainable behaviour, also in the field of technological innovation, in order to define a strategy for allocating investors' capital.

Nowadays, the digital transformation is a phenomenon that concerns all industries and not only the ICT ones. The machinewashing index has been tested on ten industries in order to explore the index's validity. Although we cannot infer general conclusions from the machinewashing strategies observed in various industries, we found that each of the ten companies shows the following peculiarities: in terms of quantity when it comes to reporting on digital issues, in terms of the types of information disclosed and in terms of the types of deceptions perpetrated. In order to be able to infer general conclusions, we can consider MW_{index}, which, once it has been applied to large samples, would allow to investigate the phenomenon according to the characteristics of each sector. This gives room for a possible future improvement of this research.

Next, we mention a few limitations of our research. Firstly, our research design based on an exploratory content analysis of the reports may involve some biases in terms of subjectivity, thus generating unreliable information as to machinewashing behaviour. Secondly, we adopted a small sample that may not adequately represent the population of listed companies. However, the sample size of the study was small owing to the exploratory nature of the study, which was merely to gain an understanding of or insights into the phenomenon under investigation, and not to generalise results. Again, given the exploratory nature of our study, there is still a need for future research to consolidate our findings. In this regard, additional future research avenues may benefit from using Likert-scale surveys to measure machinewashing stemming from stakeholder perceptions.

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CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflict of interest.

PEER REVIEW

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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ENDNOTES

[1] Some examples of such use are related to the employee surveillance systems and the assessments on their performance; to the algorithms regulating the setting of the prices of products and services; to the environmental impacts of the artificial intelligence systems.

[2] For a detailed comparison between greenwashing and machinewashing see: Seele and Schultz (2022).

[3] 'Communication about ethical AI is often labelled as untrustworthy, aspirational, and not least as machinewashing (…). Similar concerns have previously been raised about CSR as a mere marketing or public relations tool, where a substantial gap between symbolic and aspirational managerial 'talk' and the actual upholding of social responsibility standards prevails' (Seele & Schultz, 2022, p. 1082).

[4] The pilot coding process has been carried out another three times, considering the same contents. The repetition was concluded when Krippendorff alfa had exceeded the reliability threshold (0.85 > 0.80). At the end of the coding process, the reliability was re-assessed again, obtaining a correspondence higher than 90% on a significant portion of the texts. The reliability threshold is defined on the basis of a correspondence equal to or greater than 80% (Kassarjian, 1977).

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APPENDIX

TABLE A Keywords for selecting digitisation information.

Hossnofsky and Junge (2019)						
Augmented reality	Big data	Bitcoin	Blockchain	Bots	Business intelligence	Click-through rate
Cloud	Connected car	Connectivity	Cryptocurrency	Data capturing	Data processing system	Data analytics
Data architecture	Data integration	Data monetisation	Data science	Digital	E-business	E-catalogue
E-commerce	E-learning	E-mobility	E-procurement	E-publishing	E-service	E-travel
Fintech	High-tech	Industry 4.0	Influencer	Internet	Internet of things	Machine learning
New economy	Newsfeed	Online	Open source	Platform	Robotics	Self-driving car
Sharing economy	Smart content	Smart devices	Smart factory	Smart home	Smartphone	Software
Social media	Trade in data	Virtual reality	Web-based	3D print		
National Plan Industry 4.0						
Additive manufacturing	Augmented reality	Simulation	Horizontal/vertical integration	Industrial internet	Cloud	Cyber security
Big data and analytics						

Note: The words were searched in their entirety or, in cases where this proved necessary, by means of a root-word search.

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TABLE B Coding rules.

Issue	Rule
Documents to be investigated	Annual report and non-financial statement
Recording unit	Code for text units, graphs and tables. Do not code for photos
Frequency	• Frequency is the number of times that a specific text unit, associated with a defined mix of attributes, is present. The frequency is reported in the specific cell of a coding sheet matrix • If a piece of information is present two or more times in the two documents, it is counted only once • One text unit is counted as one frequency
Ambiguity	• Confusing and unclear text units were not counted • In case of concepts that can be codified into different categories, the dominance principle has to be applied
Identification of attributes	
Financial	Information characterised by monetary nature
Non-financial	Information not characterised by monetary nature
Quantitative	Information represented by numbers
Qualitative	Information represented by narrative description
Mixed	Information represented by both numbers and narratives
Non-time specific	The information shows no time orientation or describes current situations
Historical	The information has to do with past events
Forward-looking	The information has to do with future scenarios (i.e. projects, ideas, hypotheses, suppositions)

Source: Bernini et al. (2022).

TABLE C Mix of attributes representative of the information capacity.

1	Financial/mixed/historical
2	Financial/quantitative/historical
3	Non-financial/mixed/historical
4	Non-financial/quantitative/historical
5	Financial/qualitative/historical
6	Non-financial/qualitative/historical
7	Financial/mixed/non-time specific
8	Financial/quantitative/non-time specific
9	Non-financial/mixed/non-time specific
10	Non-financial/quantitative/non-time specific
11	Financial/qualitative/non-time specific
12	Non-financial/qualitative/non-time specific
13	Financial/mixed/forward-looking
14	Financial/quantitative/forward-looking
15	Non-financial/mixed/forward-looking
16	Non-financial/quantitative/forward-looking
17	Financial/qualitative/forward-looking
18	Non-financial/qualitative/forward-looking

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TABLE D Methodological framework for analysing the reliability of information.

Type	Description	Example
Vague and misleading claims	Broad statements without specific meaning	Talking about difficulties generated by the economic crisis, rather than climate change, instead of referring to customer satisfaction or reducing emissions
Inaccurate claims	Incorrect or invented statements or data	Talking about specific ESG impacts but no exact percentage quantification or concrete evidence even when checking for such indications in previous years' reports
Jargon claims	Statements using language, terms or jargon that do not resonate with interested parties (especially customers)	Reporting statements making extensive use of specific/jargon terms
Irrelevant claims	Statements that emphasise a trivial ethical aspect, while the remaining business practices are contrary to ethical or environmental standards	Statements emphasising issues that are not taken into account in the rest of the text
Exaggerations	Claims that make the organisation or its products look better than they are. Exaggerated claims that go far beyond the possibilities of the product or the capabilities of the organisation	Reporting very positive aspects of technologies without terms of comparison with other tools, without highlighting the potential negative aspects or going far beyond the skills of the company and of people

Source: Adapted from Seele and Schultz (2022).

For each content unit, we identified the recurrence of deception signals (the type of deception among the 5). For the same text unit, we considered the possibility of detecting multiple types/signals of deception. Therefore, we did not stop at the first detected deception signal. After doing this, we measured the level of unreliability as represented in the following Table E.

TABLE E Unreliability measuring process.

	Number of detected signals in a text unit	Maximum number of detectable signals	Reliability measure
Case 1	0	5	5 (reliable information)
Case 2	1	5	4
Case 3	2	5	3
Case 4	3	5	2
Case 5	4	5	1
Case 6	5	5	0

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