UNIVERSIDADE CATÓLICA PORTUGUESA

GenAI and the Pursuit of Sustainability: a Qualitative Study of International Organizations

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by

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Acknowledgements

The completion of this master's thesis represents the end of a particularly transformative cycle in my academic, professional, and personal life.

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Abstract

Although Generative AI (GenAI) is widely recognized for its potential to advance sustainable development goals, current studies often treat GenAI and sustainability as separate subjects and relies heavily on theoretical discussions, editorials, or literature reviews. This resulted in a limited understanding of how GenAI interacts with organizational processes, practices, and strategies in the context of sustainability, often overlooking the complex trade-offs, governance challenges, and contextual factors. To address this gap, I conducted a qualitative case study with 21 semi-structured interviews with GenAI experts across industries, countries, and corroborating these insights with archival data. Using the Gioia methodology, the research systematically uncovers how international organizations are integrating GenAI with the three pillars of sustainability-economic, social, and environmental. The findings reveal that while GenAI is mainly leveraged for economic and social sustainability through automation and enhanced human-AI-collaboration, environmental considerations remain secondary. By providing empirical evidence on the nuanced dynamics of GenAI adoption, this study contributes to the literature on digital sustainability, GenAI, and human-AI collaboration, and calls for more integrated, context-sensitive theories that reflect the complexity of implementing GenAI for the pursuit of sustainability.

Keywords: Generative Artificial Intelligence (GenAI), digital sustainability, economic sustainability, social sustainability, environmental sustainability, human-AI collaboration, service management

Resumo

Embora a Inteligência Artificial Generativa (GenAI) seja vastamente reconhecida pelo seu potencial para promover os Objetivos de Desenvolvimento Sustentável (ODS), a literatura atual tende a tratar a GenAI e a sustentabilidade como temas separados, baseando-se sobretudo em discussões teóricas, editoriais ou revisões de literatura. Esta abordagem resulta numa compreensão teórica limitada sobre como a GenAI interage com os processos, práticas e estratégias organizacionais no contexto da sustentabilidade, frequentemente negligenciando os complexos *trade-offs*, os desafios da gestão e os fatores contextuais. Para colmatar esta lacuna, conduzi um estudo de caso qualitativo, com base em 21 entrevistas semiestruturadas realizadas com especialistas em GenAI de diferentes setores e países, complementadas com dados de arquivo. Utilizando a metodologia Gioia, esta investigação revela de forma sistemática como as organizações internacionais estão a integrar a GenAI com os três pilares da sustentabilidade — económico, social e ambiental. Os resultados demonstram que, embora esta tecnologia seja principalmente utilizada para fins de sustentabilidade económica e social, através da automação e do reforço da supervisão, as considerações ambientais permanecem secundárias. Ao demonstrar evidência empírica sobre as dinâmicas complexas da adoção da GenAI, este estudo contribui para a literatura sobre sustentabilidade digital, GenAI e colaboração humana e inteligência artificial, e apela ao desenvolvimento de teorias mais integradas e sensíveis ao contexto, que reflitam a complexidade inerente à implementação da GenAI para a transformação sustentável.

Palavras-chave: Inteligência Artificial Generativa (GenAI), sustentabilidade digital, sustentabilidade económica, sustentabilidade social, sustentabilidade ambiental, colaboração humana e IA, gestão de serviços

Dissertation Dissemination and Strategic Preparation for Journal Submission

From its inception, this study showed significant promise, supported by comprehensive data collection and a rigorous methodological approach. Based on a common agreement between the student and the supervisor, this research was presented at international conferences, where it received highly positive feedback and validation from the academic community. Encouraged by these results and the enthusiastic comments, the research is now being refined and extended for submission to a high-impact, peer-reviewed journal. Below is a summary of key dissemination activities to date, along with future plans to further advance this work.

1. This dissertation was presented at the International Conference on Information Systems (ICIS) in Bangkok, Thailand on December 14th, 2024. During the conference, experts in AI technologies for sustainability provided valuable feedback, which has been incorporated and contributed to the current version of the dissertation. Please see the reference below.

   Faria, B. M., & Trocin, C. (2025). GenAI for sustainable development: An inductive analysis of international organizations. *Pre-ICIS SIG Services Workshop on Synergizing Service Ecosystems with AI*, Bangkok, Thailand 2024.

2. My work was selected by jury of the prestigious Europaeum Summer School on Artificial Intelligence, which will take place in July 2025, at the University of Luxembourg. Following a competitive selection process, I was invited to participate and present a paper at this event, which brings together emerging scholars and experts from across Europe. The 2025 theme, "AI and the Digital Future," focuses on the societal, ethical, and governance challenges posed by artificial intelligence.

3. Following the submission of the dissertation, this research is being further advanced in collaboration with international esteemed colleagues, with the goal of submitting it to a prestigious ABS 3-ranked journal. This will ensure that the study's significant and timely contributions to the field are disseminated to a broader academic audience and inform ongoing scholarly discourse on this critical topic.

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List of abbreviations

AI – Artificial Intelligence

API – Application Programming Interface

EU – European Union

GAI – Generative Artificial Intelligence

GDPR – General Data Protection Regulation

Gen AI – Generative Artificial Intelligence

GPT – Generative Pre-trained Transformer

IT – Information Technology

LLM – Large Language Model

ML – Machine Learning

SDGs – Sustainable Development Goals

SLM – Small Language Model

1. Introduction

"Olhando à magnitude da ameaça, todos nos devíamos interessar pela questão da inteligência artificial. Não digo que cada indivíduo se deve tornar especialista na matéria, mas ninguém deve perder de vista que a inteligência artificial é a primeira tecnologia capaz de decidir e gerar ideias autonomamente"

Yuval Noah Harari in his book Nexus[1]

GenAI excels at generating new content (e.g., text, images/videos, speech/music) in a few seconds based on user prompts (Benbya et al., 2024; Feuerriegel et al., 2024; Ooi et al., 2025). This capability introduces novel action possibilities for addressing global sustainability challenges defined as "*meeting the needs of the present without compromising the ability of future generations to meet their own needs*" (Brundtland, 1987). The aim is to harmonize the interests of people, planet, and profit through more informed and adaptive organizational practices. The Triple Bottom Line (TBL) framework offers a comprehensive lens through which organizations can assess the broader impact of their actions—not just in terms of economic performance, but also social and environmental outcomes (Elkington, 1998a; The Economist, 2009).

For economic sustainability, GenAI can enhance operational efficiency and strategic decision making by automating processes and accelerating innovation across industries. Regarding social sustainability, it has the potential to generate new opportunities for inclusive and ethical work environments by augmenting human expertise and fostering continuous learning. For environmental

[1] Harari, Y. N. (2024). *Nexus: A Brief History of Information Networks from the Stone Age to AI* (M. Romeira, Trad.). Elsinore.

Translation: "Given the magnitude of the danger, AI should be of interest to all human beings. While not everyone can become an AI expert, we should all keep in mind that AI is the first technology in history that can make decisions and create new ideas by itself."

sustainability, it can contribute to sustainable practices by using lightweight models and optimizing energy use during development and deployment.

Although GenAI has the potential to help organizations to achieve sustainable development goals (SDGs) (Brown et al., 2024; Feuerriegel et al., 2024; Modgil et al., 2025; Ooi et al., 2025; Prasad Agrawal, 2025), the current academic literature explores the two topics independently and commonly assumes a simplified alignment between the technological innovations and the sustainability outcomes. Thus, little is known about the interactions of GenAI with business processes, practices, and strategies to address sustainable challenges, overlooking complex tensions and trade-offs. Many studies explored this research venue primarily through theoretical papers (Amankwah-Amoah et al., 2024; Brown et al., 2024, 2024; Feuerriegel et al., 2024, 2024) that rely on theoretical discussions, editorials, or literature reviews. Consequently, there is a lack of empirical case studies that examine how organizations actually implement GenAI for sustainability.

Digital sustainability goes beyond simply using technology to reduce environmental impact, it involves integrating technological innovation with broader economic, social, and environmental objectives (Kotlarsky et al., 2023). This prevailing narrative results in a gap of the complex trade-offs that organizations must navigate in practice, creating a techno-optimistic bias that overlooks governance challenges and implementation constraints (Faria & Trocin, 2025; Modgil et al., 2025; Rana et al., 2024). It is therefore essential to explore how organizations are leverage GenAI not just as a tool for efficiency or profit-but as a catalyst for genuinely sustainable transformation that addresses potential conflicts and governance challenges. Understanding these dynamics is crucial to develop innovative strategies that balance these three pillars of sustainability. Thus, my research question is: how are international organizations leveraging GenAI to achieve sustainable goals?

I conducted a qualitative case study (Eisenhardt, 1989; Sarker et al., 2018) to explore how international organizations are leveraging GenAI in the pursuit of sustainable goals. I collected 21 semi-structured interviews with experts working with GenAI across industries and countries. To enrich the contextual understanding and corroborate the findings, I also collected and analyzed archival data such as organizational websites, online articles, webinars, reports, and blog posts. Gioia methodology (2013) guided the analysis of the dataset and provided a structured approach for interpreting emerging themes and patterns.

The findings reveal that international organizations mainly use GenAI to advance economic and social sustainability. Economically, GenAI accelerates innovation by automating tasks, streamlining documentation, improving content processing, and enhancing services-though technical biases and reliability issues must be addressed. For social sustainability, organizations emphasize human oversight, domain expertise, ongoing training, and strong data privacy and ethical governance. In contrast, environmental sustainability receives less focus, with efforts limited to reducing energy use and adopting more efficient, task-specific GenAI models.

This study advances the field of digital sustainability by providing empirical evidence on how international organizations are integrating Generative AI (GenAI) solutions in alignment with the three core pillars of sustainability-economic, social, and environmental (Piccoli & Pigni, 2022; Kotlarsky et al., 2023; Kirchner-Krath et al., 2024). Next, this qualitative exploration enriches the literature on GenAI by analyzing real-world adoption patterns, challenges, and outcomes in international organizations (Feuerriegel et al., 2024; Modgil et al., 2025; Ooi et al., 2025; Prasad Agrawal, 2025). This research contributes to the literature on human-AI collaboration (Jarvenpaa & Klein, 2024; Trocin et al., 2021) by elucidating the dynamics of how employees across diverse industries interact with and implement GenAI technologies. It demonstrates that value creation emerges not merely from automation, but from collaborative processes involving human oversight, contextual judgment, and adaptive supervision.

The reminder of this study is organized as follows. First, the literature review examines theoretical backgrounds on GenAI and sustainability, highlighting current understanding and identifying research gaps. Next, the research methodology details the data collection and analysis procedures. The findings section presents results organized around the Triple Bottom Line framework, exploring economic, social, and environmental dimensions of GenAI implementation. The discussion synthesizes these findings into theoretical contributions and practical implications. Finally, the conclusion summarizes key insights, acknowledges limitations, and suggests directions for future research.

2. Theoretical Background

2.1 Generative Artificial Intelligence (GenAI)

GenAI is part of AI models and has the capacity to generate new content the form of text, image/video, speech/music, and code in response to prompts (Benbya et al., 2024). Compared to other technologies, its uniqueness lies not only in its ability to perform tasks that were once exclusively within the realm of human capability but also in generating new content in a few seconds. Since gaining mainstream attention, GenAI has seen widespread adoption across various industries, driving new human-GAI interactions particularly within organizations (Brown et al., 2024) across industries and countries. GenAI solutions such as ChatGPT have shown a unprecedent rapid adoption, for example it reached 1oo million users in just 2 months after its launch on the market Ooi et al. (2025). Its technical foundation is built on advanced machine learning architectures—particularly generative models such as transformers and diffusion models—that learn complex patterns from large datasets to autonomously generate realistic and contextually relevant content (Feuerriegel et al., 2024).

GenAI is providing remarkable results for business activities (e.g., search engine optimization (SEO) to elaborate suggestions for solving real world problems across various domains such as marketing, healthcare, human resources, education, banking, retail, workplace, manufacturing, and sustainable IT management) (Ooi et al., 2025). For example, it can write texts, make suggestions on a topic useful for brainstorming such as optimizing renewable energy systems, discovering more efficient carbon capture materials and processes, and suggestions for climate-resilient agriculture (Prasad Agrawal, 2025). GenAI exhibits characteristics and offers action possibilities that might support organizations to address grand challenges such as sustainability and human impact on the planet.

The adoption of GenAI can be triggered by institutional pressures, such as coercive pressure—driven by government regulations and industry associations—and normative pressure, where customer expectations encourage organizations to adopt GenAI (Rana et al., 2024). However, hesitation around GenAI adoption persists due to ongoing uncertainties, including regulatory ambiguity (such as the AI Act[2] and EU data protection laws, as the GDPR) and executive reluctance stemming from unclear or undefined benefits. In response to this, organizations have turned to technical assessments to evaluate GenAI tools. Jung & Winter (2025) proposed a sociotechnical GenAI assessment matrix based on four key criteria: Relevance (the tool's value and usefulness), Ethics (ensuring fairness, explainability, privacy, autonomy, and redressability), Functionality (whether the tools perform as intended, with robustness and safety), and Feasibility (availability of resources, infrastructure, and data

[2] https://eur-lex.europa.eu/eli/reg/2024/1689/oj/eng

quality). For successful adoption, it is essential that GenAI tools align with the specific needs and strategic organizational goals.

As highlighted by Modgil et al. (2025), GenAI can streamline operations, boost productivity, and enhance efficiency. Additionally, GenAI can support organizations in addressing sustainability goals by optimizing resource usage, improving decision-making related to environmental and social impact, and enabling data-driven strategies for sustainable business transition. While current models demonstrate significant potential, their effective use depends on a deep understanding of the technology, complemented by human expertise throughout its implementation and use in organizations. This collaborative approach between human judgment and AI is viewed as the most effective way to unlock GenAI's full potential.

2.2 GenAI for Sustainability and the Triple Bottom Line (TBL)

United Nations Commission defined sustainability as "*meeting the needs of the present without compromising the ability of future generations to meet their own needs*" (Brundtland, 1987) and my work is aligned with this perspective. The goal is to promote efficient and responsible management of economic, social, and environmental resources[3]. Developed in the 1990s, the Triple Bottom Line (TBL) framework offers a holistic approach to evaluate organizational performance—going beyond profit to include three interconnected dimensions that are economic, social, and environmental (see Figure 1) (Elkington, 1998a; The Economist, 2009)TBL encourages a balanced approach that highlights the interdependence of these dimensions, emphasizing that companies should value

[3] What Is Sustainable Development?

social and environmental responsibility just as much as financial outcomes (Elkington, 2018).

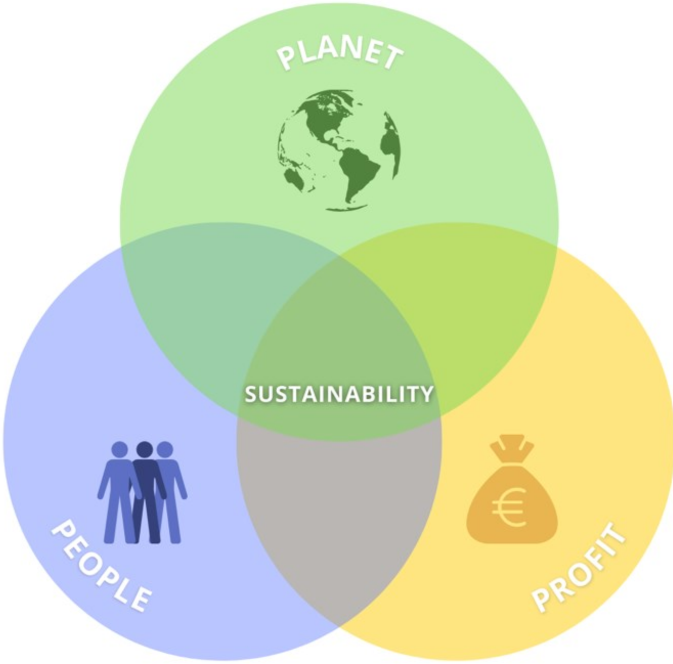

Figure 1 – Sustainability Venn diagram

Economic sustainability (profit) refers to an organization's ability to maintain and grow long-term economic value by efficiently managing resources, fostering innovation and adapting to evolving technological landscapes, for instance, Haftor et al. (2024) show that firms using GenAI can enhance economic value creation by leveraging data network effects within adaptive business models, aligning with the idea that technology can serve as a multiplier for strategic advantage and economic resilience. Handler et al. (2024) argue that Large Language Models (LLMs), reshape organizational decision-making and unlock new potentials for sustainable value creation. In the creative industries, Amankwah-Amoah et al. (2024) explored how GenAI disrupts traditional workflows while simultaneously opening opportunities for innovation and new forms of economic sustainability across sectors like advertising, design, and media. Similarly, Barlow & Dennis (2024) demonstrated that structured human-AI collaboration, when well-designed, can improve group performance and support long-term economic sustainability through enhanced productivity in virtual work environments. Therefore, economic sustainability is not just about financial viability—it increasingly depends on how organizations strategically integrate GenAI to create value while maintaining adaptability, equity, and efficiency.

Social sustainability (people) refers to an organization's ability to leverage GenAI to support and enhance employees' capabilities, uphold ethical standards, and promote inclusive outcomes such that the organization and its employees can thrive in a rapidly changing technological environment. GenAI does not operate individually or independently on the contrary it must be constantly supervised by experts or professionals with experience in the tasks it is designed to support. Human-in-the-loop approaches are essential for ensuring accountability, fairness, and reliability in decision-making—particularly in fields like healthcare and law—by enabling professionals to validate AI-generated outputs and address concerns about delegating critical judgments without proper oversight (Handler et al., 2024). The primary aim is to use GenAI to empower and augment employees' capabilities by improving access to relevant information, streamlining routine tasks, and supporting more informed decision-making—ultimately enhancing productivity, creativity, and job satisfaction (Ooi et al., 2025). For example, GenAI serves as a knowledge management tool capable of enabling employees to retrieve, generate, and apply knowledge more effectively (Alavi et al., 2024) by reducing the cognitive and operational load of routine processes, GenAI frees up human capacity for more creative and strategic activities (Benbya et al., 2024) and boosts ideation by generating diverse, high-quality ideas with lower time and resource demands (Eisenreich et al., 2024).

GenAI can support professionals in systematically complying with national and international regulations by streamlining compliance processes, monitoring updates, and ensuring adherence to legal and ethical standards (Fontoura et al., 2025; Ooi et al., 2025). Thus, GenAI can help organizations to promote equity and inclusiveness, ensuring that all employees have equal access to opportunities and resources (Dwivedi et al., 2024; Rana et al., 2024). At the same time, it can negatively impact employees' work and well-being by increasing job demands, creating stress through constant digital engagement, and contributing to feelings of surveillance, job insecurity, and reduced autonomy (Longhofer & Winchester, 2023; Zuboff, 2023; Lindebaum & Fleming, 2024; Chuang et al., 2025). Thus, social sustainability depends on how organizations thoughtfully implement GenAI to foster human development and to address ethical responsibility and take collective wellbeing into account.

Environmental sustainability (planet) refers to responsible design, development, implementation, and use of GenAI solutions to support business activities in ways that minimize environmental impact, promote efficient use of resources (e.g., energy, materials), and support data-driven strategies to address environmental challenges. For example, Eisenreich et al. (2024) explore GenAI's role in ideation processes, specifically how this technology can serve as a tool that accelerates the creative process of idea generation in sustainable innovations. Rana et al. (2024) recognize that trade-offs between performance gains and resource use must be considered for sustainable AI deployment, and Modgil et al. (2025) emphasize that GenAI could help optimize resource management, potentially reducing waste and emissions indirectly. Inappropriate uses of organizational resources, whether through under-use or over-use, exacerbates the threat of climate change that in turn results in significant losses for our society and future generations.

Green Information Systems (Green IS) offer new opportunities to leverage information technology in transforming organizational processes and practices to enhance sustainability (Kirchner-Krath et al., 2024). These initiatives aim to improve energy efficiency by optimizing data center operations, implementing smart energy management systems, and encouraging the use of energy-efficient hardware and software (Piccoli & Pigni, 2022). They also focus on reducing environmental impacts by promoting paperless operations, facilitating remote work to decrease commuting emissions, and enabling better resource management through advanced analytics and IoT integration (Smyth et al., 2024). Green IS can foster the development and introduction of environmentally sustainable products and services by supporting sustainable supply chain practices (Fosso Wamba et al., 2024), enhancing product lifecycle management, and encouraging innovation in eco-friendly product design.

While GenAI holds significant promise for advancing global sustainability (Modgil et al., 2025) the current literature often assumes a straightforward alignment between technological innovation and sustainable development goals (SDGs) [4] overlooking complex tensions and trade-offs. In addition, it predominantly explores these topics through literature reviews, opinion pieces, or theoretical papers (Amankwah-Amoah et al., 2024; Brown et al., 2024; Feuerriegel et al., 2024), resulting in a critical shortage of empirical case studies that examine how organizations actually navigate the challenging process of integrating GenAI for sustainable business transitions. According to Kotlarsky et al. (2023) digital sustainability is not just about using technology to reduce environmental impact—it's about aligning technological innovation with broader economic, social, and environmental objectives. This gap is compounded by a techno-optimistic bias that underestimates the environmental costs of AI deployment and the social implications such as workforce displacement (Modgil

[4] https://sdgs.un.org/goals

et al., 2025; Rana et al., 2024). Moreover, the prevailing narrative of digital sustainability risks oversimplifying the intricate balance required to simultaneously advance economic, social, and environmental objectives. Therefore, it is critical to explore how organizations are leverage GenAI not just as a tool for efficiency or profit-but as a catalyst for genuinely sustainable transformation that addresses potential conflicts and governance challenges. Understanding these dynamics is essential to uncover new strategies that enable organizations to harmonize the three pillars of sustainability and avoid reinforcing existing unsustainable practices.

3. Research Method

This research explores how international organizations are leveraging GenAI for sustainable goals with an exploratory approach (Eisenhardt, 1989). I used a qualitative and inductive method (Sarker et al., 2018) to collect semi-structured interviews with professionals actively involved in the development and implementation of GenAI solutions within their organizations to support sustainable transitions, supplemented by archival data.

3.1 Data collection

To conduct the qualitative study, I developed a semi-structured interview protocol with open-ended questions exploring participants' experiences with GenAI. The protocol began with background information, then covered organizational approaches, implementation, impact, ethical considerations, and future perspectives. As interviews progressed, I updated questions to address emerging themes-for example, adding questions on data governance and model reliability, including algorithm bias and LLM hallucinations, based on recurring issues identified in earlier interviews.

I contacted relevant respondents via LinkedIn, selecting individuals whose profiles indicated they were working with GenAI on sustainability-related activities. Next, I conducted an online search for organizations that, through their websites or social media profiles, indicated involvement with GenAI and sustainability. I then contacted professionals working in these organizations who appeared to be responsible for such initiatives. This allowed me to have a robust and systematic data collection. To organize and manage the data, I saved the contacts information in an Excel sheet. The document included fields for participant identification (surname, first name), contact information (email), professional details (company, job position), recruitment tracking (date contacted, invitation status: invitation sent/scheduling/accepted/denied), and professional network information (platform used, profile links).

I contacted the selected candidates with a message on LinkedIn. Next, I contacted via email those participants that agreed to take part in the interview, and I provided detailed information about the research project with the information letter and informed consent. At the end of each interview, I used a snowball sampling approach, asking respondents to recommend colleagues involved in the GenAI and sustainability development project for additional perspectives. While some provided contact details for their colleagues, only one of the suggested individuals ultimately participated in the study. However, in some companies, more than one interview was conducted with respondents from different teams and having different roles.

I conducted the interviews virtually through video conference (Google Meet, Microsoft Teams or Zoom). To ensure data quality and accurate documentation, all interviews were electronically recorded with participant consent and transcribed with automated transcription features incorporated in the video conferencing platforms. To maintain participant confidentiality, only essential professional information was retained in the raw dataset, including participants' positions, years of experience, and contact information. Personal identifiers were systematically removed from the dataset during the curation process. Participation in the study was voluntary, with participants retaining the right to withdraw their data at any point until the project's formal conclusion to ensure integrity of the collected data.

The data collection was conducted from October 2024 to February 2025, during which I completed a total of 21 interviews with 1070 total minutes (please see Table 1). The transcriptions resulted in 440 pages and 160 593 words. The selected companies were from different fields, namely a digital engineering company, a technology consulting firm, a telecommunications provider, a data analytics consultancy, a healthcare technology company, and others. This provided a wide perspective on how different organizations were approaching GenAI to implement it into their organizations. The respondents occupied different job positions ranging from Data Scientists, AI Engineers, Consultants, Heads of Departments, Founders, Professors, and Product Owners to Technical Specialists and Learning Experience Designers. One interviewee from Company F had more information to share and we scheduled a second interview, which lasted 82 minutes. The interviews lasted from minimum of 24 minutes to maximum of 82 minutes. The average length of the interviews is 51 minutes.

To enrich the dataset, I collected also archival data from each company, including data such as organizations' webpages promoting the new initiatives about GenAI and sustainability, online seminars presented by and online articles published by the organizations included in this study. In total, I collected 20 websites, 11 online articles, 3 webinars, 8 reports and 5 blog posts.

Company	Country	Field	Role of interviewee	Time	Period
Company A	Global	Industrial manufact tech	GenAI Developer	41	Oct 2024
Company B	Portugal	Software engineering	GenAI Engineer	24	Oct 2024
Company C	Global	Consulting data analytics, AI	AI Consultant	71	Oct 2024
			Data Scientist	54	Oct 2024
Company D	Global	Consulting data analytics	Head of AI, R&D	61	Oct 2024
Company E	Global	Telecommunication	GenAI Expert	47	Oct 2024
Company F	Portugal	Healthcare technologies	Head of IT	55 + 81	Oct 2024
			Data Scientist	82	Oct 2024
Company G	Germany	Edu consulting GenAI	Speaker & Author	48	Oct 2024
Company H	Brazil	AI solutions	Product owner	51	Oct 2024
Company I	Portugal	Data science & GenAI	GenAI in Drug Disc.	50	Nov 2024
Company J	Portugal	Technology & AI	Co-Founder	45	Nov 2024
Company K	Global	Data science & AI	Tech Sen Consultant	54	Nov 2024
Company L	UK	Business Consulting & AI	Founder/ Sin. Content	42	Nov 2024
Company M	Spain	Creative industry & GenAI	Prof. & Freelancer	49	Dec 2024
Company N	UK	Sustainability	Practice Lead Energy	47	Dec 2024
Company O	Portugal	Data Science, Engineering	Senior Data Scientist	41	Jan 2025
Company P	Argentina	Creative, technology	GenAI consultant	37	Feb 2025
	Portugal		Creative Technologist	42	Feb 2025
	Lithuania		Sen. Exp. Designer	48	Feb 2025
Total 21				1070 min	

Table 1. Field interviews by company, country, field, role of employees, length, and period

3.2 Data analysis

In the data analysis process, I followed an inductive approach (Corbin & Strauss, 2014) which allowed themes and trends to emerge from the raw data closely connected to the terms and reflections the informants shared during the semi-structured interviews. The Gioia methodology (Gioia et al., 2013) guided the procedures for the analysis of the data. First, I imported all transcripts into NVivo software to begin the coding process. Using the respondents' terms, I developed first-order codes while maintaining a coding journal in Word to record emerging thoughts and potential patterns, continuing this process until all 21 transcripts were fully coded.

NVivo software helped me to extract meaningful information from the data and to group them into the relative first order codes, allowing me to capture the essence of the information the respondents shared and to use codes that resonate with the terms used by them. When encountering new ideas that did not fit into the existing codes, I created new ones, collecting a total of 75 first-order codes. I used the same approach to analyze the archival data, which provided additional evidence to the themes that I extracted from the interviews.

Based on the first-order codes, I identified several commonalities among the codes, which led to the extraction of second-order themes representing more abstract concepts. Finally, I grouped the second-order themes into aggregate dimensions by identifying overarching patterns and similarities between them, which allowed me to categorize them into broader, more abstract concepts. This process involved refining the groupings to ensure they accurately captured the essence of the data and were supported by the participants' responses.

4. Findings

The findings are presented with the Triple Bottom Line framework, organized around three aggregate dimensions: economic, social, and environmental sustainability. For each dimension, I discuss the action possibilities—which correspond to the second-order themes—that organizations can pursue with GenAI. I then explain the first-order codes related to how GenAI impacts the use of resources, highlighting both positive contributions and negative consequences associated with each action possibility. Therefore, I explore the benefits and the limitations of GenAI adoption, and their broader implications for the pursuit of sustainability.

4.1 Economic Sustainability

To achieve economic sustainability, organizations are leveraging GenAI across five key action possibilities that directly contribute to operational efficiency, value creation, and scalability (see Figure 2). First, they *accelerate innovation for fast scaling* by using GenAI to create new ideas, rapid prototype solutions, and shorten time-to-market. Second, they *augment internal documentation processes* by streamlining administrative and knowledge management tasks, which reduces manual workload and increases productivity. Third, organizations *improve content processing* by using GenAI to analyze large volumes of unstructured data for better decision-making and more efficient workflows. Fourth, they *elevate service offerings* by personalizing customer interactions and introducing advanced, AI-driven features that enhance user experience and competitiveness. Finally, they work to *address biases and enhance the reliability of GenAI* by ensuring that AI-generated outputs are trustworthy, inclusive, and aligned with ethical standards. These five action possibilities illustrate how GenAI is not only a technological tool but also a strategic asset that supports sustainable economic growth when integrated responsibly and effectively as follows.

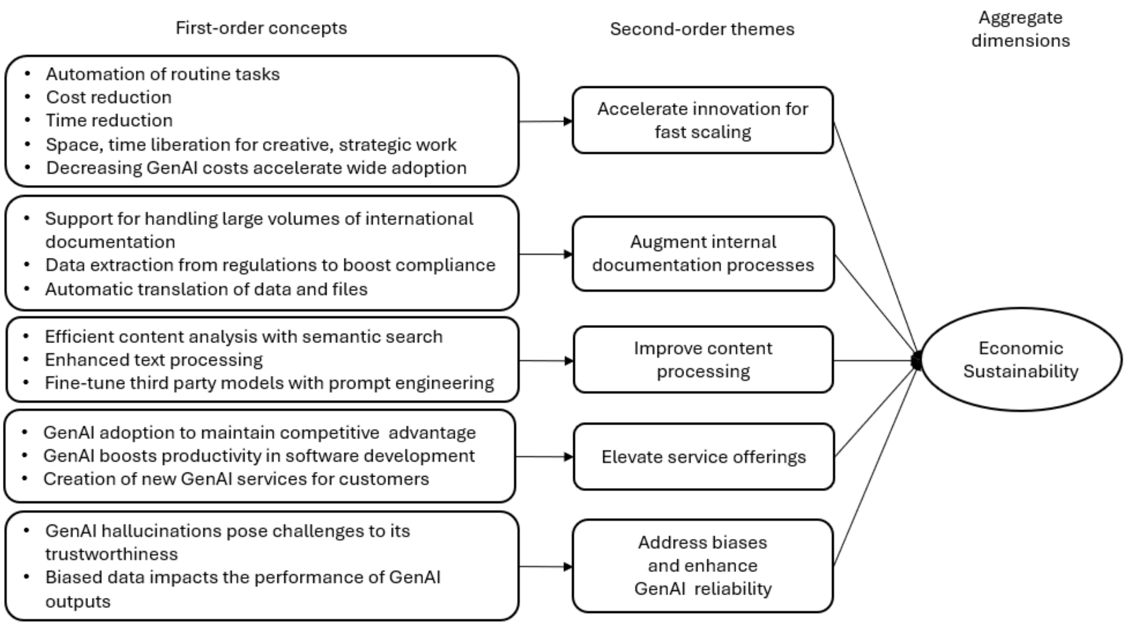

Figure 2 – Data structure for economic sustainability

Accelerate innovation for fast scaling

GenAI enables organizations to respond faster to market needs and scale their innovations efficiently, supporting rapid experimentation and serving as a catalyst for innovation. *Accelerate innovation for fast scaling* involves empowering employees to continuously experiment with multiple solutions, selecting the best option, and applying this iterative approach across various tasks related to service delivery. This fosters a dynamic, responsive environment that drives rapid growth and optimization through the following five activities.

Organizations use GenAI to perform repetitive operational tasks, which in turn frees up time for professionals and their teams, who can focus on more strategic and creative work. For example, tasks like summarizing information, generating reports, producing email responses, or formatting outputs, which are essential but time-consuming, can now be handled by GenAI (R7, R8). According to company D, a concrete example is the case of an insurance company that uses GenAI to automate insurance claims processing: Lemonade's AI-driven claims bot handles approximately one-third of claims autonomously, utilizing algorithms to analyze claims submissions and make payout decisions in seconds, significantly reducing the time and resources required for claims processing.
Whether it’s creating content at scale or simply clearing the way for more innovative work, automating the routine is a key enabler of faster and more sustainable growth. As explained by respondent 13:

> *It’s a fact it won’t solve all the problems, but it will speed up people’s daily lives, and while you could take 3 hours to do it one thing, it will take you 1 hour, for example, and another 2 hours, I can go for a walk. It makes a lot of difference.*

Next, GenAI enables organizations to reduce cost and time by performing routine, repetitive tasks, such as report writing, document analysis, and content creation by a fraction of the cost and time. For example, consultancies that previously spent hours manually searching databases can now retrieve information in seconds by "*dramatically reducing the efforts*" (R14). Even in creative industries, tasks like producing diverse product visuals for marketing—previously dependent on lengthy design processes, can now be accomplished at scale and speed with GenAI (R4). Similarly, sectors with heavy bureaucratic workloads, such as legal or administrative domains, benefit from compressing hours of manual labor into just minutes (R17). As company M highlights in their website, regarding customer support, GenAI can automate responses, allowing humans to focus on more complex issues, thereby enhancing productivity and reducing operational costs *"Even when individual time savings are measured in seconds per each task, that time is magnified by the number of employees and daily operations, making these efficiencies substantial."* This cumulative effect in time efficiency is crucial for scaling innovations quickly and effectively, as explained by respondent 14:

> *They spend X amount of time per year drawing through their databases, trying to find the information. Now they don't have to do that now they can do that within seconds rather than hours.*

GenAI frees up space and time which can be dedicated to other creative, strategic work or other valuable human activities. Respondents shared that by drastically reducing the time required for everyday tasks—like compiling information, drafting emails, or translating documents—GenAI empowers workers to redirect their focus toward innovation, problem-solving, and creativity (R4, R14). Company A discusses how AI can alleviate the burden of routine tasks, thereby enabling engineers and designers to focus on more meaningful work as written in its website "*human beings don't have time to look at every single possibility, so giving GenAI this task frees up the engineers' and designers' time to be spent on more worthwhile endeavors.*" Company M highlights how GenAI can automate specific tasks: "*GenAI may automate those tasks altogether, freeing up a* *worker's ability to focus on new tasks, or they make those tasks easier for people and create time for the individuals.*" This newly created space allows people to either invest more deeply in meaningful work or simply reclaim time in their day, improving both productivity and well-being, as stated respondent 13: *the big value will be freeing up people's time: helping with creativity, helping with efficiency. Freeing up time to do other to do other, possibly more valuable things*.

Lastly, decreasing GenAI costs accelerate wide adoption, as the price of using advanced GenAI models decreases, the technology becomes available not only for large companies but also for smaller organizations and teams. Respondents noted that the cost of APIs and model access, such as ChatGPT or Microsoft's latest release, has fallen significantly, in some cases over 144-fold in just a year (R7, R9). This democratization of access supports users to integrate GenAI into their workflows, as GenAI becomes cheaper and easier to deploy, it acts as an amplifier, fueling its widespread adoption.

Augment internal documentation processes

With the introduction of GenAI across diverse organizations, internal documentation processes are significantly enhanced by streamlining content creation, organization, and retrieval while improving accuracy, consistency, and efficiency, making knowledge more accessible across the organization. By automating, organizing, translating, and analyzing internal data and documents, GenAI makes knowledge more accessible throughout the organization, transforming how companies manage and utilize their internal documentation across departments. Specifically, GenAI provides support for three main tasks, that are handling large volumes of international documentation, extract data from regulations to boost compliance, and to translate automatically data and files as follows. The organizations harness GenAI to analyze large volumes of data from different sources and different geographical locations. By parsing, structuring, and extracting relevant information from diverse document formats and languages, GenAI helps with reducing the manual workload. For example, company D has developed AI chatbots, such as Scout AI[5], which analyze internal information sources to assist employees as highlighted by respondent 4:

> *Great demand of solutions with virtual assistants that are capable of making use of internal documentation of organizations which usually have huge amounts of documentation and that can be used by both your customers and the employees.*

Next, GenAI is used to extract the data from regulations to boost compliance by transforming dense regulatory text into structured, actionable information. GenAI enables companies to reduce or eliminate the significant manual effort previously required to interpret regulatory data, facilitating the process for example, by automatically extracting relevant clauses and highlighting requirements – thus reducing the risk of human error and expediting compliance processes as explained by respondent 9:

> *Companies have a lot of rules and documents that they have to comply with and the regulations are constantly changing, and instead of someone reading a 500-page document and then spending the month reading another 500-page document, they can quickly ask and in half an hour be able to summarize the key points and understand what needs to change from now on.*

Lastly, GenAI demonstrated its unique and rapid capabilities in instantly translating data and files across multiple languages, often within seconds and with minimal human intervention. This functionality significantly reduces the time and cost traditionally associated with multilingual communication, localization, and document handling. For organizations operating in global or multicultural environments, this means faster market entry, improved cross-border collaboration, and enhanced accessibility of services and products. The

[5] https://www.youtube.com/watch?v=QEWJaS5-1R0

ability to automate translation processes at scale not only streamlines operations but also enables organizations to allocate resources more efficiently, reduce dependency on external translation services, and increase responsiveness in international contexts. By breaking down language barriers, GenAI fosters greater inclusivity in communication while supporting strategic growth and long-term cost savings—both of which are essential components of a sustainable economic model in today's interconnected business landscape as mentioned by respondent 4:

> *It does a translation and at that level it is already a work accelerator… all of these are activities that can now be done thanks to GenAI.*

Improve content processing

Organizations leverage GenAI to *improve content processing* through efficient content analysis with semantic search capabilities. Unlike traditional keyword-based search, semantic search recognizes context retrieving more relevant information and reducing time spent on information retrieval. Enhanced text processing also allows organizations to handle larger volumes of textual data, extract insights, and identify patterns that might otherwise not be so easily accessed. This takes place through the following two activities, as follows.

First, *efficient content analysis with semantic search* capabilities that unlike traditional keyword-based search, semantic search recognizes context retrieving more relevant information and reducing time spent on information retrieval. Enhanced text processing also allows organizations to handle larger volumes of textual data, extract insights, and identify patterns that might otherwise not be so easily accessed. When a new regulation is published, semantic search can immediately locate all relevant sections that might impact business operations, even when terminology varies as respondent 7 mentioned:

We automatically take the e-mail from the client extracts, extract the intent. Then we map it again through the semantic search. We map it against all the document, it can be a thousand pages, doesn't matter, millions of pages. We map it against it through all the databases and then automatically send it to the language model. It gets the question the context information where the answer is, then it provides the answers. And we also say they answer it in the right language.

Second, organizations fine-tune third party models using strategic prompt engineering by carefully crafting input prompts that guide the AI to produce the most relevant and accurate outputs. This approach tailors the AI to better understand company-specific terminology, document structures, and information workflows. Additionally, through careful prompt design and iterative refinement, fine-tuning enables organizations to customize GenAI solutions to their specific needs without having to develop models from scratch, significantly reducing implementation costs, as noted by Respondent 4:

We use these models, that can be tuned by us whether using fine tuning strategies that is, using prompt engineering. But we are not the ones who develop a large language model from scratch (…) And therefore, this nowadays is much, much easier.

Elevate service offerings

Companies can *elevate service offerings* and enhance their competitive market position through the strategic implementation of new GenAI capabilities (content generation, personalization, decision support, real-time adaptation, multimodal integration, etc.) which ultimately strengthens and enriches the value they provide to their customers. This transformation occurs through three initiatives, as follows. First, companies strategically adopt GenAI to maintain a competitive advantage, positioning themselves to stay relevant in rapidly evolving markets. This proactive approach ensures they align with early adopters who are already leveraging the technology, while staying ahead of competitors that have yet to implement it. Adopting GenAI is not just a matter of technological advancement—it is a strategic imperative. Organizations recognize that GenAI offers transformative potential across various business functions, from streamlining operations to enhancing product development and customer engagement. By embedding GenAI into their core strategies, these companies are not only future proofing their operations but also signaling innovation leadership within their industries. The early and strategic adoption of GenAI can drive long-term value creation, enable resource efficiency, and build resilient competitive positioning in the face of market uncertainty and technological disruption as shared by respondent 15 first quote and stated in the Company P report second quote:

> *They (organizations) are reacting because they are afraid of losing their competitive advantage so in my opinion, most of the companies are rushing to GenAI… The need was not to be left behind.*

> *GenAI represents a seismic technological shift, offering unparalleled capabilities to transform business operations (…) the era of maintaining outdated processes and technologies is over and the choice is clear: innovate or be left behind.*

Second, GenAI significantly boosts productivity in software development by assisting in code generation, debugging, and testing, thereby by reducing development time and minimizing human error. GenAI-powered tools can quickly analyze large codebases, suggest improvements, and even offer real-time solutions to bugs or inefficiencies. This acceleration in problem resolution not only streamlines the development lifecycle but also helps teams meet tight deadlines and adapt more quickly to changing project requirements. In doing so, GenAI enhances both the speed and quality of software delivery—key factors in achieving operational efficiency as expressed by respondent 13:

It was giving me this error and now I write it on ChatGPT or in any accelerator that you created and that automatically erases your error explains that it generates the code again correcting the error.

Several companies have enhanced customer satisfaction by integrating GenAI-powered chatbots to offer instant, round-the-clock assistance. Customers benefit from faster resolution and a more seamless service experience, which strengthens brand loyalty. Moreover, trust and reduce frustration, particularly during peak service times. For instance, company Q uses the QA Forum Chatbot to provide quick answers based on forum articles (knowledge database) and to reduce the need to search through numerous posts. Another example is the In-App Chat integrated into the Woo application, which answers user queries using FAQs and RAG, achieving an 80% accuracy rate and reducing the number of interactions that reach human assistants. Company Q shared its experience in an article:

While in the past deploying chatbots often led to customer dissatisfaction, recent advancements in LLM technology have significantly improved what chatbots can do and how they engage with customers.

Third, the creation of new GenAI-driven services enables organizations to stand out in an increasingly competitive marketplace by offering innovative, personalized experiences that drive customer engagement and unlock new revenue streams. Personalization powered by GenAI allows companies to tailor products, recommendations, and interactions to individual customer preferences, creating more value for users while deepening brand loyalty. On its blog, Company D illustrates this transformation by highlighting how AI agents can automate processes that previously demanded complex human intervention—ranging from multi-step customer support workflows to detailed service customization. With GenAI, businesses are now equipped to deliver faster, more intelligent customer service solutions that anticipate user needs and respond in real time. These capabilities not only improve customer satisfaction but also reduce operational costs and expand an organization's ability to scale without compromising service quality. In this way, GenAI becomes more than a tool—it becomes a strategic enabler of growth and differentiation in the digital economy. As discussed by respondent 2:

> *Continente online experiments GenAI to suggest recipe to customers based on the acquired products.*

Address biases and enhance reliability of GenAI

Inherent technical challenges in GenAI systems create obstacles that prevent organizations from fully implement these technologies with reliability, and these limitations pose as barriers for the sustainable implementation of this technology in business processes, potentially undermining the long-term viability of these systems despite their initial promise. The technical limitations are particularly challenging due to the probabilistic nature of LLMs and because they affect fundamental aspects of the model's functionality – accuracy and data quality. Therefore, the organizations regularly *address biomasses and enhance reliability of GenAI* through the following two activities.

First, hallucinations present a critical challenge to the trustworthiness of GenAI, as they are not simply occasional mistakes but a fundamental byproduct of how these models generate responses. Unlike humans, who can typically cross-check information, apply contextual reasoning, and distinguish between factual accuracy and speculation, GenAI models generate outputs based on probabilistic patterns learned from training data—without a true understanding of truth or reality. This limitation means that GenAI can produce convincingly worded yet entirely false or misleading content, especially in complex or ambiguous situations. As such, while the fluency of GenAI responses can create an illusion of reliability, the underlying architecture makes consistent factual accuracy difficult to guarantee. This inherent limitation raises concerns not only for everyday use but also for critical applications in sectors such as healthcare, law, and finance, where trust and accuracy are paramount. Addressing this issue is essential for the broader acceptance and sustainable integration of GenAI into professional workflows as mentioned by respondents 14:

> *The actual nature of these models is that they will always be hallucinations, it's just how they work, and there will always be a reason to have a human in the loop, particularly when you're talking about high stakes situations, for example a customer facing a chat box from a bank. DoorDash have it in theirs it's to make sure that the AI chat bot isn't completely talking nonsense and promising the world.*

There are ongoing uncertainties and limitations in addressing GenAI hallucinations. While there is a basic understanding that hallucinations stem from the probabilistic nature of how these models generate content, a reliable and foolproof solution has yet to be found. Despite advancements in model training and data curation, hallucinations remain an inherent challenge that current methods struggle to eliminate entirely. The respondent 8 acknowledges that while progress has been made in diagnosing the issue, a complete and dependable fix is still out of reach:

> *We don't really know how to solve cases like hallucinations... you still don't have a solution that works completely. You can already understand that it was something probabilistic, but you still can't come up with any method bulletproof.*

The challenge of biased data significantly impacts the performance of GenAI outputs, as these models are trained on existing data, which often contains historical biases. Consequently, GenAI can replicate or even amplify these biases in its outputs, thereby undermining the fairness and relevance of its responses. Participants in the study highlighted how this issue threatens the long-term economic sustainability of GenAI applications, with concerns that these biases could limit the applicability of GenAI across diverse industries and user groups. As respondent 19 noted, the inherent bias within the data used to train these models creates a barrier to eliminating unfair outcomes, suggesting that as long as models are simply mirroring human-created data, bias is an unavoidable issue. Respondent 8 raised an additional concern about the perpetuative cycle that could arise when GenAI systems start generating content based on outputs generated by other AI systems. This recursive loop of AI-generated data could lead to diminishing model performance, as relying on AI-created content may reduce the richness and diversity of data, ultimately leading to less accurate and more biased outputs. This cycle highlights a critical challenge for the development of truly unbiased and reliable GenAI systems, which must be addressed for them to reach their full potential in a sustainable and equitable manner as referred by the respondents 19 and 8:

> *How do we make these models unbiased? As long as they are based on data that has already been created by us and are simply machines to repeat and imitate this data, we probably won't be able to eliminate the bias.*

> *If you start using this to generate all of your company content... Some of these models are fed by existing data. Then you reach a point where the data itself is being generated by AI. This becomes worrying because the scientific community has been seeing that AI, when fed with data generated by AI, loses performance.*

4.2 Social Sustainability

To achieve social sustainability, organizations make use of GenAI for 6 major activities that directly contribute to ethical responsibility and workplace development (see Figure 3). First, they *implement human supervision to assess GenAI outputs* in order to ensure accuracy and alignment with goals. Second, they *reinforce expertise and specialization* by using the technology to complement human capabilities rather than replacing them, creating new specialized roles and elevating the current contributions of workers. Third, organizations *foster a culture of continuous learning* by integrating GenAI tools that facilitate workforce adaptation to technological change. Fourth, they *launch systematic GenAI training across functions,* developing educational programs that democratize AI literacy at all organizational level. Fifth, organizations *safeguard data privacy, security and ethics* by implementing robust governance frameworks that protect sensitive information and help maintain trust in the organization. Finally, organizations *mitigate ethical risks and social disparities in GenAI use* by addressing biases, ensure equitable access and promoting inclusivity. These six actions illustrate how GenAI serves as both a powerful enabler of social progress and a catalyst for organizational transformation through sustainable development.

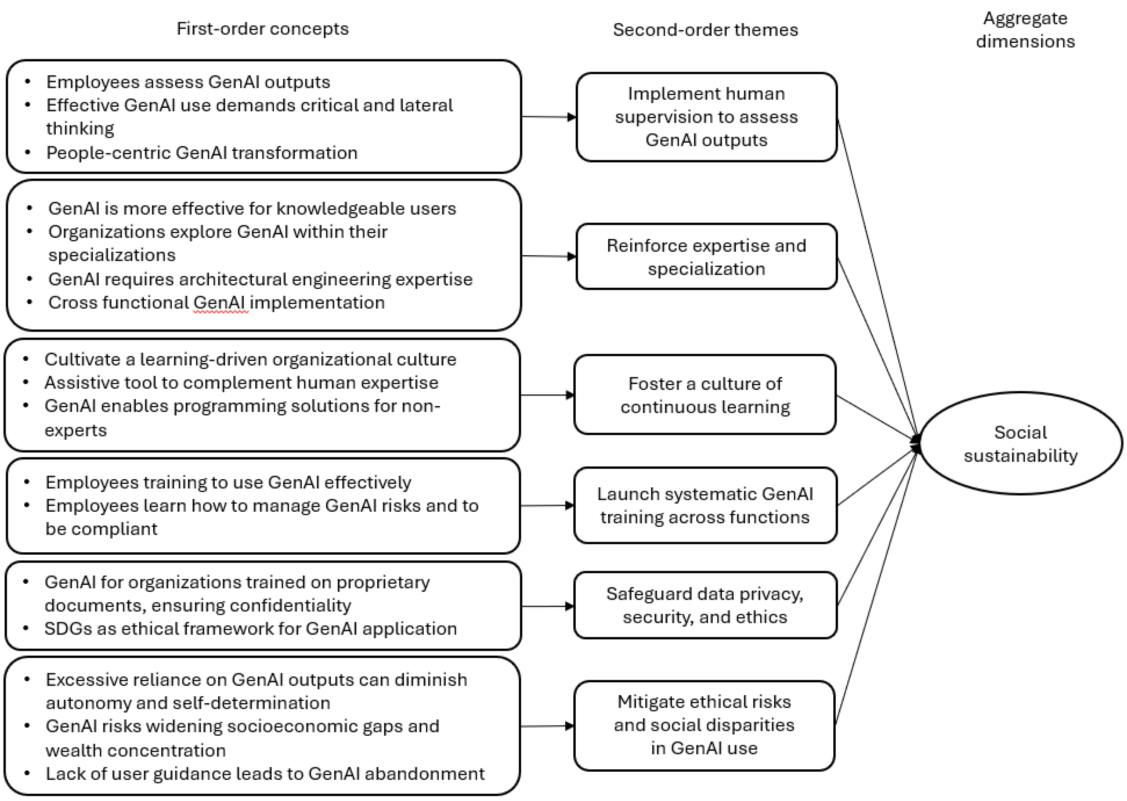

Figure 3 - Data structure for social sustainability

Implement human supervision to assess GenAI outputs

This theme refers to the necessity of keeping humans involved in the processes that use GenAI to be the ones who validate and ethically assess outputs. Human judgement remains essential to ensure responsible and accurate use, especially in situations that are higher stake. This takes place through three activities. First, human supervision for GenAI output assessment involves companies having humans assessing the technology output, company P shared on a blog post that while these models have transformative potential, human judgment is crucial to validate outputs and ensure alignment with organizational objectives.
Respondent 14 shared:

> *There will always be a reason to have a human in the loop, particularly when you're talking about high stakes situations... You still need to interrogate. Make sure that what's come out of that is correct.*

Organizations recognize that ultimate responsibility for decisions cannot be delegated to AI systems, particularly in high-stakes situations like healthcare, finance, or regulatory compliance. This accountability stems from AI's inherent limitations: its inability to grasp ethical nuances, contextual subtleties, or the full consequences of its outputs. For instance, Company D highlights the persistent challenge of AI hallucinations-instances where GenAI models produce plausible but factually incorrect or misleading content. On their blog, they stress that human oversight is non-negotiable for ensuring reliability, as unchecked errors could lead to legal liabilities, reputational harm, or threats to public safety as highlighted by respondent 20:

> *In terms of decision making. Still, the ultimate decision relies upon me, my team, and the context that we know about the company. This is like the ultimate filter that all the information.*

Second, effective use of GenAI demands critical and lateral thinking. This means that users should actively question the technology's suggestions and thoughtfully adapt them to their specific goals. For example, users need to recognize the limitations of GenAI, identify potential errors, and apply their own contextual knowledge when refining AI-generated outputs. Respondents 15 and 16 emphasize that such an approach is essential to harness the full potential of GenAI while maintaining accuracy and relevance:

> *You need to be very critical to what AI provides you, need to dab yourself, to have lateral thinking to use this technology and be able to go through the answer and think if that's right or wrong. (R15)*
>
> *Having enough knowledge over what you're using it for to be able to tell if it's hallucinating or coming up with something that's just completely incorrect, but also to be able to question it. (R16)*

Third, a people-centric GenAI transformation emphasizes using this technology as an enabler to support and elevate human work rather than replace it. In this approach, the human user remains central to all decision-making processes. The core idea is that GenAI functions as a flexible tool designed to adapt to human needs, workflows, and goals-rather than forcing humans to conform to the technology's constraints or workflows. Respondent 20 highlights this perspective, emphasizing that successful GenAI adoption depends on maintaining human agency and control, ensuring that technology augments human creativity, judgment, and expertise. This human-centered approach fosters collaboration between people and AI, where GenAI handles routine or data-intensive tasks, freeing humans to focus on strategic, ethical, and context-sensitive decisions.

> *I do think that GenAI is a tool and the final solution really depends on you adding this human touch, and you have to stay critical and you have to stay creative. You are the person who guides these tools, and they serve you.*

Also, company D on its website elaborates on the importance of a people-centric approach to AI transformation, suggesting that prioritizing employees leads to increased engagement, adaptability, innovation, and trust within organization.

Reinforce expertise and specialization

Organizations are leveraging GenAI to reinforce and enhance human expertise and specialization. This reinforcement occurs through four key activities. First, GenAI is more effective for knowledgeable users, and it delivers the best outcomes when used by individuals with domain expertise. For these users, GenAI acts as a powerful tool that amplifies their existing capabilities. Experts can provide better context, craft more precise prompts, and critically evaluate AI-generated outputs using their specialized knowledge. As stated by respondent 17, this synergy enables knowledgeable users to maximize GenAI's potential, ensuring outputs are relevant, accurate, and aligned with professional standards.

> *It maximizes what you want to do with it. In other words, if you are a very creative person, then you can maximize that creativity.*

Rather than replacing expertise, GenAI amplifies it-making specialized knowledge more valuable than ever. GenAI serves as a powerful augmentation tool, enabling experts to focus on higher-value tasks that require human judgment, creativity, and contextual understanding. By automating repetitive or routine activities, GenAI frees professionals to apply their deep expertise to complex problem-solving, critical analysis, and innovation. This synergy not only enhances productivity but also elevates the role of human expertise, positioning it as a cornerstone of effective GenAI use in organizations as highlighted by respondent 5:

> *It could be a source of confusion if it done incorrectly, and it can definitely be an accelerator if it's done correctly. Because most of the benchmarks show that someone using GenAI properly can be much more productive than someone who doesn't.*

Second, organizations are exploring GenAI applications tailored to their specific areas of expertise. Rather than adopting generic, one-size-fits-all solutions, many companies strategically customize GenAI to address the unique challenges and opportunities within their domains. For example, Company S integrates GenAI through their proprietary organizational platform, as highlighted by respondent 16, demonstrating a focused and specialized approach to leveraging this technology:

> *It's a platform that we have for interaction with our customers and for internal initiatives, and while we were focusing on this very specific company need, we were also discovering new ways on how we can adapt AI for training purposes.*

Third, GenAI implementation requires architectural engineering expertise, which involves designing systems that seamlessly integrate with existing processes and technologies. Successful deployment depends on a deep understanding of both the technical intricacies of GenAI and the organizational context in which it operates. As respondent 16 explains, organizations often need to build these capabilities internally or collaborate with external specialists to ensure effective integration and maximize the technology's value:

> *A lot of companies are going to need a whole lot of help unless they have an incredible IT and technology team. Internally, they are going to need to work with the consultant or an IT services company to fully implement and make best use of something like GenAI… You certainly need to have good data and be able to use it.*

Lastly, organizations are implementing GenAI across multiple functions, which occurs using a holistic approach to the technology and understanding that it can provide value throughout the organization, rather than restricting it to specific departments. An example of this is company J in which the initiatives shared on their blog involve collaboration across various sectors, indicating a cross-functional approach to GenAI implementation. As explained by respondent 10:

> *We started to set up specific teams and that's when we got GenAI to become horizontal from the company that was previously very vertical… Now I no longer have a technology front in my company, I have to connect with a company, I have artificial intelligence present in all of them.*

Foster a culture of continuous learning

GenAI enables organizations to foster a culture of continuous learning by creating opportunities for education, skill development, and knowledge acquisition. This transformation in how employees learn and adapt in the current environment takes place through three distinct activities. First it is achieved by cultivating a learning-driven organizational culture, where organizations encourage experimentation, share knowledge across teams, and create environments where employees feel permitted to develop new skills and approaches to working with GenAI technologies. As example, Respondents 19 company launched a learning program:

> *We have this program within their teams, we started to do training for each of the teams to try to explore what tools can work for that specific workflow that they have.*

Second, GenAI as an assistive tool to complement human expertise highlights the collaborative synergy between humans and AI, where each brings unique strengths to the table to achieve superior outcomes. Rather than replacing human skills, GenAI enhances them by handling repetitive, data-intensive, or computationally complex tasks, allowing humans to focus on strategic thinking, creativity, and nuanced decision-making. This partnership leverages the speed and scalability of AI alongside the contextual understanding, ethical judgment, and domain knowledge of human experts. This collaborative model not only improves productivity and innovation but also fosters trust and accountability in AI-assisted workflows. Respondent 20 succinctly captures this relationship, emphasizing that the most effective results emerge when humans guide and refine AI outputs, ensuring relevance, accuracy, and alignment with organizational goals.:

> *Explore, work with it, transform it, but then the way you interpret it, the way you organize it, the way you deliver it, it still has to come from you.*

Lastly, GenAI enables programming solutions for non-experts, democratizing programming capabilities by empowering employees without formal programming expertise to program. This allows a broader range of employees to contribute to solving problems they previously could not address. By translating natural language descriptions into executable code, GenAI lowers the barrier to entry for software development and automation, enabling citizen developers to prototype solutions, automate routine tasks, and customize existing applications without requiring specialized technical skills. This democratization of programming not only increases organizational agility and innovation but also empowers individuals to take ownership of their digital workflows and contribute to broader technological solutions as mentioned by respondent 7:

> *I think being able to use AI to build things, because code development is getting really strong with AI, and you don't need to even know coding.*

Launch systematic GenAI training across functions

Organizations are investing in training programs to equip employees with the skills needed to effectively use GenAI, ranging from basic familiarity training to comprehensive skill development programs. This initiative takes place through two distinct activities. First, organizations implement upskilling programs available to all employees, regardless of their function or role. The aim is to develop widespread competency in using GenAI tools, ensuring confident and competent GenAI use across the workforce. As explained by respondent 4 this integration into workflows maximizes productivity and promotes a seamless blend of human and AI capabilities:

> *We had a request that by the end of this year the aim was to train everyone, regardless of the field - human resources, marketing, financial services.*

The CEO of Company A in the USA also emphasized in an interview the importance of employees adapting to and effectively harnessing AI tools, highlighting that developing these skills is essential for staying competitive and driving organizational success in the evolving digital landscape.

Second, organizations are prioritizing employee education not only on the technical use of GenAI but also on managing associated risks and ensuring compliance. This comprehensive training approach goes beyond teaching how to operate the technology-it encompasses critical topics such as data privacy, potential biases in AI outputs, and broader ethical considerations. Employees are made aware of the importance of safeguarding sensitive information, recognizing and mitigating algorithmic biases, and adhering to legal and regulatory frameworks relevant to AI use. Several respondents emphasize that building this risk awareness and compliance knowledge is just as vital as developing technical proficiency. This dual focus equips employees to navigate the complexities of GenAI deployment safely and ethically, reducing potential harm while maximizing the technology's benefits. For example, respondents 4 and 15 highlight their experience where integrating risk management training alongside technical skills has helped employees use GenAI responsibly, fostering a culture of accountability and trust within the organization:

> *The training was also done not only in the sense of people learning but also to understand the risks and to be compliant, since there are strong compliance procedures that are defined in the organization.*

Launching the responsible AI guidelines because not everyone thinks about it. I think it's basic to give confidence to the employees, so they feel safe when using AI.

In addition, Company D emphasizes the importance of robust Governance, Risk, and Compliance (GRC) frameworks on their website to effectively manage risks associated with AI implementations. Complementing this, Company P highlights that user awareness and clear ethical guidelines are crucial for the responsible deployment of GenAI technologies, ensuring alignment with organizational values and regulatory requirements.

Safeguard data privacy, security and ethics

The organizations need to safeguard data privacy, security, and ethics when their employees use GenAI solutions such that they can protect sensitive information, comply with regulations, maintain data security standards, and adhere to ethical principle. Concerns around privacy breaches, unauthorized data use, model bias, and lack of transparency remain central topics of discussion among employees using GenAI technologies. Many users are often unaware of how their personal or organizational data is processed, stored, or potentially reused by these systems, which raises significant risks related to informed consent and the erosion of user autonomy. To address these challenges, there is a pressing need to develop comprehensive sociotechnical assessments of GenAI systems that evaluate not only their technical performance but also their social, ethical, and legal implications. Safeguarding data privacy, security, and ethics involves two key activities.

First, organizations are increasingly training GenAI models on proprietary documents, meaning they use their own internal data and resources to fine-tune AI systems for their specific needs. By leveraging proprietary information, these models can generate outputs that are highly relevant and tailored to the organization's unique context, processes, and terminology. This approach not only enhances the accuracy and usefulness of GenAI-generated content but also addresses critical concerns around data privacy and confidentiality. Ultimately, this practice enables organizations to harness the full potential of GenAI while maintaining strict control over their proprietary knowledge and safeguarding sensitive data. As explained by respondents 1 and 10, training AI on internal documents ensures that sensitive information remains within the organization's secure environment, reducing the risk of data leaks and unauthorized access:

> *They train it only with your documents and it will only respond exactly with your documents. It stays trained only for you.*

> *What we did was through an internal platform in the company, it's like a library that we call it *****, with the aim of making it available in a safe way.*

Second, organizations are increasingly adopting the United Nations Sustainable Development Goals (SDGs) as an ethical framework to guide the application of GenAI. By aligning their GenAI initiatives with the SDGs, companies ensure that these technologies contribute positively to environmental, social, and economic sustainability objectives. This approach not only provides clear ethical guidance but also encourages organizations to leverage GenAI in ways that support broader societal goals. Respondent 16 specifically highlights the value of the SDGs in shaping how GenAI can advance sustainability across multiple dimensions, suggesting that integrating established ethical frameworks like the SDGs helps promote more responsible and beneficial AI implementations:

> *I keep the entire 17 UN sustainable goals in my head, that is as far as I'm concerned, the best umbrella that we have for thinking what are all the things we need to solve and move towards and specifically the intersection of environment, social and economics and making all of them, work together.*

This approach is reinforced by industry practices, as evidenced by Company D achievement of the ISO/IEC 42001 certification, which validates that an organization is managing its AI systems responsibly and ethically, ensuring they are trustworthy, transparent, and accountable.

Mitigate ethical risks and social disparities in GenAI use

Organizations are increasingly recognizing the importance of addressing the ethical risks and social disparities associated with GenAI. These efforts focus on mitigating potential negative societal impacts such as threats to human autonomy, the exacerbation of existing inequalities, and the risk of technology abandonment due to poorly designed or implemented AI systems. To tackle these challenges, organizations are adopting comprehensive strategies that include developing ethical guidelines, implementing bias detection and mitigation processes, and promoting transparency in AI decision-making. They also emphasize inclusive design practices to ensure that GenAI benefits diverse user groups and does not disproportionately disadvantage marginalized communities. Furthermore, organizations are investing in stakeholder engagement and user education to build awareness about the responsible use of AI and to empower users to interact with these technologies safely and effectively. By proactively managing these ethical and social considerations, organizations aim to foster trust, promote fairness, and ensure that GenAI contributes positively to society while minimizing harm. This takes place through three main activities.

First, excessive reliance on GenAI outputs can undermine employee autonomy and self-determination by encouraging constant deferral to AI-generated solutions. This overdependence risks diminishing critical thinking and creative problem-solving skills, potentially fostering a dependency that weakens human judgment and initiative. Respondent 15 emphasizes the importance of striking a balance in integrating GenAI into work processes to ensure that technology supports rather than replaces human decision-making and innovation:

> *I think it's really easy to use it for everything. It's really easy to take things as they are from there. So, for example, I love writing and since I started using GPT I realized that I write less than I would before just because it's quicker.*

Company J's exploration of AI's moral and ethical implications highlights a growing concern that excessive reliance on machine intelligence could fundamentally erode human autonomy and self-determination. Their blog post articulates how the convenience of AI-generated solutions might gradually diminish our capacity for independent thought and decision-making, potentially creating unhealthy dependencies on algorithmic guidance. This perspective aligns with broader industry discussions about maintaining a healthy balance between leveraging AI's capabilities and preserving essential human cognitive functions and agency. The concern extends beyond individual impacts to societal implications, where collective over-reliance on AI systems could reshape cultural values and diminish creative problem-solving abilities across communities. Company J's analysis serves as an important reminder that as we integrate GenAI technologies more deeply into our workflows and daily lives, we must consciously preserve spaces for human judgment, creativity, and autonomous decision-making.

Second, GenAI has the potential to widen socioeconomic gaps and concentrate wealth because access and the ability to effectively use the technology may give some an advantage over others, exacerbating existing inequalities and concentrating wealth in fewer hands. As Respondent 11 explained, those with the resources to invest in GenAI tools and training, as well as those who understand how to leverage them effectively, may see significant gains in productivity, innovation, and income. Conversely, individuals and organizations without access to these resources may fall further behind, creating a digital divide that reinforces existing disparities. This concentration of benefits could lead to increased wealth inequality, as those who are already well-positioned in the economy are able to capture the majority of the value created by GenAI. To mitigate this risk, it is important for policymakers and organizations to consider strategies for promoting equitable access to GenAI resources and training, as well as policies that ensure that the benefits of this technology are more broadly shared across society:

> *Other risks also have to do with the perpetuation of a socioeconomic gap, access to technology, becoming concentrated in large technology companies, the trend is towards concentration of wealth.*
>
> *Whoever has access to these development tools, etc., will have much more capacity to find themselves at the top of the tail, in society, than other people, and I think this is a risk. (respondent 17)*

Lastly, a lack of user guidance often leads to GenAI abandonment. When organizations fail to provide adequate training, clear use cases, and ongoing support, employees can become frustrated with the technology, resulting in resistance to adoption. This not only undermines the potential benefits of GenAI but also wastes valuable implementation efforts. As respondent 15 explains, ensuring proper user support and education is critical to fostering sustained engagement and maximizing the impact of GenAI within the organization:

> *It's a change and this needs a comprehensive strategy to be launched: a communication plan, listening to the teams so that there's no resistance, there's really usage of the tools that you implement.*
>
> *Another challenge that that we see is integration to current workloads. What does this mean? Many people don't realize what the full capabilities are and benefits of AI, so they're not sure how to adopt it, in many companies that I have seen, it hasn't been implemented so sustainably, maybe people use it one or two times and then they forget. (respondent 18)*

Industry research underscores the importance of understanding user needs for the successful integration of GenAI technologies. Company N's report highlights that when organizations fail to align GenAI solutions with the specific requirements and workflows of their users, it can lead to frustration and disengagement. This disconnect ultimately increases the risk of technology abandonment, preventing organizations from realizing the full benefits of their GenAI investments.

4.3 Environmental Sustainability

Many organizations are currently prioritizing the use of GenAI for economic and social sustainability, such as improving operational efficiency, enhancing customer experiences, and supporting workforce development. These efforts often focus on driving business growth, fostering innovation, and promoting social inclusion through accessible AI-driven tools and services. However, there is comparatively less emphasis on leveraging GenAI for environmental sustainability, such as reducing carbon emissions, optimizing resource use, or supporting climate action initiatives (see Figure 4). As a result, the full potential of GenAI to address pressing environmental challenges remains underexplored, highlighting an opportunity for organizations to expand their sustainability strategies to include environmental objectives alongside economic and social goals.

The companies involved in this study leveraged GenAI for environmental sustainability for only two action possibilities: *reduce energy consumption in GenAI development and use*, by implementing efficient training methods and to *adopt lightweight models to reduce resource consumption* by deploying smaller and specialized AI architectures, small language models (SLMs) that match specific business needs instead of energy intensive LLMs for all purposes. While it is true that GenAI systems are energy-intensive, these two actions demonstrate that they can also be leveraged to support environmental sustainability. By strategically deploying GenAI to optimize resource use and reduce waste, organizations can mitigate some of the technology's environmental impact. This illustrates that GenAI has the potential not only to present challenges but also to drive meaningful progress in sustainability efforts. However, very little attention and effort have been dedicated to harnessing GenAI specifically for environmental sustainability. This gap should be addressed with equal priority, forming a balanced, "triple bottom line" approach that considers economic, social, and environmental dimensions in the development and deployment of GenAI technologies.

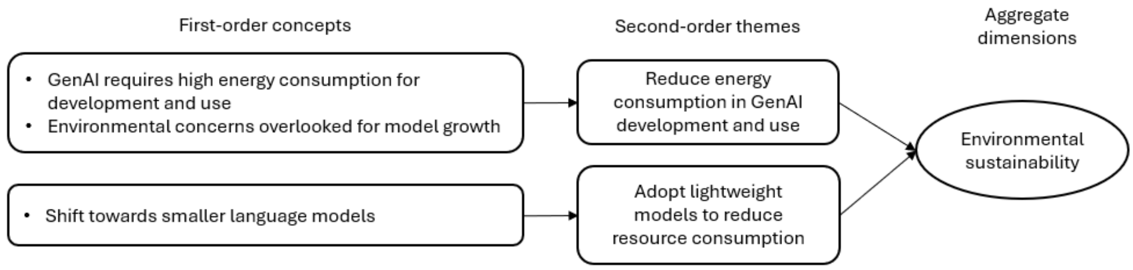

Figure 4 - Data structure for environmental sustainability

Reduce energy consumption for GenAI development and use

Organizations are increasingly adopting new strategies to reduce the energy consumption associated with GenAI development and use. These efforts aim to enhance the energy efficiency of GenAI models not only during their initial training and deployment but also throughout their ongoing, day-to-day operations. Given the inherently energy-intensive nature of GenAI, improving efficiency across its lifecycle is essential to minimizing its environmental footprint. This takes place through two activities. First, GenAI requires high energy consumption for development and use takes place especially during the training of large language models, which rely on significant computational power. The carbon footprint of these technologies is growing rapidly, with insufficient measures in place to counterbalance this impact, a shared concern between interviewees, as explained by respondents 17 and 20 respectively:

> *I'm not sure if what companies will do for their carbon footprint will be enough to guarantee the brutal increase we will have in terms of energy expenditure.*

> *This testing and experimenting… it takes up a lot of resources… people use it all the time and it requires significant energy resources, which is not sustainable, and which is not good to our environment.*

The respondents highlight significant environmental concerns related to GenAI development and deployment. Respondent 4 emphasizes that training these sophisticated AI models requires enormous energy resources. They further warn that as user adoption increases, the energy consumption issue will only become more pronounced and problematic. Respondent 8 noted that training a single AI model consumed *"the equivalent of 120 American families' annual energy consumption in just 3 days*." This underscores the massive carbon footprint behind seemingly simple AI interactions, with the respondent concluding that "*it's cool to play with ChatGPT, but behind the scenes the climate impact is enormous*." These perspectives are reinforced by Company N's blog, which warns that GenAI's substantial energy requirements could potentially undermine efficiency and decarbonization efforts if sustainability considerations aren't integrated early in the implementation process. The company acknowledges that while GenAI has the potential to improve operational efficiency, its current environmental impact remains a significant sustainability challenge that must be addressed. Together, these perspectives highlight the tension between GenAI's promising capabilities and its considerable environmental costs, suggesting that organizations must carefully balance innovation with ecological responsibility as they adopt these technologies.

Second, despite growing awareness of GenAI's environmental impacts, these concerns are frequently overshadowed by the industry's drive for ever-larger models and improved performance. Respondents point out that the pursuit of technological advancement and competitive advantage often takes precedence over sustainability considerations. As a result, the significant energy consumption and carbon footprint associated with training and deploying massive GenAI models are often overlooked in favor of financial and market gains. This trend underscores a critical gap between recognizing environmental risks and taking meaningful action to mitigate them within the rapidly evolving GenAI landscape. Respondent 14 specifically highlights that the industry's focus remains on scaling up models to achieve state-of-the-art results, with little regard for the resulting environmental costs:

> *People have concerns around the environmental factor as well, there is an element of that, but at the end of the day, it has taken a back foot.*

Adopt lightweight models to reduce resource consumption

The move towards smaller language models reflects a strategic effort to balance AI capabilities with sustainability and efficiency. Instead of defaulting to the largest and most resource-intensive models, organizations are increasingly adopting models that require fewer computational resources while still delivering the specific functionalities needed for particular tasks. This targeted approach allows for more precise alignment between model complexity and actual use cases, avoiding unnecessary energy consumption associated with oversized models. By optimizing model size and resource use, organizations can achieve more sustainable AI practices without compromising on effectiveness or innovation. As respondent 14 highlights, this shift not only maintains valuable AI performance but also significantly reduces the environmental footprint of GenAI deployments:

> *The task at hand that could be a small language model because of the efficiency's sake, you don't actually need to have a massive model every single time. Not every solution needs to know the histories of ancient Greece.*

A major challenge in adopting more sustainable GenAI practices is the widespread lack of knowledge and awareness regarding the availability and benefits of smaller AI models. Many users and organizations default to using larger models for all tasks without fully understanding the significant environmental costs associated with this choice. This gap in understanding often leads to unnecessary energy consumption and missed opportunities to reduce the environmental impact by selecting appropriately sized models for specific use cases as pointed out by respondent 20:

> *Using this model which requires more resources when for simple queries the mini model could work perfectly, but they could not be aware that they are using the bigger more consuming model.*

Company M's article emphasizes a growing trend where organizations are moving away from relying solely on large language models (LLMs) and instead adopting small language models (SLMs) tailored to specific functional use cases. This shift is driven by the dual benefits of cost savings and reduced environmental impact, as smaller models require significantly less computational power and energy to train and operate. By focusing on targeted applications, organizations can deploy SLMs that are more efficient and practical for their unique needs without sacrificing performance. In line with this perspective, Company N's report highlights that SLMs can be designed to deliver powerful and accurate results despite their compact size. These models are typically trained on precise and controlled datasets, which enhances their relevance and effectiveness for particular business tasks. This approach not only lowers operational costs but also minimizes the carbon footprint associated with AI development, making SLMs an attractive option for businesses seeking sustainable and cost-effective AI solutions. Together, these insights underscore the strategic value of adopting smaller, purpose-built language models as a way to balance performance, cost, and environmental responsibility.

5. Discussion

5.1 Implications for Theory

My work offers several contributions to theory, as follows. First, it provides new insights for research that explores the use of GenAI for the pursuit of sustainability (Kirchner-Krath et al., 2024). While much of the current academic work on GenAI and sustainability relies on conceptual papers, literature reviews, or editorials (Amankwah-Amoah et al., 2024; Brown et al., 2024; Feuerriegel et al., 2024) little attention was dedicated to empirical research on real-world practice. By conducting a qualitative case study with several experts across industries and regions, this research adds to grounded, practice-based analysis. Specifically, it challenges the oversimplified alignment often assumed between technology adoption and sustainability outcomes, highlights the real trade-offs organizations navigate in practice, and calls out techno-optimistic narratives that overlook issues of governance, equity, and unintended consequences (Modgil et al., 2025; Rana et al., 2024)

Second, this study contributes to the literature on human-AI-collaboration (Jarvenpaa & Klein, 2024; Trocin et al., 2021), by illustrating that GenAI's strategic value is co-created through integration with human expertise, it emerges not from autonomous deployment, but from its contextualized and supervised use within organizational processes and shows that digital technologies contribute to competitive advantage when inserted in responsible and human-centric systems.

Third, my work contributed to the TBL framework (Elkington, 1998b), by empirically showing how GenAI can be applied across economic, social, and environmental sustainability dimensions. Economically, GenAI drives efficiency and innovation through automation, intelligent content processing, and enhanced service offerings (Handler et al., 2024; Ooi et al., 2025). Socially, it supports ethical and inclusive work environments by reinforcing human expertise, enabling upskilling, and embedding governance mechanisms for fairness and transparency (Benbya et al., 2024; Eisenreich et al., 2024). Environmentally, practices such as the adoption of lightweight models and energy-efficient deployments, reduce GenAI's resource footprint (Kirchner-Krath et al., 2024; Modgil et al., 2025).

Lastly, this qualitative exploration showed that GenAI creates foundational changes and redesigns the interactions among service providers, users, and platforms, contributing to the discussions on digital service ecosystems and platform governance (Benbya et al., 2024). GenAI is not just an efficiency tool—it actively reshapes the dynamics of service delivery by enabling real-time personalization, automating customer interactions, and supporting user co-creation through assistive content generation. The findings highlight how platforms embedding GenAI must address increased demands for transparency, fairness, and ethical accountability. Respondents emphasized the growing need for explainable AI, robust human oversight, and mechanisms to ensure that AI outputs align with both user expectations and organizational values, which suggests a reconfiguration of value co-creation processes in digital service ecosystems, where trust and interpretability become central design principles. This study extends current knowledge by illustrating how GenAI integration requires new governance structures that balance automation with human judgment.

5.2 Implications for Practice

This study offers valuable practical insights. First, it highlights the critical need to enhance both AI literacy and sustainability awareness among employees to ensure they are equipped not only to leverage the latest technological advancements but also to contribute meaningfully to organizational and broader sustainable development goals. Successful adoption of GenAI requires comprehensive literacy across all organizational functions, extending well beyond technical training. Education programs should incorporate ethical considerations, risk management, and the environmental and social implications of GenAI (Handler et al., 2024; Rana et al., 2024). Organizations that implemented systematic, cross-functional GenAI training reported higher employee acceptance, more innovative applications, and fewer implementation challenges. Therefore, these programs must emphasize not only the practical skills needed to use GenAI tools effectively but also the critical thinking abilities necessary to assess and interpret the outputs of AI models responsibly (Benbya et al., 2024).

Second, implementing GenAI for the pursuit of sustainability requires close coordination among IT, sustainability, and operational units. Practitioners should actively foster cross-functional collaboration to ensure that GenAI solutions are designed and deployed in ways that effectively align with environmental, social, and economic objectives (Kotlarsky et al., 2023) (Eisenreich et al., 2024). Additionally, service organizations need to carefully consider model complexity and match it appropriately to specific task requirements. Research shows that organizations often default to using large, resource-intensive language models for all applications, even when smaller, specialized models would be sufficient-and in many cases, more effective (Kirchner-Krath et al., 2024; Modgil et al., 2025). By selecting the appropriate model size for each task, managers can significantly reduce environmental impact without compromising service quality, thereby advancing sustainability goals while maintaining operational excellence.

Third, for service organizations, implementing robust data governance frameworks is crucial to safeguarding privacy, maintaining security, and ensuring the ethical use of GenAI (Jung & Winter, 2025; Rana et al., 2024). Such frameworks involve establishing clear policies and controls that manage data quality, access, and compliance with relevant regulations, thereby minimizing risks associated with data misuse or breaches. The findings emphasize the importance of training GenAI models on proprietary, internal documents rather than relying on external services, as this approach not only improves the accuracy and relevance of AI-generated outputs but also protects sensitive information from exposure to third parties (Benbya et al., 2024; Handler et al., 2024). By combining strong governance with ongoing employee training and regular system audits, organizations can foster responsible AI use that balances innovation with privacy protection and ethical accountability.

Fourth, adopting GenAI requires service organizations to rethink roles, develop new capabilities, and update how they measure success. Recommended best practices include conducting regular performance and ethics reviews of GenAI applications, and investing in explainable AI tools to make GenAI decision-making transparent for both employees and customers (Feuerriegel et al., 2024; Modgil et al., 2025), fostering communities of practice across functions to share knowledge (Alavi et al., 2024), and aligning GenAI initiatives with broader sustainability frameworks such as the UN Sustainable Development Goals (Kotlarsky et al., 2023; Prasad Agrawal, 2025).

For policymakers, setting benchmarks for transparency and environmental impact is essential to fostering a fair and responsible technological landscape and preventing harmful practices (Modgil et al., 2025; Rana et al., 2024). Incentivizing the adoption of energy-efficient AI models or support research and development in green computing can help align technological advancement with environmental sustainability goals while promoting transparency in AI model energy and encouraging more informed and aware choices (Kirchner-Krath et al., 2024; Piccoli & Pigni, 2022). Based on my research, platforms should move beyond efficiency alone and consider broader factors like social impact and governance. A recurring insight is the need for more transparent and explainable AI—systems that clearly communicate how decisions are made—to build user trust and ensure alignment with ethical and sustainability commitments (Feuerriegel et al., 2024; Handler et al., 2024). Additionally, GenAI can support sustainable innovation, such as generating ideas for recyclable packaging, selecting eco-friendly materials, or optimizing delivery routes to reduce emissions (Eisenreich et al., 2024; Prasad Agrawal, 2025).

6. Limitations and Future Research

While this study adhered to international standards for qualitative research, the following limitations should be acknowledged. First, while the primary focus of this research was on GenAI for sustainability, it is important to note that there might be other AI technologies—such as machine learning algorithms, optimization models, and predictive analytics—that may also play a significant role in helping organizations achieve their sustainability goals. By concentrating exclusively on GenAI, the study potentially overlooks the broader landscape of AI technologies that could complement or provide alternative solutions for sustainability challenges. This narrow focus may limit the full spectrum of AI applications in sustainability efforts. Future studies could benefit from examining a wider range of AI technologies to understand how different approaches, whether individually or in combination, can impact sustainability outcomes across various industries and organizational contexts.

Second, GenAI solutions are evolving at an exceptionally rapid pace, which introduces both technological and contextual constraints for organizations seeking to adopt them. The insights presented here capture a specific snapshot between late 2024 and early 2025, a period marked by frequent changes in tools, capabilities, and pricing models-such as new model features, API cost adjustments, and architectural innovations-that may quickly render some technical or strategic recommendations outdated.

Third, the majority of participating organizations were early adopters with relatively high digital maturity, which may not accurately reflect the challenges faced by less digitally advanced companies or those in different industries and roles. This variability underscores the need for continuous reassessment of GenAI strategies as the technology and its ecosystem evolve rapidly. Future research should therefore focus on longitudinal studies to track how GenAI adoption and its sustainability impacts evolve over time, comparative analyses across industries and organizational maturity levels, and investigations into emerging technical innovations and their implications for sustainable development goals.

Fourth, this study collected data from multiple organizations across different industries and countries, which provides valuable diversity but also introduces complexity due to varying industry dynamics, regulatory environments, and cultural contexts. These differences can influence how organizations adopt and utilize GenAI for sustainability, making it challenging to capture the full depth of sector or region-specific challenges and opportunities. Future research could address this limitation by conducting in-depth case studies focused on a single industry or country to gain richer, more contextualized insights. Additionally, other studies might undertake cross-case comparisons across industries or countries to identify patterns, differences, and best practices in GenAI adoption for sustainable development. Such approaches would deepen understanding of how contextual factors shape the integration of GenAI in sustainability initiatives.

Fifth, archival data used for triangulation (e.g., blogs, websites, webinars, online courses, podcasts) were public and curated with a strategic communication intent. These materials generally reflect favorable portrayals of GenAI initiatives, for instance, emphasizing its collaboration with Microsoft. Other companies highlighted success stories and leadership insights about AI's integration into their workflows. Most of these archival sources, such as expert views, and company-led training courses, positioned GenAI as an innovative and beneficial force, often omitting critical challenges such as ethical concerns, implementation risks, or workforce displacement. Thus, while valuable for understanding how organizations communicate about GenAI, these curated public sources tend to present an optimistic and promotional lens, which introduces potential bias, necessitating critical interpretation when triangulating such data with interview or observational findings.

Lastly, I conducted an exploratory case study to better understand how organizations across the world are using and integrating GenAI in their daily operations, capturing their real-world challenges, understanding and tracing how their practices have evolved since the emergence of the technology in 2022. But future studies can conduct quantitative studies such as surveys or big data analytics, which could also be used to understand adoption patterns, to test and validate these findings at scale, explore industry-wide patterns or long-term outcomes. and gathering multiple perspectives using data more deeply.

7. Conclusions

This study explored how international organizations are leveraging GenAI to pursue sustainable development goals through an exploratory qualitative approach (Eisenhardt, 1989; Sarker et al., 2018). Between October 2024 and February 2025, I conducted 21 semi-structured interviews with professionals from diverse sectors to explore a broad range of perspectives on GenAI's sustainable applications. In addition to interviews, I collected archival data from organizational websites, articles, webinars, reports, and blog posts to enrich the analysis. Gioia methodology (2013) guided data analysis and interpretation, which enabled a nuanced understanding of current organizational practices, challenges, and strategies in integrating GenAI for sustainability, bridging a critical gap in the literature that often lacks empirical insights into how international organizations operationalize this technology to balance innovation with sustainable development. The findings show that the international organizations are dedicating more attention and resources to economic sustainability by accelerating innovation, reducing operational costs through automation, streamlining internal documentation and compliance processes, enhancing service personalization, and improving content processing—all while addressing technical limitations such as bias and hallucinations to ensure reliability and social sustainability by prioritizing human oversight, reinforcing expertise rather than replacing it, fostering continuous learning cultures, implementing organization-wide GenAI training, and establishing governance mechanisms to safeguard data privacy, ethical integrity, and equitable access.

However, environmental sustainability – one of the three core dimensions with profound impact on our planet-has received limited attention and reflection, despite its urgent importance for organizations to address.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of my written work/thesis, *"GenAI and the Pursuit of Sustainability: a Qualitative Study of International Organizations"*, OpenAI's ChatGPT, Anthropic's Claude, and Google's Gemini was used to support the following tasks: refinement of academic writing style and tone; rewording or paraphrasing for clarity and conciseness; translation support between English and Portuguese; summarizing academic articles; brainstorming for NVivo codes and refinement of paragraph structure.

All content generated with the assistance of this tool was carefully reviewed, edited, and adapted by me to meet the academic and ethical standards expected for this dissertation. I take full responsibility for the final content presented.

I also declare that I am aware of and respect the Artificial Intelligence Rules of Conduct of Católica Porto Business School.

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