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Optimizing ESG Risk Assessment Processes with AI-Driven Process Mining: A Framework for Proactive Sustainability Management

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Abstract

The growing focus on sustainability and mitigation of environmental risks has made the ESG (Environmental, Social and Governance) framework a central element in the strategic and operational management of modern organizations. In a context marked by increasingly stringent regulatory pressures – such as the Corporate Sustainability Reporting Directive (CSRD) and the recommendations of the Task Force on Climate-related Financial Disclosures (TCFD) – companies are now called upon to integrate ESG metrics into their decision-making processes, in order to address global challenges such as climate change, biodiversity loss and the necessary ecological transition. However, the fragmentation of available data and the lack of adequate predictive tools continue to hinder truly effective and future-oriented ESG management. This study proposes an innovative operating model based on the synergistic integration between Artificial Intelligence (AI) and Process Mining, with the aim of improving monitoring, automation and transparency in ESG processes. AI allows the processing of large volumes of heterogeneous and unstructured data, while Process Mining allows you to map and optimize business flows, detecting inefficiencies and ensuring traceability. The model proves to be particularly effective for financial institutions and companies operating in sectors with high climate exposure, providing concrete answers to the needs of regulatory compliance and strategic sustainability. The adoption of this approach makes it possible not only to anticipate environmental risks, but also to strengthen organizational resilience and support the transition to a "sustainability-first" paradigm. The study highlights the transformative potential of AI-driven Process Mining in ESG management, offering scalable and replicable solutions for sustainable innovation that combines efficiency, responsibility and competitiveness in the long term.

Keywords: Artificial Intelligence, ESG, Process Mining, Environmental Risk Assessment, Climate Change

Paper type: Academic Research Paper

1 Introduction

Climate change represents one of the most complex and pervasive challenges for the global economic and financial system. The incessant expansion of human activities has led to a significant increase in greenhouse gas emissions, aggravating global warming and generating negative consequences such as extreme weather events, sea level rise and destruction of ecosystems (Di Bella, 2020). These phenomena have significant impacts not only on the environment, but also on the stability of firms, on the security of investments and on economic competitiveness (Engel et al., 2015).

At the regulatory level, the United Nations 2030 Agenda and the European Green Deal have strengthened the centrality of climate sustainability in political and industrial agendas. However, despite growing awareness, many companies are still unprepared to identify and manage climate risks (Ai & Gao, 2023). According to Omar et al. (2020), strengthening climate resilience requires companies to develop capacities to assess and absorb risk information, translating this knowledge into strategic actions. In this context, the ESG (Environmental, Social and Governance) framework is established as an essential tool for guiding organizations towards sustainable, transparent and resilient business models. The integration of ESG metrics into risk management is now critical not only for regulatory compliance, but also for long-term value creation (Leoni, 2024). The growing focus on sustainability has prompted supranational institutions and regulators, such as the European Union with the Corporate Sustainability Reporting Directive (CSRD) and the Task Force on Climate-related Financial Disclosures (TCFD), to adopt increasingly stringent and detailed regulations (Brende & Sternfels, 2022; Zhao et al., 2024).

Alongside the regulatory component, a crucial role is played by the ability of companies to integrate digital tools for predictive analysis, reporting automation and proactive sustainability management. Emerging technologies, such as Artificial Intelligence (AI), Process Mining and Natural Language Processing (NLP), offer new possibilities to transform ESG assessment from a manual and reactive process to an intelligent, automated and strategic system (Amiri et al., 2024; Minz & Khattar, 2024). The joint use of AI and Process Mining makes it possible to improve traceability, identify anomalies in ESG flows and support timely decisions (Gerassis et al., 2021).

Despite the growing importance of ESG principles, many organizations struggle to implement them effectively. The difficulties stem from structural factors such as data fragmentation, the absence of standardized methodologies and the reliance on outdated assessment tools (Kalogiannidis et al., 2024). In the face of these critical issues, this study proposes the integration of two synergistic approaches: on the one hand, a structured methodology for the self-assessment of climate-related and environmental risks, in accordance with the ECB Guidelines (2020) and the expectations of the Bank of Italy; on the other hand, an innovative digital framework based on Artificial Intelligence (AI) and Process Mining, to optimize the analysis and reporting of ESG risks (Amiri et al., 2024; Minz & Khattar, 2024).

The aim is to provide a theoretical and operational basis to support companies in the adoption of intelligent and integrated tools, capable of addressing environmental and regulatory challenges with proactive and data-driven approaches.

2 Theoretical framework

2.1 The strategic role of ESG in corporate governance

The integration of ESG principles into corporate governance models is now recognized as a necessary condition for effective risk management and for strengthening organizational resilience. Environmental risks, particularly those related to climate change, are increasingly being transformed drivers for business models. They impact not only economic aspects, but also social and environmental ones, triggering changes in value chains, operational management and stakeholder relations (Di Bella, 2020; Ai & Gao, 2023). Climate change manifests itself through direct effects, such as extreme weather events and sea level rise, but also through indirect impacts, such as fluctuations in demand, price volatility and rising insurance costs (Engel et al., 2015). Numerous studies underline that companies are not yet fully aware or ready to face these risks. According to Omar et al. (2020), it is crucial for companies to improve their capacity to absorb and transform climate-related information in order to maintain competitiveness and business continuity. Failure to prepare can result in financial losses, reputational damage and reduced access to credit.

To promote a resilient and sustainable economy, companies must adopt a systemic view of ESG risks, capable of integrating technological tools, business strategies and regulatory compliance. A multidimensional approach allows to simultaneously consider physical risks (e.g. floods, droughts, heat waves), transition risks (e.g. new regulations, carbon taxes, technological innovation) and liability risks, such as legal claims arising from environmental damage caused by business activities (FSB, 2015; ECB, 2020). In this context, the ECB Guidelines (2020) and the EBA take on a central role, setting out precise expectations for the banking system in terms of identifying, managing and communicating climate-related and environmental risks. These documents clearly indicate that financial institutions must incorporate ESG risks into their strategic models and risk management mechanisms. In particular, it is required to identify the most exposed sectors and geographical areas, assess the impact on products and services and define climate and environmental risk reduction objectives in business plans (Pasquini, 2020).

ESG risks are reflected in all traditionally monitored risk categories: credit, market, operational, reputational, strategic and liquidity risk. Acute climate change, such as the increase in scorching days, has already been associated with a decline in business performance and increased fragility of supply chains (Pankratz et al., 2023). In addition, the adaptation to a low-carbon economy has impacts on operating margins, demand for goods and asset valuation, triggering an overall reorganisation of business models, especially in emission-intensive sectors. Within this paradigm, the "E" (environmental) component is the one on which the most attention is focused by companies, supervisors and investors (Naeem et al., 2022). Initiatives such as the United Nations 2030 Agenda and the Network for Greening the Financial System (NGFS) have pushed for greater harmonization in the classification and management of environmental risks. The NGFS has introduced a detailed classification table that distinguishes the main components of physical and transition risks, thus providing a useful tool for financial institutions in the risk identification and assessment phase (Pasquini, 2020).

2.2 Regulatory and technological integration in ESG management

The growing awareness of the importance of climate risk management has also led to greater attention to the role of technological innovation, with particular reference to Artificial Intelligence (AI) and Process Mining. The integration of these technologies makes it possible to overcome the inefficiencies of traditional ESG models, which are often manual and not very dynamic, improving the quality and timeliness of the information available. Technologies such as Natural Language Processing (NLP), deep learning and predictive analytics make it possible to analyze large amounts of ESG data from heterogeneous sources (regulatory reports, media, social networks), thus supporting proactive and data-driven risk management (Amiri et al., 2024; Gerassis et al., 2021).

Process Mining allows you to visualize and monitor operational processes in real time, mapping any deviations from ESG standards and identifying inefficiencies or bottlenecks in the reporting chain (Schreiber, 2020). This synergy between AI and Process Mining translates into greater transparency and traceability of corporate ESG flows, facilitating regulatory compliance and improving communication with stakeholders. Empirical evidence shows how the adoption of advanced digital tools can facilitate a shift from a reactive to a proactive logic in risk management. According to Burnaev et al. (2023) and Kim & Lee (2022), the automation of ESG processes not only reduces manual workload, but also allows for hidden patterns in data and predictive scenarios useful for strategic planning. In addition, the application of sentiment analysis techniques makes it possible to detect the external perception of the company in real time, providing an additional tool for reputation management (Kiriu & Nozaki, 2020).

The adoption of a theoretical framework based on the integration of regulatory requirements, digital innovation and a long-term strategic vision is the main way to effectively address the challenges of climate change. Companies that are able to systematically integrate ESG tools into their decision-making models will not only strengthen their resilience, but will gain a competitive advantage in terms of reputation, attractiveness for investors and sustainability in the long term. A central reference point is the ECB Guidelines (2020) and the EBA Recommendations, which outline the obligation for banks to integrate environmental risks into their business models and business strategy. In particular, two main types of climate risk are defined: physical risk, deriving from extreme climatic events or gradual environmental changes, and transition risk, linked to regulatory, technological and reputational adaptation towards a sustainable economy (Pasquini, 2020; Caldecott et al., 2021).

Physical risk can manifest itself in direct damage to structures and assets, disruptions in the supply chain, or reduced productivity, with concrete impacts on revenues, cash flows, and business value (Pankratz et al., 2023). Transition risk, on the other hand, is expressed through costs related to regulatory compliance, market loss for carbon-intensive sectors, and possible legal disputes for environmental liabilities (EBA, 2020). In addition to these, there is a third level of risk that is often less considered: "liability risk", i.e. legal and reputational liability linked to environmental damage caused by corporate activities, as highlighted in the most recent European regulatory consultations (FSB, 2015; EBA, 2020). Alongside the regulatory dimension, contemporary literature emphasizes the role of technological innovation in ESG management. In particular, Artificial Intelligence (AI) and Process Mining are establishing themselves as enabling tools to overcome the limitations of traditional evaluation models. Natural Language Processing (NLP), predictive analytics, and deep neural networks enable meaningful insights to be extracted from large volumes of unstructured data, such as business reports, social media, and regulations (Amiri et al., 2024; Gerassis et al., 2021). In addition, deep learning finds application in areas such as agriculture and natural resource management, making it possible to predict emissions, deforestation, and biodiversity loss more accurately and in a timely manner (Ezenkwu et al., 2024).

2.3 Synergies between AI and Process Mining for ESG Transformation

Process Mining, on the other hand, makes it possible to map and optimize sustainability-related business processes, improving the traceability of ESG flows, detecting inefficiencies and facilitating regulatory compliance in real time (Schreiber, 2020; Minz & Khattar, 2024). This technological integration is particularly relevant in regulated and information-intensive sectors, such as banking, insurance and energy, where transparency and accountability are critical.

The review of the literature (Kim & Lee, 2022; Burnaev et al., 2023) suggests that the AI–Process Mining combination is divided into three main directions:

1. Advanced ESG data analytics: With the support of AI, you can improve the quality and consistency of your data by spotting anomalies and emerging trends.
2. Optimization of ESG processes: Process mining enables continuous tracking of compliance and the identification of bottlenecks.
3. Automation and decision support: thanks to the digitization of reporting processes, errors and time are reduced, improving the timeliness and quality of strategic decisions (Yaseen, 2023; Sokolov & Abramova, 2023).

In addition, several studies underline that the adoption of these digital tools allows not only a faster reaction to emerging risks, but also the construction of moral and reputational capital useful for dealing with future crises (Lins et al., 2017; Deng et al., 2013). This dynamic approach allows companies to adopt a resilience-oriented mindset, capable of integrating sustainability within the corporate culture and core decision-making processes. The evolution of governance models, which increasingly incorporate stakeholder engagement practices and transparency in the disclosure of ESG data, should also be considered. In this context, AI can also support sentiment analysis on social media and the assessment of public perception, providing real-time feedback on corporate reputation and the effectiveness of environmental and social strategies (Kiriu & Nozaki, 2020). Finally, ESG-based technologies are also showing an increasing impact on sustainable investing. The growing interest from institutional investors in robust and documented ESG practices is driving companies to structure digital and measurable strategies to improve their ESG rating (Naeem et al., 2022; Popescu & Yu, 2024). The traceability offered by Process Mining, combined with the predictive capacity of AI, is a key element in attracting capital and strengthening stakeholder trust. The proposed theoretical framework is based on a twofold innovation: on the one hand, the standardized structuring and classification of ESG risks, in line with current regulations; on the other, the adoption of intelligent technologies that allow predictive and adaptive management of sustainability. This integrated vision represents a game-changer for companies that want to address climate change not only as a threat, but as an opportunity for transformation and sustainable growth.

3 Methodology of approach and proposed solutions

3.1 High-level process

The present work has developed an operating model based on the digitization of business processes and the synergistic use of technologies such as Artificial Intelligence (AI), Robotic Process Automation (RPA) and Machine Learning (ML). The approach adopted resulted in the construction of a Business Process Model and Notation (BPMN) (Mahdi et al, 2024) that describes, in detail, the phases that lead to the definition of risk. This scheme, which represents the skeleton of the theoretical model, has been developed with the aim of identifying for each process area the value-added activities and those that are repetitive or standardizable, in order to optimize the entire path through automation. The mapping of the processes has made it possible to highlight numerous critical areas, often linked to manual or untraceable operations, which slow down the risk analysis and reduce its effectiveness.

In the first phase of the model, the analysis focuses on the definition of operating environments and the identification of internal processes that do not generate value. In this phase, Process Mining (Aalst 2022) was used, an advanced tool that makes it possible to reconstruct the real flows of the organization starting from the information systems, highlighting inefficiencies and redundancies. The output of this analysis provided the basis for a targeted redefinition of processes through the design of RPA solutions (Tripathi et al, 2025), capable of automating recurring and operationally intensive tasks.

Considering the high-level process, the BPMN model (figure 1) has been divided into different operational areas, where the first macro area is dedicated to risk calculation. In this first phase, a questionnaire that can be adapted for each company is used, aimed at defining the reference environments, KPIs, weights associated with each risk category, and assessing the current risk through a scoring system. The second macro area concerns strategic planning, which is responsible for representing the results obtained, organizing them into risk clusters by importance, and illustrating the mitigation plan with the corrective actions to be taken. The third macro area concludes the process with the definition of a managerial action plan, focused on monitoring deviations and continuously updating strategies based on the results of the analysis.

Figure 1. High level BPMN of the process. Our elaboration.

Once the different steps had been defined, a careful analysis was launched aimed at identifying the most suitable algorithms for their automation. The choice fell on the use of multiple and integrated models, which collaborate with each other in a modular way (Wang et al, 2024). This solution has proven to be more efficient than using a single monolithic model, as it allows performance to be optimized with less information usage. In addition, the adoption of intermediate outputs along the various stages of the process allows constant and timely monitoring, improving control and operational transparency (Stern et al, 2023 and Wu et al., 2021).

3.2 Risk Assessment Process

More specifically, in the macro area of Risk assessment, the final goal is to divide customers into clusters to identify a level of gross risk for the company. This action allows for the breakdown according to the risk that they pose to the business. To achieve this, several steps are carried out in the process.

Going into the details of the model, the study of the same has shown the presence of a risk analysis based on static elements and repetitive manual tasks of information exchange. The development opportunity identified in the study proposes the use of machine learning algorithms, the training of which is aimed not only at risk classification, but also at its evaluation with a view to minimizing losses.

In fact, the risk definition process is divided into several steps with different levels of manual skill and analysis.

The first step of the macro area of the Risk assessment involves the use of two separate questionnaires to identify risk categories. The first questionnaire is aimed at identifying the presence of risks generated by customers; the second is aimed at measuring the severity of the risk in individuals identified as suffering from potential criticalities. It was therefore decided to automate the generation of these questionnaires through the use of Robotic Process Automation (RPA), developing a bot capable of producing a standardized checklist. According to the framework developed by Wellmann et al. (2020), repetitive and standardised activities, such as the production of questionnaires, fully fall within the technical feasibility criteria. Introducing RPA in this operational phase helps reduce the risk of human error and ensure consistency in information collection.

Furthermore, the sole limitation to the administration of questionnaires is partially efficient although perfectly manageable by humans. This dimension can be broadened by introducing more in-depth analysis techniques (Kelley-Quon LI., 2018).

Therefore, in parallel with the automation of the generation of checklists for corporate risk assessment through RPA, an additional component based on Web Scraping techniques has been introduced, with the aim of enriching the decision-making process through the automatic and systematic collection of data from both internal sources (company documentation, management reports, digital archives) and external sources (institutional sites, financial indicators, regulatory portals and sectoral databases). This technique allows to automatically aggregate data from multiple sources, structuring them into consistent outputs that can be integrated with internal company systems (Ferrara et al., 2012). In addition, according to Wellmann et al. (2020), to validate all the criteria provided by RPA, it is necessary to use applications to support the model. This activity is part of a broader logic of business intelligence, where the ability to access and analyze distributed and not always structured information is essential to build a dynamic and updated representation of the operating context and potential risks.

This process translates into a double advantage: on the one hand, it improves the ability to identify weak signals or anomalies in the external context, and on the other hand, it allows the internal parameters used in risk assessment models to be kept up to date. Furthermore, thanks to the ability to access structured content in real time, Web Scraping helps to automatically populate risk indicators (KPIs), strengthening the reliability of the analysis model (Ferrara et al., 2012).

The second step relating to the Risk assessment is the definition of the weights for each of the risk categories identified in the first step. In our case, the approach adopted is oriented towards a logic of minimizing losses, focusing on a central concept: the protection and monitoring of a minimum company assets, understood as a critical threshold below which the integrity and operational continuity of the company could be compromised. The deterioration of company assets becomes the metric through which the severity of the risk is measured: the more significant the expected damage, the greater the weight assigned to the detected risk.

In this case, the process involves the search for information and data from authoritative sources such as the European Union or the Italian Government for a qualitative attribution of weights supported as much as possible by objective criteria. However, this system has a subjective component that can affect the comparability and objectivity of the results (Koradecka et al., 2010).

In fact, in this case, a structured analysis of the sources has been provided. Three machine learning techniques have been identified that can make the assignment of weights objective. The three techniques selected are respectively Random Forest, Gradient Boosting Machine and Logistic Regression. These solutions are comparable and can be integrated with each other.

The first model, the Random Forest, proves to be particularly suitable for its robustness and flexibility in business contexts where it is necessary to assign weights to risk variables starting from complex, heterogeneous and sometimes redundant datasets. The main advantage of this algorithm lies in its ability to identify the most relevant variables for risk prediction, through internal selection mechanisms based on measures of importance (Speiser et al., 2019). However, the Random Forest technique is known to be a "black box" model. This reduces the transparency of decisions, which is crucial for the application of this study as already highlighted. Furthermore, if not properly optimized, the model can involve high processing times, especially in the training phase, in the presence of very large or complex datasets, so its use is recommended in small business contexts.

The second model, the Gradient Boosting Machine (GBM) algorithm, is an ensemble learning technique (combination of multiple predictive models) based on sequential optimization of weak models. This method is able to build highly accurate models through an iterative process that aims to correct, step by step, the errors made by previous predictions. Unlike the Random Forest, which works in parallel on independent trees, the GBM builds the model sequentially, which makes it particularly sensitive to parameter adjustment, but also very powerful from a predictive point of view (Tian et al., 2020). However, this system can be subject to overfitting especially in the presence of large datasets (Tian et al., 2020).

The third model, Logistic Regression, is a well-established technique widely used in risk modeling. Second, Logistic Regression represents an extremely effective tool to analyze binary variables, such as in the case of risk events, while allowing to include multiple explanatory variables in the model and to estimate the probability of occurrence of an event that can also be interpreted in the decision-making field. One of the main strengths of this model is its transparency and simplicity of interpretation, which makes it particularly useful when it is necessary to explain the modeling choices to non-technical stakeholders (Sperandei, 2014).

Therefore, the power of the first two models and the transparency of the results of the third can be combined to provide an accurate weight definition that is understandable to outside observers.

Once the risk categories and the weights associated with them have been defined, the process continues in the mapping of the business processes that are put in the matrix with the risk areas to understand their probability and impact, thus defining the gross risk. This process is totally discretionary and is based on the collection of information carried out up to that moment. The calculation of probability and impact, then, are exclusively linked to a current calculation without considering historical trends. Furthermore, in the specific context of the company in question, the result is extremely influenced by the characteristics of the customers of the process who must be clustered in order to be evaluated. This work is carried out manually through an initial skimming of the riskiest subjects and an in-depth investigation exclusively on them. This approach is effective, although limiting, if carried out by a person. The approach we suggest is a wide-ranging analysis of the basic information of all customers and a model capable of reconstructing the historicity of the subjects to include the forecast within the considerations.

In this context, it was decided to integrate Artificial Intelligence as a tool to support these activities. Flammini et al. (2023) proposes a methodological approach to risk management through AI systems. This model is not limited to data collection or technical automation alone, but aims to generate operational intelligence through the continuous processing of performance and risk indicators. This strengthens the organization's ability to respond promptly to potential critical events. It suggests an AI tool capable of carrying out an in-depth and structured analysis capable of generating a dynamic clustering of customers.

3.3 Strategic definition and creation of the action plan

Once the level of risk has been defined, the process continues with strategic planning in which the most critical areas are identified and priorities are set. This plan defines both the monitoring and implementation times of the measures envisaged, with the aim of arriving at an objective assessment of the degree of mitigation obtained. Finally, the last step of the process involves the construction of an action master plan. In the creation of the latter, targeted interventions are identified and developed through a structured analysis. Given the high interconnection between the second and third macro areas of the model, the decision was made to adopt a single automated approach for both phases.

In the current process we find a definition of priority levels based on brainstorming and analysis approaches with experts to determine priorities together with forecasting future impacts and monitoring actions. Also in this case, discretion plays a decisive role in the result.

To limit the discretionary contribution, the framework of Flammini et al. (2023) was again considered, which with its power of analysis is able to provide objective elements to the decision-making process. Therefore, the final steps of the process can be grouped and simplified by having the tool produce several intermediate outputs that can help decision-makers to have the correct guidelines.

4 Conclusions

In conclusion, the model developed in this work is configured as an integrated ecosystem of intelligent technologies applied to risk management, capable of combining automation, predictive analysis and decision support in a single operational architecture. The adoption of tools such as RPA, AI and Machine Learning, supported by a solid mapping of processes through BPMN, has made it possible to outline a systemic path oriented towards efficiency, the reduction of human error and the enhancement of company data.

A key aspect of the model is the ability to segment customers based on the risk they bring to the business. Using clustering techniques, customers can be grouped into homogeneous clusters, making it easier to identify high-risk customers and take targeted corrective measures.

The innovative contribution of this model lies in the ability to transform risk management into a modular, adaptive and proactive process, overcoming the traditional static and fragmented approach. The integration of Web Scraping techniques and Business Intelligence tools has also significantly expanded the scope of information available, enriching assessments with dynamic and contextual elements from inside and outside the organization.

These developments have opened the door to higher investigations and considerations. Among the most interesting ones, certainly, is the opportunity to integrate the results of risk assessment into predictive models that convey the same results into mathematical optimization models. This would provide decision-makers with a clear guideline in the field of short- and long-term strategic planning that has never been addressed before. The introduction of machine learning algorithms such as Random Forest, Gradient Boosting Machine and Logistic Regression could open the door to better reliability of forecasts and to refine the definition of weights in risk categories, adapting modeling choices according to the complexity and transparency required in the different operational areas. The synergistic use of these models has proven to be more efficient than monolithic solutions, favoring incremental data processing and constant monitoring of outputs.

Looking ahead, the framework outlined can also be extended to other business decision-making areas, where the complexity of data and the need for rapid responses require the adoption of flexible, intelligent and automated models. At the same time, the approach remains open to subsequent evolutions, including the introduction of emerging technologies, such as Large Language Models or generative AI systems to further enrich risk analysis, forecasting and simulation capabilities.

Ultimately, this work intends to contribute to the development of a new vision of corporate risk management, based on the integration of organizational know-how and technological potential, capable of enabling increasingly timely and sustainable decision-making models.

5 Ethics declaration

The present research did not require the approval of an ethics committee, as it does not involve human subjects, sensitive personal data or experimentation on living beings. All the information used comes from publicly accessible sources and scientific literature.

6 AI declaration

Generative Artificial Intelligence tools have not been used for the drafting or processing of the contents of this document. All sections of the paper were developed independently by the authors, without the aid of generative AI applications.

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