Embedding Environmental Sustainability in GenAI Usage

A design science approach to explore interventions for sustainable GenAI interaction

SEN233: CoSEM Master Thesis

Anne van Laarhoven

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by

Anne van Laarhoven

4690532

First supervisor:	Dr. Jolien Ubacht	TU Delft, ICT
Second supervisor:	Prof. Dr. Martijn Warnier	TU Delft, Multi Actor Systems
Company supervisor:	Jasper Snijder, MSc	EY, Technology Consulting
Company supervisor:	Erik Vermeulen, MSc	EY, Technology Consulting
Project Duration:	March 15, 2025 - August 12, 2025	
Faculty:	Technology, Policy & Management	

Preface

Dear reader,

It feels both strange and rewarding to be writing the final words of my thesis. It began with the exploration of two broad and rapidly emerging topics, environmental sustainability and Generative Artificial Intelligence (GenAI), which I did not know much about. Driven by curiosity and a lot of energy, this thesis became a research journey that challenged me both academically and personally. Luckily, throughout this process, I have been supported by people who, from the beginning, have provided me with knowledge, confidence, and motivation.

Firstly, I want to thank my academic supervisors, Dr. Jolien Ubacht and Prof. Dr. Martijn Warnier, for their continuous guidance while also giving me the freedom to explore and find my path during this research. Dr. Jolien Ubacht, thank you for your continued support. Your patience and calm complemented my working style perfectly, exactly what I needed and something from which I have learned a lot. You always asked the right questions, prompting my thinking and leading to critical insights, while giving me a confidence boost exactly when I needed it most. Prof. Dr. Martijn Warnier, your feedback was always strong and precise, bringing clarity to key points helped me make crucial progress at important moments.

I also want to thank the Technology Stategy & Transformation team at EY for welcoming me into their forward-thinking and always supportive environment. My thanks go especially to my counsellor, Jasper Snijder, who guided me throughout this process, not only through your encouragement, but also by bridging academic thinking with practical perspectives. Knowing that I could always reach out to you meant a great deal to me. I would also like to thank Erik Vermeulen for his great knowledge of this topic. Your fresh perspectives and insights pushed my thinking further and helped strengthen the outcome of this research.

I am proud of the final result. Over the last couple of months, I have not only learned about the topic of environmental sustainability in GenAI, but also about applying my skills from Complex Systems Engineering and Management to real-world challenges. This project has strengthened my ability to think critically, navigate complexity, and apply my knowledge in practice. It has also increased my confidence and readiness to bring these skills into my professional career while continuing to learn and grow.

While the GenAI hype continues and is far from saturated, I am curious to see what the future holds for this field, both in terms of technology and environmental implications. I am thrilled to have contributed to its evolution and look forward to further expanding my knowledge and raising awareness of the environmental impacts of GenAI.

Enjoy reading,

Anne van Laarhoven
Delft, August 2025

Executive Summary

Artificial Intelligence (AI) is transforming industries, redefining how businesses operate, and reshaping human-computer interaction. Generative AI (GenAI), in particular, has quickly become embedded in organisational workflows, offering opportunities for productivity, value creation, and innovation. Yet this rapid adoption comes at a cost. The energy demands of GenAI, especially during the inference phase when models are used at scale, raise significant environmental concerns. Current projections suggest that global data centre electricity demand could double by 2030, driven largely by AI workloads, further exacerbating carbon emissions. While technical solutions, such as energy-efficient algorithms and improved hardware, are emerging, they are not sufficient on their own. To achieve broader environmental sustainability goals and foster internal accountability and responsibility, organisations must embed pro-environmental GenAI practices directly into the ways they use these tools. This approach aims to prepare organisations to thrive in a future where AI must coexist with sustainable business practices.

This research investigates how environmental sustainability can be integrated into GenAI usage within organisations. Applying a Design Science Research (DSR) approach, it develops and evaluates targeted interventions aimed at supporting sustainable GenAI practices in daily organisational contexts. The central research question guiding this work is:

> *How can organisations integrate environmental sustainability within the use of Generative Artificial Intelligence through targeted interventions?*

The study unfolds across five phases:

- **Chapter 3** examines *What are the current environmentally sustainable initiatives in the operational phase of Generative Artificial Intelligence?* A systematic literature review shows that most initiatives focus on upstream phases, while overlooking the inference phase. Yet it is precisely at this point, when employees interact with GenAI, that organisations can have direct influence over sustainability outcomes. Additionally, while a single query consumes 0.43 Wh, scaling this to numerous queries per day results in substantial environmental impacts. As a result, the usage phase becomes an important determinant of organisation-wide CO_2 emissions. These findings directly inform the focus of the next sub-question.
- **Chapter 4** addresses *What factors enable environmentally sustainable Generative Artificial Intelligence usage within organisations?* Through interviews with GenAI users and AI experts, enabling factors were identified and mapped using the COM-B model. Enabling factor reveals practical knowledge on how to act pro-environmentally, despite creating general awareness. Moreover, habitual prompting behaviours and limited perceived control, due to unclear impact and personal contribution, were also noted, highlighting key barriers to pro-environmental behaviour. At the same time, opportunities exist in organisational support, feedback mechanisms, and leveraging social influence. Importantly, sustainability must coexist with innovation and experimentation.
- **Chapter 5** explores *What are the requirements for interventions that support environmentally sustainable Generative Artificial Intelligence usage?* These enabling factors were translated into 14 high-level functional and non-functional requirements, along with the design principle of a user-informed approach for the development of interventions. More detailed information on the high-level requirements is reflected in the associated low-level requirements. The requirements, validated through expert brainstorming, focus on practical guidance, transparency, social reinforcement, and integration into existing organisational processes.
- **Chapter 6** presents an overview of *What interventions support the embeddedness of environmentally sustainable Generative Artificial Intelligence usage within organisations?* The design of these interventions was guided by behavioural change theories, including Nudging, the Theory of Planned Behaviour (TPB), and Affordance Theory, which informed the associated requirements. Based on

these requirements, three intervention packages were developed for distinct user personas: (1) *sustainable by default*, which targets externally motivated users with energy-efficient model settings and a monitoring dashboard; (2) *sustainability guidance*, which supports aware but uncertain users through a sustainable prompt builder and impact estimator widget; (3) *collective sustainability*, which engages unaware users with monthly emissions feedback and green tips rotation.

- **Chapter 7** evaluates *To what extent do the interventions support the embeddedness of environmentally sustainable Generative Artificial Intelligence usage within organisations?* Surveys and expert interviews assessed the desirability, alignment with organisational goals, and technical feasibility of the interventions. The interventions were found to raise awareness, provide actionable guidance, and strengthen social influence and collective engagement. Normative alignment does not directly trigger pro-environmental behaviour; however, social influence, collective engagement, and the nudging technique of labelling are identified as more effective drivers. Experts emphasise the feasibility of implementing the interventions within existing infrastructures. However, potential additional compute usage introduced by the interventions must be evaluated to determine whether it offsets the environmental gains. They also stress the importance of transparency in CO_2 emissions for successful monitoring and reliable feedback mechanisms.

The proposed interventions offer a novel approach to potentially reducing the environmental impact of GenAI usage. By leveraging organisational structures and influencing user behaviour, they demonstrate that embedding sustainability into GenAI use requires a socio-technical perspective that integrates behavioural, cultural, and technical dimensions. This research identifies both challenges and opportunities for future studies on human–GenAI interaction and the promotion of pro-environmental behaviour in the use of these tools, particularly as adoption and usage are projected to increase in the coming years.

This research contributes a practical and theoretically grounded framework for organisations seeking to align AI adoption with sustainability objectives. It also aligns closely with the MSc Complex Systems Engineering and Management program at TU Delft, showing how complex socio-technical challenges as AI's environmental impact, can be addressed through systemic, interdisciplinary, and design-oriented approaches.

Contents

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Nomenclature

Abbreviations

Abbreviation	Definition
API	Application Programming Interface
AI	Artificial Intelligence
CO_2	Carbon Dioxide
COM-B	Capability, Opportunity, Motivation - Behaviour
DSR	Design Science Research
ESG	Environmental, Social, and Governance
FPO	Floating Point Operations
FLOPS	Floating Point Operations Per Second
GenAI	Generative Artificial Intelligence
GHG	Greenhouse Gas
kWh	Kilowatt Hour
LLM	Large Language Model
MLOps	Machine Learning Operations
MoE	Mixture of Experts
NLP	Natural Language Processing
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RAG	Retrieval-Augmented Generation
SDG	Sustainable Development Goals
TPB	Theory of Planned Behaviour

Definitions

Term	Definition
Artificial Intelligence	The field of study and development of computer systems capable of performing tasks that typically require human intelligence, such as visual perception, speech recognition, decision-making, and language translation.
Deployment	The phase where trained AI models are integrated into production environments and made accessible for end-users or applications.
Development	The phase in the AI lifecycle involving the design, training, and testing of AI models before they are deployed.
Generative Artificial Intelligence	A subset of Artificial Intelligence that focuses on creating new content, such as text, images, or audio, by learning patterns from existing data and generating outputs that resemble human-created content.
Inference	The phase where a deployed AI model processes input data to generate predictions, classifications, or other outputs.
MLOps	A set of practices that combines Machine Learning and DevOps principles to streamline the deployment, monitoring, and maintenance of machine learning models in production environments.

1
Introduction

This chapter introduces research on integrating environmental sustainability into the use of Generative Artificial Intelligence (GenAI) within organisations. While AI holds transformative potential, its increasing energy demands, amplified by the inference phase and continuous usage, raise significant environmental concerns. A systematic literature review was conducted and discussed, forming the basis for the main research question. Subsequently, the Design Science Research (DSR) approach is introduced and justified, leading to the formulation of a set of supporting sub-questions that guide the development and evaluation of practical interventions. This structure is visualised using a Research Flow Diagram (RFD).

1.1. Problem identification

Generative Artificial Intelligence (GenAI) is defined by Oxford Dictionary as "computer systems that can copy intelligent human behaviour and produce new content, especially text or images" (Oxford University Press, 2025). It has emerged as one of the most visible and transformative branches of Artificial Intelligence (AI), with platforms such as GPT, DALL-E, and Copilot reshaping the way we work (Feuerriegel et al., 2024).

GenAI forms part of the broader concept of AI, a field focused on enabling machines to perform tasks requiring human-like intelligence, including data analysis, pattern recognition, prediction, and decision-making (Oxford Reference, 2011). Makridakis (2017) argue that the impact of the AI revolution in the next 20 years is expected to surpass that of both the digital and industrial revolutions. Notably, with its capabilities in data analysis, pattern recognition, and predictive modelling, AI can also contribute to addressing sustainability challenges (Greif et al., 2025).

Despite AI's potential, its widely adoption presents environmental challenges, creating a paradox that needs to be addressed (Greif et al., 2025). Throughout their lifecycle, AI systems contribute to substantial emissions, stemming from both embodied sources, such as the production and disposal of hardware, and operational sources, including model development, training, and inference. These environmental impacts are prompting growing concerns (Dhiman et al., 2024). The operational emissions of AI depend on factors such as the efficiency of the hardware and software, the carbon intensity of the electricity used, and the rebound effect (Sandalow et al., 2024). In response, the concept of "Sustainable AI" or "Green AI" have emerged, promoting energy-efficient algorithms, improved hardware design, and the use of renewable energy sources (Tabbakh et al., 2024). However, despite these efforts, the future trajectory of AI's energy and carbon footprint remains uncertain. While efficiency improvements may mitigate some impacts, it is overly optimistic to assume they will fully offset the growing energy demands (de Vries, 2023). This challenge is closely linked to the Jevons' paradox or rebound effect, where technological improvements in efficiency lead to increased overall consumption (Shumskaia, 2022). This is reflected in recent projections estimating that global data centre electricity consumption could rise by 165% by 2030, potentially accounting for up to 13% of global power usage, with AI as a major driver (Goldman Sachs, 2024). Similarly, the International Energy Agency (IEA) warns that electricity demand from data centres could more than double due to AI (Harvey, 2025).

This trajectory raises concerns about infrastructure lock-in, as increasing computational power requirements and the rapid adoption of AI may hinder the transition to greener alternatives (Robbins & van Wynsberghe, 2022). Moreover, growing energy demands also risk a return to carbon-intensive energy sources, such as gas and coal (Harvey, 2025).

While the training phase of AI often draws attention due to its high energy demands, the usage phase also carries long-term environmental costs (Garg et al., 2025). Individual AI queries can consume up to ten times the electricity of a standard web search, and their high frequency of use results in substantial cumulative impacts (de Vries, 2023). The mass adoption of AI applications will increase the weight of the inference phase even further. A Google report revealed that between 2019 and 2022, up to 60% of its AI-related energy consumption came from inference processes (Patterson et al., 2022). Moreover, despite the computational efficiencies achieved by recent developments such as DeepSeek-R1 and OpenAI's o1, they are much more energy demanding in the inference phase. This is because they are using reasoning models and "think" more intensively while completing queries (International Energy Agency, 2025).

This underscores the urgency of addressing environmental sustainability in its widespread and ongoing operational use. As AI continues to reshape business operations, addressing its environmental impact requires embedding sustainability into organisational practices (Bharadiya & Thomas, 2023). This entails fostering internal accountability, promoting sustainable organisational behaviour, and cultural change in the way AI is deployed.

This research, conducted in collaboration with EY, aims to address the environmental challenges associated with AI adoption. By positioning itself as its own 'Client Zero,' EY actively tests AI implementations internally. This allows EY to gain practical experience and insights that help guide organizations in effectively adopting AI. Through internally deploying generative AI tools, EY creates a real-world environment to explore the challenges and opportunities of embedding AI within organizations. As concerns about the environmental impact of GenAI usage continue to grow, it becomes increasingly important to investigate how the deployment of AI can be aligned with broader sustainability efforts. Embracing sustainability during the operational phase of AI not only demonstrates alignment with environmental, social, and governance (ESG) principles but also prepares businesses to thrive in a future where AI must coexist with sustainable business practices.

1.2. Academic context and Main research question

In this section, the literature review is presented to examine existing research on the topic. First, the method and selection process used to identify relevant sources are outlined. This is followed by a discussion of the findings, which highlight gaps in current literature on environmental sustainable AI strategies and frameworks. Finally, these insights lead to the formulation of the main research question.

1.2.1. Method: Literature review

To ensure a transparent and reproducible review process, the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) method was followed (Sarkis-Onofre et al., 2021). Figure 1.1 presents the PRISMA flow diagram, outlining the identification, screening, eligibility, and inclusion process.

The literature search was conducted using the Scopus database between March 3rd and 5th, 2025. The following search string was applied: ("sustainable AI" OR "green AI" OR "AI sustainability") AND ("strategies" OR "framework") AND "use". This search yielded 28 articles. After initial screening, 8 articles met the inclusion criteria. The exclusion criteria were:

- Focus on green by AI (AI for sustainability outcomes) rather than green in AI (making AI itself more sustainable).
- Focus on social or governance impacts of AI, rather than environmental impacts.
- Technical articles centred on AI model training techniques without environmental context.

An additional 3 articles were identified using the snowballing method, based on their relevance to the environmental impact of AI. These are marked with an asterisk (*) in Table 1.1. This resulted in a final selection of 10 articles for the review.

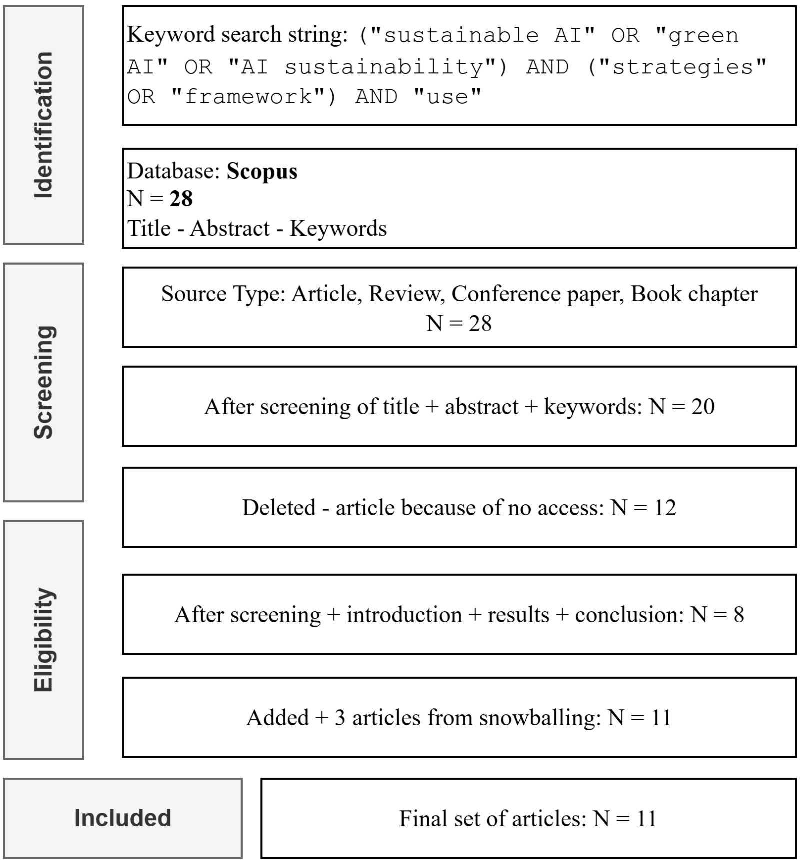

Figure 1.1: PRISMA flow diagram of literature review process for environmental sustainable AI strategies and frameworks

1.2.2. Academic knowledge gap

The articles are reviewed on the following concepts, considered relevant for the topic:

1. Scope: This refers to the breadth and focus of each study.
2. AI assessment: This evaluates the methods used to measure AI's environmental impact.
3. Results: Key findings and conclusions of the study.
4. Future topics: Topics for further exploration.

Based on this criterion, Table 1.1 presents an overview of the literature review. The main takeaways in this literature review are the following:

1. Technological lock-in and high-emission trajectories pose a growing concern.
2. Policy and regulatory mechanisms for guiding environmental sustainable AI adoption remain underdeveloped.
3. AI sustainability metrics are fragmented and lack practical applicability in organisations.
4. Environmental sustainability remains insufficiently embedded within organisational practices.
5. Growing concerns about the environmental impact of the inference phase.
6. Stakeholder involvement and interdisciplinary collaboration are ambiguous.

Literature highlights that AI's environmental impact is intertwined with system-level interdependencies across technological, infrastructural, and organisational dimensions. The issue of technological lock-in and high-emission trajectories, raised by Robbins and van Wynsberghe (2022) and Kaack et al. (2022), highlights that AI systems become embedded within technical infrastructure, making it difficult to transition to greener alternatives. This underscores the need to critically assess the environmental costs of AI infrastructure before committing to long-term, energy-intensive investments, and to consider the broader systemic implications of such decisions. A complementary perspective is offered by Rohde et al. (2024), who evaluates AI as a socio-technical-ecological system, presenting the Sustainability Criteria and Indicators for AI Systems (SCAIS) interventions. Additionally, Rohde et al. (2024) emphasises the need for regulatory mechanisms to support sustainable AI adoption. This is echoed by Kindylidi and Cabral (2021), advocating for the integration of environmental impact assessments into AI regulations, supported by and in collaboration within the AI ecosystem.

To support such efforts, various studies have proposed interventions to assess the environmental footprint of AI, each differing in scope, methodology, and focus (Eilam et al., 2023; Falk et al., 2024; Kaack et al., 2022; Rohde et al., 2024). Kaack et al. (2022) offer a high-level classification of AI-related greenhouse gas emissions in three levels: (1) computing-related emissions, (2) immediate impacts stemming from AI's application, and (3) system-level consequences, referring to structural changes in society and the economy due to widespread adoption of AI. Building on this, Falk et al. (2024) apply the planetary boundaries interventions to AI, mapping environmental impacts across the entire hardware lifecycle, from resource extraction to disposal, and linking these to planetary limits such as climate change, biosphere integrity, land-system change, and ocean acidification. This work underscores the role of embodied emissions alongside the operational emissions.

In contrast, Eilam et al. (2023) focus specifically on the AI model lifecycle, proposing a matrix-based metrics intervention that extends standard data centre sustainability metrics to include the Embodied Product Cost of AI software artefacts. Their methodology incorporates emissions from all phases of the AI lifecycle, including data preparation, model training, retraining, and inference, as well as service operations such as software maintenance. This intervention emphasises the need for accurate measurement and strategic model management to reduce carbon emissions in a meaningful and actionable way.

These discussed impact metrics contribute valuable insights; their diversity also reveals a persistent difficulty in assessing AI's environmental impact. Differences in scope, methodology, and system boundaries across assessments make it challenging to establish a unified or comparable evaluation standard.

The research in more sustainable technical solutions in this area focuses on model optimisation and energy-efficient hardware alternatives, but lacks concrete strategies for organisational implementation (Eilam et al., 2023; Falk et al., 2024; Kunkel et al., 2023; Tabbakh et al., 2024; Verdecchia et al., 2023). Tabbakh et al. (2024) examine various sustainable AI techniques, including model optimisation methods, efficient algorithms, and energy-efficient hardware alternatives. Similarly, in the literature review of Verdecchia et al. (2023), note that Green AI research has reached a considerable level of maturity. It emphasises that only 23% of publications involve industry partners, reflecting the disconnect between academia and real-world AI sustainability practices. While sustainable practices have predominantly focused on the model development and training phases, the inference phase also warrants attention. As noted by de Vries (2023), there are growing indications that this phase may contribute significantly to the overall environmental costs of AI systems. Although inference consumes less energy per operation than training or development, Kaack et al. (2022) highlight its high frequency of use across deployed AI applications, resulting in substantial environmental emissions.

In conclusion, while various techniques exist to reduce both the operational and embodied emissions of AI, environmental sustainability remains insufficiently embedded in organisational practice. This shortfall is compounded by ambiguous stakeholder responsibilities, the absence of supportive policies and regulatory frameworks, and fragmented sustainability metrics. Furthermore, the risk of technological lock-in and continued reliance on high-emission trajectories underscores the urgency for organisations to assume ownership. This urgency is further raised by growing concerns about the environmental impact of the inference phase and continuous use. These challenges reveal a gap in the current literature: the lack of actionable, organisation-driven interventions that embed environmental sustainability into the everyday use of GenAI.

Table 1.1: Overview of literature review on environmental sustainable AI strategies and frameworks

Reference	Scope	Assessment	Results	Future Topics
Kunkel et al. (2023)	Stakeholder involvement	Scoping review of AI sustainability interventions	Exact processes of stakeholder involvement are not explained in analysed interventions	Clarifying stakeholder roles, uptake of sustainability interventions into practice
Robbins and van Wynsberghe (2022)	Lock-in of AI through infrastructure interdependencies	Infrastructure interdependencies	AI infrastructure leading to sustainability lock-in	Assess environmental cost before AI model creation
Eilam et al. (2023)	Developing a sustainability metric for AI	Metric to evaluate the efficiency of AI models	New metric to evaluate the efficiency of AI models	No demonstration of the usefulness of the metric
Tabbakh et al. (2024)	Overview of Green AI	Interventions for Green AI	Overview of energy-efficient hardware and sustainable AI techniques	Effective interdisciplinary collaborations, accessibility for organisations

Continued on next page

Source	Scope	Assessment	Results	Future Topics
* Kaack et al. (2022)	AI's direct and indirect climate impacts	Interventions categ: AI's impact: computing-related, immediate application, and system level	Levers to reduce GHG emissions impacts	Developing climate-conscious AI policies, ensuring access to AI innovation
Rohde et al. (2024)	AI sustainability across social, ecological, and economic dimensions	Literature review	Sustainability Criteria and Indicators for AI Systems (SCAIS) interventions	Need for regulation, assess interdependencies between AI system impacts
Falk et al. (2024)	The lifecycle of AI hardware	Planetary boundary interventions	The lifecycle stages of AI development to the planetary boundaries they impact and geographical distribution	Identifying strategies for minimising negative impacts, need for regulation
Verdecchia et al. (2023)	Green AI	Literature review	Systematic review of Green AI trends and best practices	Bridging academia and industry for practical implementation, understanding practices through interviews
* Bashir et al. (2024)	Aligning AI growth with environmental and social sustainability goals	Benefit-cost evaluation	Action items for stakeholders to build benefit-cost evaluation	Exploring incremental vs. transformational changes in AI sustainability
Kindylidi and Cabral (2021)	Consumer protection and sustainability in AI	Legal and policy analysis of AI	Sustainability of AI is overlooked in regulation	Policy initiative on sustainable AI requires support and collaboration of the AI ecosystem
* de Vries (2023)	Energy consumption during inference	Analysis of AI's energy footprint, focusing on inference	Inference may consume more energy than training and risk of rebound effect	Greater focus on inference in sustainability efforts and calls for transparency before deployment

1.2.3. Main research question

Building on the takeaways and identified knowledge gaps, this research aims to guide AI environmental sustainability into organisational practices. Highlighting the importance of long-term environmental impact, considering GenAI deployment and continued usage. The following research question is formulated:

How can organisations integrate environmental sustainability within the use of Generative Artificial Intelligence *through targeted interventions?*

1.3. Research approach

As shown in the literature review in the previous chapter, various metrics for assessing environmental impact and sustainable AI techniques are discussed in the literature (Eilam et al., 2023; Falk et al., 2024; Kaack et al., 2022; Rohde et al., 2024). However, the organisational integration of these strategies remains limited (Verdecchia et al., 2023). Existing research highlights a clear gap between academic insights and their practical application in industry, when it comes to embedding sustainable AI practices into organisational processes (Kunkel et al., 2023; Tabbakh et al., 2024; Verdecchia et al., 2023).

Several studies highlight systematic challenges that hinder the embeddedness of sustainable AI practices. For instance, **Kunkel2023Robbins2022**; Bashir et al. (**Kunkel2023Robbins2022**; 2024), emphasise the lack of interdisciplinary collaboration, while others underline the pressing need for stronger regulatory and policy alignment (Falk et al., 2024; Kindylidi & Cabral, 2021; Rohde et al., 2024). Concerns about environmental impacts focus on the risk of high-emission trajectories and the growing energy consumption related to the inference phase, due to its high frequency of use and widespread deployment (Kaack et al., 2022; Robbins & van Wynsberghe, 2022).These challenges underscore the need for organisations to identify actionable measures they can undertake themselves, thereby bridging the gap between academic insight and practical implementation.

This research addresses the identified gap by designing and evaluating an artefact, which, in this study, takes the form of targeted interventions aimed at supporting environmentally sustainable GenAI usage within the socio-technical systems of organisations. The goal is that this can be evaluated and engaged by EY. To structure this research, the Design Science Research (DSR) methodology is adopted, enabling a systematic and iterative process of knowledge generation and practical evaluation.

Advantages

The DSR approach is a well-established methodology within Information Systems (IS), with comprehensive interventions discussed by Hevner et al.; Johannesson and Perjons; Peffers et al. (2004, 2021, 2007). These academic resources give a strong foundation for guiding the research, ensuring a structured approach. DSR emphasises an iterative "build-and-evaluate" process, in which artefacts are developed, tested, and refined. This cyclical approach ensures that the interventions are rigorously assessed and adjusted based on stakeholder feedback and real-world applications. Furthermore, a goal of the DSR approach is its focus on utility (Hevner et al., 2004). The contribution of interventions lies in the ability to deliver value. The methodology ensures that the interventions remain adaptable to stakeholder needs, highlighting the importance of interdisciplinary collaboration. This inclusivity enhances the relevance and applicability of the resulting interventions, ultimately leading to practical tools for environmentally sustainable GenAI usage.

Limitations

However, the DSR approach is not without limitations. The iterative nature of the process requires substantial time and resources, and requires expertise and stakeholder collaboration. The rapidly changing technological landscape adds a degree of uncertainty to the development of a robust and long-lasting solution (Hevner et al., 2004). Therefore, evaluating the utility of artefacts in dynamic, real-world contexts presents complexities, particularly given the fast-evolving nature of AI systems.

Another challenge, due to the fast pace of AI advancements, is the risk of obsolescence. This increases the likelihood that the interventions may become outdated or irrelevant over time. Ensuring its adaptability and scalability will be crucial to maintaining its effectiveness in the long term.

1.4. Research Sub-Questions and Research Flow Diagram

The main research question,

How can organisations integrate environmental sustainability within the use of Generative Artificial Intelligence through targeted interventions?,

is addressed through five sub-questions. These sub-questions follow a logical sequence aligned with the DSR. Structured around the activities introduced by Johannesson and Perjons (2021), reflecting a progression from problem investigation and requirement definition to artefact design, development, and evaluation. An overview of this process is provided in the Research Flow Diagram (RFD) (Figure 1.2).

- *What are the current environmentally sustainable initiatives in the operational phase of Generative Artificial Intelligence?*

This sub-question aligns with the first activity of the DSR framework: problem investigation.

As discussed in the literature review, environmental sustainability is not yet systematically integrated within organisational practices for AI. It is recognised that problems can emerge not only as threats but also as missed opportunities (Johannesson & Perjons, 2021). In this context, the lack of embedded environmental sustainability in GenAI represents a significant opportunity for intervention.

To explore this further and to gain an understanding of existing practices, a literature review was conducted on sustainable initiatives in the operational phase of GenAI. This analysis revealed a clear gap: while several initiatives address infrastructure, hardware, and training phases, there is limited attention to environmental sustainability in the inference (or usage) phase of GenAI.

Growing concerns about the energy consumption of the inference phase further underscore the importance of addressing this gap. In addition, several systemic challenges hinder progress toward greener practices, including lock-in to high-emission trajectories, underdeveloped policies, and a lack of interdisciplinary coordination. As upstream phases are largely determined by the AI system, the usage phase represents a domain where organisations retain agency, making it the primary focus for further research and intervention development.

- *What factors enable environmentally sustainable Generative Artificial Intelligence usage within organisations?*

This explores the factors that enable the adoption of environmental sustainability GenAI usage. Understanding these factors is essential for developing an intervention that facilitates and supports environmentally sustainable AI usage. To this end, semi-structured interviews are conducted with both AI experts and GenAI users to gather insights into current practices, attitudes, and behaviours. Interviews are considered an effective method for exploring complex topics, as they allow for in-depth discussions and the collection of rich qualitative data (Johannesson & Perjons, 2021). A known drawback of interviews is that they can easily become rigid or limited in scope due to their structured nature (Johannesson & Perjons, 2021). However, this issue is partly mitigated by using semi-structured interviews, which encourage respondents to be more reflective and creative.

- *What are the requirements for interventions that support the embeddedness of environmentally sustainable Generative Artificial Intelligence usage within organisations?*

As the environmentally sustainable initiatives in the operational phase are understood, the lack of guidance in the inference phase is recognised, and the enabling factors have been mapped and analysed, the next step in the DSR process is to define the requirements.

As outlined by Johannesson and Perjons (2021), several methods exist for defining such requirements within DSR. In this study, the requirements are derived from insights gained in the second phase, particularly from the analysis of semi-structured interviews with both GenAI users and AI experts. This process translates the identified enabling factors for pro-environmental behaviour into actionable requirements for intervention design.

In addition, Johannesson and Perjons (2021) suggests the use of focus groups to overcome the limitations of one-on-one interviews, as focus groups can stimulate more creative and diverse ideas. However, due to time constraints, this research could not incorporate full focus groups. Therefore, brainstorming sessions were held with professionals to validate the current set of requirements and to generate new suggestions that may have been overlooked during the semi-structured interviews.

The final set of requirements forms the foundation for designing a set of interventions and provides actionable insights for organisations seeking to embed environmentally sustainable practices in their continuous usage of GenAI.

- *What interventions support the embeddedness of environmentally sustainable Generative Artificial Intelligence usage within organisations?*

Building on the established requirements, this sub-question aligns with activity three of the DSR: artefact design and development. The objective is to conceptualise and develop interventions that guide organisations in integrating environmentally sustainable GenAI.

The intervention design process will be guided and informed by established theories, including Nudging, Affordance Theory, and the Theory of Planned Behaviour (TPB).

- *To what extent do the interventions support the embeddedness of environmentally sustainable Generative Artificial Intelligence usage within organisations?*

Following the design and development phase, the interventions must be demonstrated and evaluated, aligning with activities four and five of the DSR framework. To conduct the evaluation, the interventions were presented to GenAI users and AI experts within the consulting organisation. Functional and non-functional requirements were assessed through a survey and semi-structured interviews. This enabled an evaluation of both the desirability of the interventions and their organisational and technical feasibility. The process involved collecting stakeholder feedback to support further refinement and to identify opportunities and challenges for implementation.

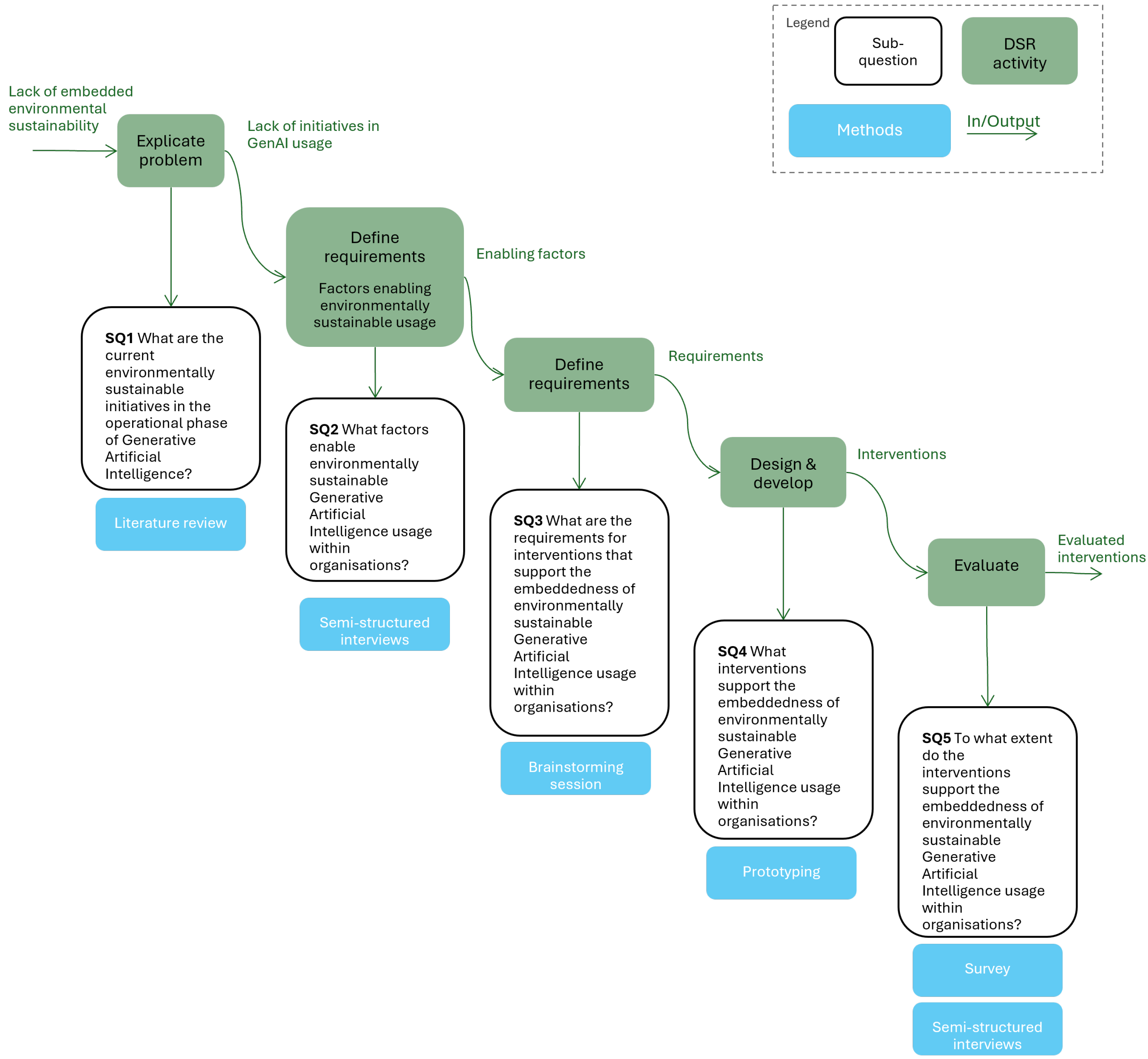

Figure 1.2: Requirements Flow Diagram (RFD), adapted from Johannesson and Perjons (2021)

2

Sustainability initiatives in the operational phase of AI

In this chapter, the sub-question *SQ1: What are the current environmentally sustainable initiatives in the operational phase of Generative Artificial Intelligence?* is examined. A literature review was conducted to identify sustainability initiatives addressing operational emissions in AI. This review provides insights into existing practices and highlights potential intervention points for reducing energy consumption and associated emissions. In addition, emission metrics and their determinants are discussed to develop a deeper understanding of the key factors influencing environmental sustainability during the operational phase of AI.

2.1. Environmentally sustainable initiatives in the operational phase of AI

This section presents the findings from a literature review on current initiatives aimed at improving environmental sustainability in the operational phase of AI systems.

A brief overview of the AI lifecycle and AI model lifecycle is included in Appendix A to provide context on the different levels and their relevance to environmental emissions. This research focuses specifically on the operational emissions during the inference (usage) phase.

2.1.1. Method: literature review

To investigate existing research on environmentally sustainable AI initiatives, a systematic literature review was performed. To ensure transparency and reproducibility, the PRISMA methodology was applied (Sarkis-Onofre et al., 2021).

The search string used was: "Green AI" AND "Artificial intelligence" AND "carbon footprint" AND "sustainab"*. As illustrated in Figure 2.1, the initial search yielded 20 results. After screening for relevance and accessibility, 8 articles were selected. Three additional articles were identified through snowballing, and two more were included based on expert recommendations highlighting specific methods for inclusion. These articles are marked with an asterisk (*) in Table 2.1. The final selection resulted in 13 articles reviewed for environmentally sustainable AI initiatives. Table 2.1 presents an overview of the literature review. The articles were reviewed on their focus and the specific lifecycle phase in which the environmental sustainable initiatives operate.

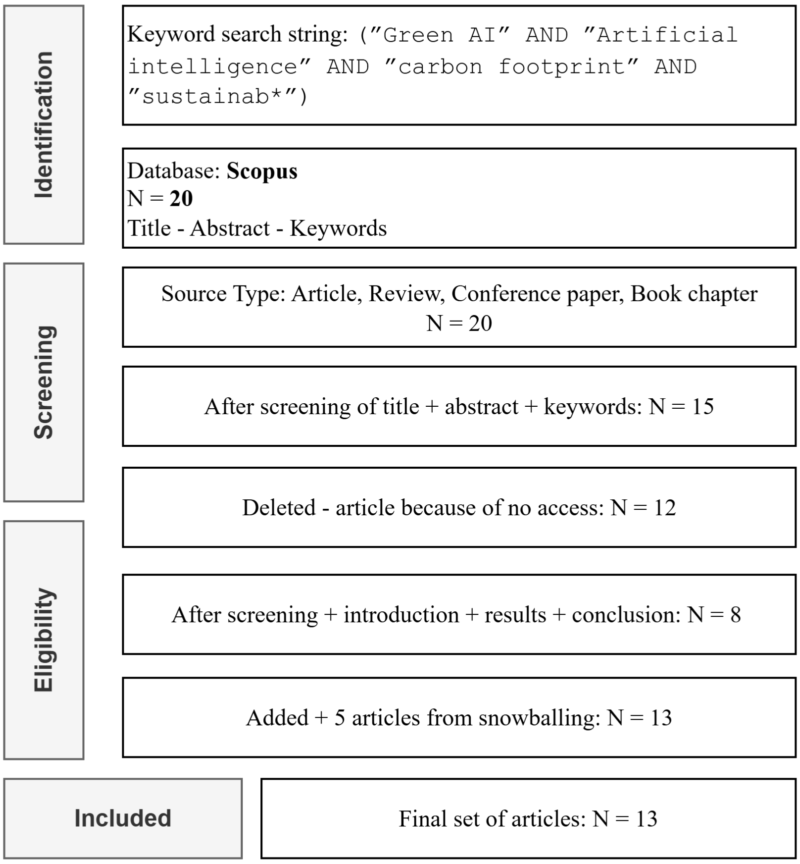

Figure 2.1: PRISMA flow diagram of literature review process for environmental sustainability initiatives in AI

Table 2.1: Overview of literature review on sustainable AI initiatives

Reference	Focus	Lifecycle phase
Vergallo and Mainetti (2024)	Carbon-aware cloud training strategies (e.g. flexible start, pause, resume)	Training
* Dodge et al. (2022)	Flexible cloud scheduling for energy efficiency	Training
Costagliola et al. (2024)	Carbon foot printing tools and carbon-aware workload relocation	Deployment
Alzoubi and Mishra (2024)	Environmental impact monitoring and footprint estimation tools	Monitoring
Järvenpää et al. (2024)	Cloud-fog network design, federated learning, model pruning, and sustainable algorithm design	Develop/Training/Deployment
Budennyy et al. (2022)	Emission monitoring via code-based tools (e.g. CarbonTracker)	Monitoring
* Nawghare et al. (2024)	Web-based monitoring tools for energy estimation in AI workloads	Monitoring
Castellanos-Nieves and García-Forte (2023)	Model pruning and hyperparameter optimisation for efficiency	Training
Castellanos-Nieves and García-Forte (2024)	Energy-efficient algorithms and model optimisation techniques	Develop / Training
Verdecchia et al. (2023)	Efficient hyperparameter tuning to reduce resource use	Training
* Schwartz et al. (2020)	Diminishing returns of model complexity; advocating for efficiency as evaluation metrics	Training
* Han et al. (2024)	Use of Mixture-of-Experts for reducing inference cost	Develop/Inference
* Barbieri et al. (2021)	Quantization methods to reduce computational load	Training

2.1.2. Environmentally sustainable initiatives

Table 2.2 provides an overview of the environmental sustainable initiatives identified, grouped into an overarching categories. These categories are: cloud optimisation, monitoring tools, model efficiency, and sustainable algorithmic approaches.

Table 2.2: Overview of sustainable AI initiatives

Sustainable AI initiative	Focus	Reference
Cloud optimisation	Carbon-aware cloud training strategies as Flexible Start, Pause & Resume	Vergallo and Mainetti (2024), Dodge et al. (2022)
	Cloud provider tools for environmental impact estimation	Costagliola et al. (2024), Alzoubi and Mishra (2024)
	Cloud Fog Network Architecture	Järvenpää et al. (2024)

Sustainable AI initiative	Focus	Reference
	Workload relocation to different geographic locations based on real-time or predicted carbon intensity	Costagliola et al. (2024), Vergallo and Mainetti (2024)
	Federated training on edge devices	Järvenpää et al. (2024)
Monitoring tools	Code-based tools (Eco2AI, CarbonTracker, CodeCarbon)	Budennyy et al. (2022), Nawghare et al. (2024), Alzoubi and Mishra (2024)
	Cloud provider carbon footprinting tools	Costagliola et al. (2024), Alzoubi and Mishra (2024)
	Web-based tools	Nawghare et al. (2024)
Model efficiency	Energy aware pruning	Järvenpää et al. (2024), Castellanos-Nieves and García-Forte (2023)
	Hyperparameter optimisation	Verdecchia et al. (2023), Castellanos-Nieves and García-Forte (2023), Castellanos-Nieves and García-Forte (2024), Järvenpää et al. (2024), Schwartz et al. (2020)
	Mixture-of-Experts	Han et al. (2024)
	Quantization	Barbieri et al. (2021)
Sustainable algorithms	Lightweight algorithm alternatives, diminishing returns of increasing model complexity	Järvenpää et al. (2024), Schwartz et al. (2020)
	Energy-efficient algorithm	Järvenpää et al. (2024), Castellanos-Nieves and García-Forte (2024), Schwartz et al. (2020), Verdecchia et al. (2023)
	Reinforcement learning	Järvenpää et al. (2024)

Cloud optimisation

Cloud optimisation plays a significant role in Sustainable AI by offering various strategies to reduce the environmental impact of AI workloads running on cloud infrastructure (Costagliola et al., 2024; Liu & Yin, 2024; Vergallo & Mainetti, 2024). One of the most direct cloud optimisation strategies for Green AI is choosing cloud regions that have a lower carbon intensity (Costagliola et al., 2024; Dodge et al., 2022; Vergallo & Mainetti, 2024). The workload is relocated, actively migrating AI computations to different geographic locations based on real-time or predicted carbon intensity. Both Vergallo and Mainetti (2024) and Dodge et al. (2022) provide specific strategies anticipating carbon intensity, as Flexible Starts and Pause & Resume, that leverage the temporal variability of carbon intensity on the electricity grid. Flexible start is delaying the start of training until a period of low carbon intensity, where Pause & Resume, pause the training during of high carbon intensity and resume when it's lower.

Additionally, hyperscalers as Amazon AWS, Microsoft Azure, NVIDIA and Google provide specific tools that allow users to optimize infrastructure and workload deployment to minimize their power consumption (Costagliola et al., 2024) (Alzoubi & Mishra, 2024).

Järvenpää et al. (2024) introduces the concept of a Cloud Fog Network (CFN), a distributed computing model that brings cloud-like capabilities closer to edge devices. Similarly, federated learning promotes training AI models directly on decentralised devices as mobile phones or IoT devices where data originates (Järvenpää et al., 2024). Training models on edge devices explicitly aims to decrease the resources needed for transferring large amounts of data to a central server, resulting in improved energy efficiency. Both CFN and federated learning aim to reduce reliance on centralised data centres by processing data locally. This minimises data transfer across networks, thereby lowering energy consumption and enabling more energy-efficient AI processing.

Monitoring tools

To understand the related emissions of AI models and minimise them, monitoring tools have an important role. Monitoring refers to the process of tracking and measuring energy consumption, carbon emissions, and other resource utilisation of AI models (Verdecchia et al., 2023). Code-based carbon emission trackers are software packages and designed to help researchers directly track the energy consumed by their models during training and inference. Both Budennyy et al. (2022) and Nawghare et al. (2024) compare emission trackers, highlighting differences in functionalities as well as in their monitoring and estimation methods. Both studies mention open-source emission trackers: CodeCarbon, estimates carbon emissions based on infrastructure, location, usage, and runtime; Carbontracker, tracks and predicts energy consumption and carbon footprint during model training, and can stop training when it exceeds a rational threshold; Eco2AI, an open-source library focused on accurate energy tracking and regional CO_2) emissions accounting. Notably, Järvenpää et al. (2024) mentions the use of power capping, leveraged by monitoring tools, as a tactic for Green AI.

Cloud providers as Amazon AWS and Azure support estimating environmental impact, such as Customer Carbon Footprint Tools and Microsoft's Azure Emission Impact Dashboard (Alzoubi & Mishra, 2024; Costagliola et al., 2024). These tools provide monitoring and track being able to make informed decisions regarding optimisation. Less accurate tools to use are online carbon footprint estimation tools. These web-based tools allow users to estimate the carbon footprint of computations by inputting parameters like training length, hardware used, and location (Nawghare et al., 2024).

Model efficiency

Within model efficiency within AI, reducing Flouting Point Operations/token, four strategies emerge from the literature: energy-aware pruning, hyperparameter optimisation (HPO), quantisation and Mixture-of-Experts (MoE). These techniques aim to reduce the computational cost and environmental impact of AI models.

Energy-aware pruning is a model optimisation technique that focuses on reducing the complexity of a trained neural network (NN) (Castellanos-Nieves & García-Forte, 2023) (Järvenpää et al., 2024). By removing less important connections and parameters, pruning leads to smaller models with lower computational demands (Castellanos-Nieves & García-Forte, 2023). Energy-aware pruning specifically uses energy consumption as a guiding criterion for deciding which parts of the network to eliminate, further optimising for efficiency (Järvenpää et al., 2024). This process contributes to creating sparse models that require fewer resources.

Similarly, quantisation approaches are used to reduce the precision of the numbers used in computations. Quantisation approaches are utilised to represent the NN weights with fewer bits, improving energy demand (Barbieri et al., 2021). Findings by Barbieri et al. (2021) highlight that using compressed communication, which includes quantisation, is particularly beneficial for energy savings in continual learning scenarios and provides energy savings (>80%) compared to retraining from scratch. However, using fewer bits can reduce the accuracy of the model.

In contrast, the MoE technique reduces energy consumption while still maintaining relatively high performance (Han et al., 2024). Han et al. (2024) describe MoE as a model that includes several "experts," which are smaller parts of the network trained to handle different types of input. These experts are typically made up of fully connected networks (FFNs), and the model also includes a routing network, or "router," that decides which experts to activate. During inference, the router selectively activates a small number of experts that are most suitable for each input. By reducing data movement through selective expert activation, MoE reduced associated energy consumption.

HPO aimed at identifying the optimal set of hyperparameter values for a model to achieve optimal performance on a given dataset (Castellanos-Nieves & García-Forte, 2023) (Castellanos-Nieves & García-Forte, 2024). Traditionally, the primary goal of HPO has been to maximise performance metrics such as accuracy (Schwartz et al., 2020). The complexity of an AI model, which is heavily influenced by hyperparameter choices, directly impacts its energy consumption (Järvenpää et al., 2024) (Schwartz et al., 2020). However, by incorporating energy efficiency metrics into the optimisation process, AI systems can identify hyperparameter configurations that achieve a good balance between performance and sustainability, contributing to more energy efficient models (Verdecchia et al., 2023). In order to find a balance between performance and sustainability, this can be mathematically formalised as finding the hyperparameter configuration that maximises an objective function (e.g., accuracy) subject to certain constraints (e.g., computational resources) (Castellanos-Nieves & García-Forte, 2023). By incorporating energy efficiency metrics and utilising appropriate HPO algorithms, it is possible to develop high-performing AI models with a reduced carbon footprint (Schwartz et al., 2020) (Castellanos-Nieves & García-Forte, 2023).

Sustainable algorithms

Sustainable algorithm approaches are central to creating AI solutions that are not only high performing but also environmentally sustainable by minimising their energy consumption (Schwartz et al., 2020) (Verdecchia et al., 2023). Widely recognised in literature is the emphasis on the goal to offer comparable performance and accuracy with reduced energy consumption (Järvenpää et al., 2024) (Schwartz et al., 2020) (Verdecchia et al., 2023). Green AI refers to efficiency as a primary evaluation criterion along with accuracy (Schwartz et al., 2020), which involves choosing inherently energy-efficient algorithms, exploring lightweight algorithm alternatives, and considering the diminishing returns of increasing model complexity (Järvenpää et al., 2024).

Castellanos-Nieves and García-Forte (2024) discuss the importance of balancing model performance with sustainability, highlighting precision energy trade-offs and model compressions as key strategies. Schwartz et al. (2020) notes that the relationship between model performance and complexity is logarithmic, meaning exponentially larger models are required for linear gain. Ass adding more complexity leads to diminishing returns, advocates to focus on smaller, efficient models. Additionally, Järvenpää et al. (2024) explicitly list to consider reinforcement learning for energy efficiency. Reinforcement models can dynamically opt for energy-efficient options at run-time by adjusting model parameters based on feedback.

It is important to recognise that model efficiency techniques, such as energy-aware pruning, hyperparameter optimisation (HPO), quantisation, and Mixture-of-Experts (MoE), align well with the principles of sustainable algorithm design, particularly through their focus on lightweight and energy-efficient computation. However, these techniques are often motivated by multiple goals, not just sustainability. For example, they may also aim to improve speed, reduce hardware requirements, or enable deployment on edge devices. In contrast, sustainable algorithm approaches place energy efficiency and reduced carbon emissions at the core of their objectives. While both perspectives overlap in methods and outcomes, priorities may differ.

2.1.3. Emission metrics

To develop a clear understanding of the factors influencing environmental sustainability during the operational phase of AI, this section discusses emission metrics and determinants.

Literature provides several metrics for assessing the energy consumption and environmental impact of AI models. One of the most fundamental aspects is electricity consumption, captured in units as kilowatt-hours (kWh)/joules (J). Representing the total electrical energy devoured by hardware, as the model learns during its training time and later makes predictions in the inference phase (Järvenpää et al., 2024). The longer the model trains, usually measured in hours or even days, the more energy it consumes (Castellanos-Nieves & García-Forte, 2023). During the inference phase, the energy consumption is driven by the number of interactions, model complexity and hardware efficiency (Jegham et al., 2024).

However, knowing electricity consumption alone is insufficient to fully grasp the environmental impact. Carbon emissions provide a more comprehensive metric (Verdecchia et al., 2023). These quantify the release of greenhouse gases, primarily carbon dioxide (CO_2) and its equivalents (CO_2e), resulting from electricity use during AI operations. CO_2e includes not only direct carbon dioxide emissions but also other greenhouse gases associated with the production and lifecycle of the hardware and energy sources involved (Castellanos-Nieves & García-Forte, 2024)

Beyond direct energy and emission metrics, hardware-agnostic measures of computational effort are also considered. Schwartz et al. (2020) uses Floating Point Operations (FPO) as a metric to assess the computational workload required by AI models. This allows researchers to compare the inherent efficiency of algorithms independently of the hardware used. In contrast, hardware-dependent metrics such as Floating Point Operations per Second (FLOPS) measure computational speed and are influenced by the processing power of the hardware (Järvenpää et al., 2024).

Next to the efficiency of the hardware, the number of parameters within a model gives an indication of its complexity; more parameters generally mean more computation and thus higher energy needs (Castellanos-Nieves & García-Forte, 2024). Research by Jegham et al. (2024) shows that o3 and DeepSeek-R1 emerge as the most energy-intensive models, consuming over 33 Wh per long prompt, compared to GPT-4o's 0.43 Wh. Thus, model choice highly depends on the energy consumption and related emissions.

Once a model is trained, its efficiency can also be assessed by its prediction time (or inference time), how quickly it can generate an output (Järvenpää et al., 2024). Shorter prediction times often point to a more streamlined and efficient model, reducing energy. Furthermore, the carbon intensity of the electricity powering data centres directly affects the total emissions during prompting (Costagliola et al., 2024; Dodge et al., 2022; Vergallo & Mainetti, 2024). Additionally, the prompt length, determined by the number of input and output tokens, effects the energy consumption and emissions (Dauner & Socher, 2025).

The cumulative effect of user interaction and queries must also be considered. While a single short GPT-4o query consumes 0.43 Wh, scaling this to more queries a day results in substantial annual environmental impacts (Jegham et al., 2024). While the training phase of AI models has received most scientific attention due to its high energy demands, this focus is shifting towards the inference phase with the rise of large-scale AI applications and rebound effect (de Vries, 2023). Recent data from Meta and Google supports this, showing that inference accounts for approximately 60–70% of total energy use, while training contributes only 20–40% (International Energy Agency, 2023). On top, Järvenpää et al. (2024) emphasises the need for specific tactics aimed at raising awareness of the energy footprint associated with this phase.

In summary, determining the CO_2 emissions during the operational phase of GenAI requires consideration of multiple factors. Including electricity carbon intensity, model complexity, inference time, hardware efficiency, prompt lengths, and overall usage scale. Together, they influence the energy consumption and related operational emissions of GenAI usage.

2.2. Conclusion

This chapter examined current environmentally sustainable initiatives in the operational phase of AI to answer *SQ1: What are the current environmentally sustainable initiatives in the operational phase of AI?* The literature review revealed several key strategies for sustainable AI, including cloud optimisation techniques (e.g., workload relocation and carbon-aware scheduling), monitoring tools for energy and emissions tracking, and approaches to improve model efficiency such as energy-aware pruning, quantisation, HPO, reinforcement learning and lightweight algorithms. Most of these initiatives focus primarily on the training and monitoring phases of the AI lifecycle, except for MoE, which target the inference phase (see Table 2.1). Notably, all identified initiatives represent technical approaches, while the inference (usaeg) phase remains largely unaddressed.

Emission metrics and their determinants were also analysed, revealing that CO_2 emissions are influenced by multiple factors, including the carbon intensity of electricity, model complexity, inference time, hardware efficiency, prompt length, and overall usage scale. While sustainable initiatives target several of these factors through technical measures, prompt length and overall usage scale remain untargeted. Although a single query consumes only 0.43 Wh, scaling this to numerous queries per day can result in substantial environmental impacts. Consequently, the inference phase emerges as a critical driver of organisation-wide CO_2 emissions.

These insights informed the decision to focus more closely on the inference phase and user interaction with GenAI. This directly leads to the next sub-question, which examines the organisational and behavioural factors that enable environmentally sustainable GenAI use in practice.

3

Factors enabling environmentally sustainable GenAI usage

This chapter answers the following sub-question: *SQ2: What factors enable environmentally sustainable Generative Artificial Intelligence usage within organisations?* It focuses on identifying the factors that enable environmentally sustainable GenAI use during inference. To investigate this, a series of semi-structured interviews with GenAI users and AI experts is conducted to examine current barriers and enablers and to gain insights into current GenAI usage practices. These barriers and enablers were then translated into enabling factors, which are categorised under Capability, Opportunity, and Motivation. These components are essential for any behaviour (B) to occur according to the COM-B model proposed by Michie et al. (2011).

3.1. Factors enabling pro-environmental behaviour

The GenAI usage or inference phase reveals a gap in existing sustainability initiatives, becoming clear in Chapter 2 and Table 2.1. However, at this stage, moderating the usage is necessary and should be considered in efforts to manage energy demand and related environmental costs associated with GenAI. As Carey et al. (2019) argues, sustainability stems not only from reducing the environmental impact of products and services, but more fundamentally from a transformation in individual attitudes and behaviours. Consumers' perceptions of corporate sustainability are influenced not only by the outputs of organisations but also by how individuals engage with and evaluate these outputs, highlighting that user interaction and behavioural expectations are determinants of broader sustainability outcomes (Jung & Ha-Brookshire, 2016).

Accordingly, this research undertakes an examination of the usage phase to explore strategies that can encourage pro-environmental behaviour in the interaction with GenAI tools. In this thesis, pro-environmental behaviour is understood as individual or collective actions that aim to reduce negative impact on the environment or enhance environmental sustainability, whether through intention or effect (Arya & Chaturvedi, 2020).

3.1.1. Method: Interviews

To understand what encourages sustainable GenAI usage during the inference phase, semi-structured interviews were conducted with both GenAI users and experts. This approach enables a nuanced investigation into participants' experiences, perceptions, and attitudes related to environmental sustainability in the context of GenAI tools. This method facilitated open-ended, reflective discussions, allowing participants to articulate their understanding of environmental impact and share their behaviours.

In this study, GenAI users were interviewed to examine how these tools are used in practice and to assess the extent to which users are aware of or consider environmental sustainability in their usage. This included mapping when, how, and why employees use GenAI tools; evaluating their awareness of the energy and environmental impacts of their usage; and determining whether they have received organisational guidance on sustainable use. The interviews also explored behavioural and contextual factors that could influence environmentally sustainable practices, including individual motivations and organisational conditions that enable or constrain such behaviour.

The interviews provided insight into how users define environmental sustainability in the context of GenAI, the extent to which their practices align with these definitions, and the possible factors that enable them to act sustainably.

At the same time, AI experts were interviewed to examine how GenAI tools are managed and deployed, and to assess if environmental sustainability is currently integrated into these processes. This included exploring practices related to GenAI deployment, identifying stakeholders involved in oversight and sustainability-related decision-making, and examining how sustainability is prioritised within the organisation. The interviews also investigated challenges and enablers for embedding sustainability into GenAI usage, focusing on how organisational and technical priorities are balanced with sustainability goals and what forms of support, incentives, or structural changes could facilitate more sustainable GenAI use.

These insights provide two complementary perspectives: (1) the user perspective, which reveals attitudes and behaviours related to sustainable GenAI usage; and (2) the organisational perspective, which highlights the factors that could influence the integration and adoption of environmentally sustainable GenAI usage. Together, these perspectives inform the design of interventions aimed at promoting pro-environmental use of GenAI tools in practice.

3.1.2. Interview protocol

To examine the factors that encourage the adoption of environmentally sustainable practices in AI usage, interviews are conducted with two selected groups:

1. **GenAI users:** employees who actively use GenAI tools in their day-to-day work, selected to capture behavioural, psychological, and contextual factors that influence pro-environmental behaviour during the inference or user interaction phase.
2. **AI experts:** professionals with strategic responsibility for the deployment or governance of GenAI tools, selected to investigate organisational and structural factors that shape the adoption and implementation of sustainable GenAI within organisations.

A total of 9 GenAI users and 6 AI experts were interviewed. The list of interviewees can be found in Appendix B Table B.1. The selection of participants was guided by predefined criteria to ensure relevance. GenAI users were only selected based on their active use of GenAI tools as part of their daily work. Roles spanned consulting, compliance and data analytics to ensure variation in application context and user interaction patterns.

AI experts were chosen based on three criteria: (1) professional experience and roles in the deployment or governance of GenAI tools, either within the organisation or for external clients; (2) social recognition in the field, with AI experts being recommended by peers or coordinators to ensure credibility and relevance; and (3) minimum of three years of work experience in the field of data, AI or digital transformation.

Participants were recruited through communication channels, including Microsoft Teams and Microsoft Outlook. They received the interview questions in advance, along with an Informed Consent Form that they were asked to review, sign, and return before the interview. Participation was entirely voluntary. Respondents had the freedom to decline participation, ask questions at any point, and decide whether to permit audio recording of the interview and the use of quotations in the research. Interviews were conducted either online (via Microsoft Teams) or in person, depending on participant preference, and each session lasted approximately 30 to 60 minutes.

The interview questions for the GenAI users and AI experts can be found in Appendix B. The interview questions for GenAI users and AI experts are different and are outlined as follows:

Interview GenAI users

1. To understand how GenAI tools are used in practice, and whether users are aware of or consider sustainability, by:

   (a) Mapping when, how and why employees use GenAI
   (b) Assessing about their awareness of the energy or environmental impact of using these tools
   (c) If they have received guidance on sustainable use
2. Explore behavioural and contextual factors that could support more sustainable use of GenAI, by:
   (a) Understanding what could motivate users to engage in more sustainable practices
   (b) Identifying organisational factors that either support or hinder environmentally conscious behaviour in GenAI use

Interview AI experts

1. To understand how GenAI tools are managed and deployed, and whether sustainability is considered, by:
   (a) Exploring current operational practices related to GenAI
   (b) Investigating how sustainability in relation to GenAI is valued within the organisation
   (c) Assessing whether sustainability interventions are applied or explored
2. To identify challenges and enablers for embedding sustainability into GenAI operations, by:
   (a) Examining how organisational and technical priorities are balanced with sustainability goals
   (b) Investigating what forms of support, incentives, or structural changes could promote environmentally sustainable GenAI use within the organisation

3.1.3. Data analysis

The qualitative data from the semi-structured interviews are manually analysed using the qualitative analysis tool Atlas.ti. Inductive codes were developed in a bottom-up manner, resulting in 340 codes. The codes were very descriptive, but also led to fragmented information. Key insights, particularly the identification of enablers and barriers to pro-environmental behaviour, in GenAI usage were too low-level. Coders of this type are referred to in literature as splinters (Friese, 2023). Recommended is to stop with coding and review the coding and start to merge these codes into overarching codes, in more manageable units for analysis (Male, 2016).

To this end, the COM-B model of behaviour change proposed by Michie et al. (2011) is used to structure the data into categories. This model is selected because of its broad application in studies on behavioural change and its relevance to contexts promoting pro-environmental behaviour (Owen et al., 2023). An overview of the behavioural model is given in Figure 3.1.

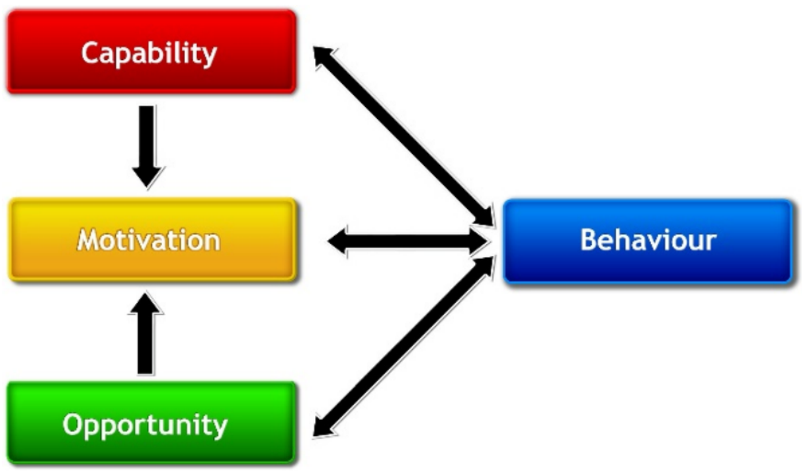

Figure 3.1: COM-B model. Adopted from (Michie et al., 2011).

The COM-B model identifies three core components (Capability, Opportunity and Motivation) that are essential for behaviour (B) to occur. Each category comprises two subcomponents. Applying this model provided a structured lens to categorise and interpret the barriers and enablers relevant to pro-environmental GenAI use.

The six components, which were used as categories in the coding process, are defined as follows (Michie et al., 2011):

- **Capability** refers to an individual's psychological and physical capacity to engage in the behaviour, including the necessary knowledge and skills.
  - *Physical* skills for operating equipment or performing tasks requiring manual effort.
  - *Psychological* cognitive skills and knowledge such as reasoning.
- **Motivation** encompasses all brain processes that motivate behaviour, both automatic and reflective.
  - *Reflective* thought processes such as plans and evaluation.
  - *Automatic* intrinsic processes such as emotional responses and impulses.
- **Opportunity** includes all external factors that make the behaviour possible, such as aspects of the physical and social environment.
  - *Physical* the environment, availability of time, and access to resources.
  - *Social* culture norms that dictates the way we think.

The Physical Skills subcategory under Capability did not receive any related codes, as the use of GenAI tools does not require physical effort or manual strength. For the other COM-B categories, each code was assigned to one of the predefined domains, providing insight into the barriers and enablers within each category.

To preserve the distinct perspectives of both user groups, the analysis was conducted separately for GenAI users and AI experts. This approach enabled cross-validation of codes identified in the user interviews, with expert confirmations adding robustness. Additionally, the expert perspective contributed further valuable enablers and barriers that could promote or hinder the integration of environmentally sustainable GenAI use within the organisation. For example, under Psychological Capability, AI experts emphasised the importance of effective prompting as an enabler of sustainable use: *"How do you get the most efficiency of prompts? So there's at least there's a value gained from the information that you receive of the tool. So because you know, if you're not teaching people how to prompt correctly then I guess that would be a, an inefficient way of using AI tooling and then that would actually then generate or burn more energy than you need."* (Interviewee 3 - AI expert). In contrast, GenAI users highlighted a lack of knowledge about energy trade-offs between tools as a barrier to sustainable behaviour: *I don't know what the influence is, for example, GenAI tools compared with a Google search, and then in the same width, so 10 Google searches compared to 1 prompt. So that's knowledge I need* (Interviewee 1 - GenAI users).

An overview of the codes identified for GenAI users is provided in Table 3.1, and for AI experts in Table 3.2. To provide additional context, illustrative quotes from interviewees are included in the final column to support each code.

Table 3.1: Overview of enablers and barriers of pro-environmental behaviour from the perspective of GenAI users

Category	Code	Code group	Quote
Capability Psychological	Aware of environmental impact	Enabler	"When I Google something, I'm not thinking about the environment, but with ChatGPT, I am. So I notice that I am aware of that."
	Actionable knowledge gap	Barrier	"I have no idea how I could use it in a more environmentally friendly."
	Knowledge about prompt engineering	Enabler	"Just pay attention to your word usage. You can sometimes ask something much shorter and that's good enough. Prompt engineering is important."
	Knowledge about task based GenAI selection	Enabler	"And they choose for, you have now a kind of toggle, for small tasks, use this model. Because that is good enough for small questions. And if you do more difficult things, then you use the bigger, more expensive model."
	Lack of knowledge about energy trade-off between tools	Barrier	"I don't know what the influence is, for example, GenAI tools compared with a Google search, and then in the same width, so 10 Google searches compared to 1 prompt. So that's knowledge you need."
Motivation Automatic	Feeling of guilt upon seeing emissions	Enabler	"You're left with a kind of guilt. So if you're going to get a plane ticket and it says there, oh, for so many euros you can get CO_2 compensation. If it weren't there, I might not think about it as much. But if it is there, I do feel like , who am I not to act on it?"
	Presence of automatic prompting behaviour	Barrier	"I'm just going to play with it and ask follow-up questions."
Motivation Reflective	Preference for autonomy and casual motivation	Enabler	"I'm personally more driven by casual motivation. I don't really respond well when something is presented in a 'you must do it this way' kind of manner."
	Creating awareness	Enabler	"But I think that by creating awareness, it would really help me, and I believe it would help many people around me as well."
	Aware but inactive when using	Barrier	"No, for sure thought about the environmental impact, but not that it is a recurring theme when I use it."
	Compliance with organisational norms, policies, structures	Enabler	"I think lastly, the company should come with making it tangible, making it visible, and making the employers aware of it, that has to be done by the company."
	Feeling of personal ownership	Enabler	"You are not stuck in traffic, you are traffic. So you're part of the problem yourself when you do something."
	Lack of clarity in the magnitude of the impact	Barrier	"And if it really had a lot of negative impact on the environment, that people would be more aware of it. Or that impact on the environment is not that much, can that also be a message?"
	Lack of clear source level information	Barrier	"It is just like where your data centers are placed. The hardware in there, there are 200 windmills next to it. That all plays out."
	Lack of insight in personal impact	Barrier	"But with sustainability, it's naturally something that doesn't personally affect you directly, it's usually about the long term and large groups of people. It can sometimes be difficult to motivate yourself because, on your own, you have so little impact."
	Clear, simple and accessible sustainable action	Enabler	"Because if it becomes a 50-page document about what you can and cannot do, I don't read that."
	Perceived impact via cost cues	Enabler	"Because their is also financial advantage to choose the cheaper model."

Category	Code	Code groups	Quote
	Accuracy and value creation can not be compromised	Enabler	“But then I would need something that gives the same result, but in an environmentally friendly way.”
	Convenience and ease must be maintained	Enabler	“If within those frames of speed and ease, if there are sustainable solutions to use, for sure. But if that’s not the case, I think I would choose that option less quickly.”
	Speed of generating output must be maintained	Enabler	"It’s just that I think it still needs to remain easy to use, that’s the most important thing. After all, you use a GenAI tool for convenience and to save time. So if it starts taking much longer to use, you’re less likely to use it."
	Motivated by reward	Enabler	"The only reason I think that if I, so at least that’s how I understand your question, the only reason I think that I myself am more motivated to make the decision to choose something more efficient, could be because I get a reward from the company."
Opportunity Physical	Sustainability feedback	Enabler	"If you could see something like: you’ve now done this and that, you’ve asked 10 questions to solve this problem using the GenAI tool. So this was the impact, this was the energy usage, or here’s a summary just to give you a bit more information."
	Lack of tangibility	Barrier	"And that’s why I find it difficult.The numbers don’t mean much to me."
	Lack of embedded transparencyt	Barrier	"So you would actually have to have a kind of metric of how many tokens you send is so much emissions. So, yes, the tangibility, the measurability, that would help."
	Low frequency of sustainability cues	Barrier	"I think it works better if you know the numbers. When you prompt this now, you’re also setting this process in motion. Rather than just vaguely having heard once that ’this isn’t so great."
Opportunity Social	Innovation culture is prioritized	Barrier	"We are also technology consulting, so then you’re already thinking about innovation quickly. And questions as; How we want to be involved with innovation? How can we incoorperate this in our work? Then you don’t think about the drawbacks quickly, I think."
	Peer comparison	Enabler	"If you see that you are heavily above it, then I can imagine that you might think, maybe I can do this more efficiently or something."
	Social attention	Enabler	"It is more social attention. So just by hearing things from all sides, from different channels and different people, that you are dealing with this kind of thing, that we are dealing with the climate, that’s why it’s on my agenda."
	Leadership as social modelling	Enabler	"If they are not extra happy when they have an project that focuses on sustainability, and they think, wow, chill, it’s a pain that we can really deliver something, and that we can work together with this, or if we just treat it like any other standard project, then it also gives it some kind of priority."
	Prefers local engagement	Enabler	"That’s why I find it easier and more motivating when it comes from that kind of setting, rather than from the board of the company that doesn’t know who I am and just sends out a generic email."
	Conversation trigger reflection	Enabler	"Conversations with colleagues and friends could definitely encourage me."
	Working in group/team motivating	Enabler	"But maybe because it’s closer, because it becomes more personal, because you start thinking about it with your colleagues and then you have the feeling that we are actually going to apply it."

Table 3.2: Overview of enablers and barriers of pro-environmental behaviour from the perspective of AI experts

Category	Code	Code group	Quote
Capability Psychological	Actionable knowledge gap	Barrier	"“Do you want to be environmentally conscious?” 100% will say yes. Total agreement. But if you then ask, “How are you going to do that with AI?”, they won’t know. “Should I still use it at all? Or should I not?” I don’t think they know.”
	Lack of knowledge about the underlying processes and related costs of prompting	Barrier	"I do wonder, going back to adoption, do people even realise, when they sit down for an hour and ask for, say, a photo of a clown wearing a certain football shirt, what’s happening in the background? No, definitely not. And neither do they at Google."
	Performance based GenAI selection	Enabler	"You could say: for certain basic skills or tasks, just automatically assign a simpler model. If you’re just brainstorming ideas, you don’t need the heaviest GPT-4 model. Or if you’re searching for specific text in a legal document, do you really need the full GPT-4 turbo version to do that? Probably not. "
	No awareness of environmental impact	Barrier	"I think the main issue is people just don’t know. So I think, first of all, they don’t realise that it actually has an environmental impact."
	Use where it adds value	Enabler	"The whole principle behind it is of course based on lots of data , tons of information being gathered from everywhere to provide the best AI support in information delivery or processing tasks. I do hope that at some point we’ll start looking much more at where it actually adds value. Instead of, “Give me a recipe for soup,” or something like that."
	Getting the most value creation out of a prompt	Enabler	"How do you get the most efficiency of prompts? So instead of just. So there’s at least there’s a value gained from the information that you receive of the tool. So because you know, if you’re not teaching people how to prompt correctly then I guess that would be a, an inefficient way of using AI tooling and then that would actually then generate or burn more energy than you need. Then what actually the value getting out of from it."
Motivation Automatic	Presence of non purposeful usage	Barrier	"First, there’s the nonsense that gets generated."
Motivation Reflective	Balanced use of technology adoption and sustainability	Enabler	"I think it should be a healthy balance, that we do use the technology, but in a very conscious and considered way."
	Speed must be maintained	Enabler	"Because I think at the moment a lot of people want speed, so."
Opportunity Physical	Showing visibly environmental consequences	Enabler	"And you can also sketch a future where you continuously show people what’s happening. The pictures on cigarette packets , they’re terrible, but they show the consequences of smoking every single time."
	Track and set baseline	Enabler	"You could track how much each person is using it. You could limit that in certain ways or reduce it a little bit."
	Lack of tangibility	Barrier	"That’s a tough one. I think the more tangible you make it, the more people will take it seriously."
	Lack of measurability	Barrier	"Well, like I said, one is measurability."
	Incentives enhance pro-environmental behaviour	Enabler	"I think like there should be a step in there, which I’m thinking which is you get, I don’t know, you get a discounted rate or something like that or you get. You get a benefit of some sort if you then decide to pick a more sustainable model."

Category	Code	Code groups	Quote
Opportunity Social	Social attention	Enabler	"I think it's just exposure. Right."
	Leadership as social modelling	Enabler	"And I think leadership plays a role too. If you have someone at the top of the company talking about sustainability, and showing that they make green choices, that really helps. It sets the tone."
	Peer pressure	Enabler	"There's of course, look at smoking again, a huge element of peer pressure. There's a concept around that, social enforcement. There's now quite a bit of pressure not to do it."
	Helping each other act pro-environmental	Enabler	"Hopefully, as a society, we'll find the environment important enough to call each other out. Or at least help each other with it."
	Culture on adoption and innovation	Barrier	"Another is that the technology is still so new. Everyone's still experimenting and discovering what's possible. So right now, the focus is really on innovation , not sustainability."
	Strategic priority over sustainability	Barrier	"I think we really want to embrace AI, start using it and rolling it out to clients. That's also going to give us a competitive advantage. I think that's more important right now than considering the environmental impact."
	First users of AI	Enabler	"“You can only use the lightweight model”, they'll say, “Hang on, I just got started!” It's still a bit too early to set firm boundaries. You can encourage it, yes, but strict rules might slow down innovation."

3.1.4. Understanding current GenAI use

Understanding current usage patterns of GenAI tools, particularly through the lens of pro-environmental behaviour, is essential for designing interventions that reduce environmental impact during and through use. The following section discusses insights drawn from interview data with both GenAI users and experts, based on the identified barriers and enablers.

Among the nine GenAI users interviewed, two stated that they currently engage in pro-environmental behaviour, such as avoiding unnecessary use, not activating turbo mode when it is not needed, and using Google as an alternative. Two others indicated they had made efforts to act pro-environmental: *"And I have tried to write my prompt better."* (Interviewee 2 - GenAI user). The other GenAI users demonstrated only awareness of environmentally conscious practices, such as adjusting prompt engineering or selecting tools based on the task, without actively implementing them. *"The only thing you really know about it, is that you should try to write your prompt correctly in one go, and that sometimes it might be better to just Google things instead."* (Interviewee 2 - GenAI user). They acknowledged that they do not always act on this knowledge. Both GenAI users and experts observed a gap between knowing what environmentally preferable actions are and knowing how to implement them effectively in daily use. This suggests the presence of an actionable knowledge gap. The existence of this gap is further supported by explicit requests for guidance from GenAI users. Interviewee 4 - GenAI user asked for *"on the one hand, information about what the consequences are, and on the other hand, practical tips on how to use it more sustainably"*, seeking for tips & tricks in how to act pro-environmental.

A small subset of users lacked intrinsic climate motivation, they indicated that peer influence or group dynamics could positively affect their behaviour. Conversely, GenAI users and AI experts expressed the intention to use or promote GenAI in a more environmentally sustainable manner. Some GenAI users reported a sense of personal ownership and cited environmental concern as a core value. However, despite the presence of both awareness and intention, the interviews also revealed a lack of corresponding action. This discrepancy reflects the well-documented intention–behaviour gap. As Pekaar and Demerouti (2023) explain, this gap may arise from insufficient resources, skills, or organisational support.

While many GenAI users acknowledged that these tools have an environmental impact, AI experts highlighted a general lack of awareness among the broader user base. This duality may be explained by the fact that many of the interviewees work in the technology sector, where there is greater exposure to and interest in topics such as AI and its negative externalities. The broader unawareness among users may stem from a lack of understanding of the underlying computational processes behind GenAI, which makes it difficult for them to assess the actual environmental cost of usage. As one expert noted, *"I do wonder, going back to adoption, do people even realise, when they sit down for an hour and ask for, say, a photo of a clown wearing a certain football shirt, what's happening in the background? No, definitely not."* (Interviewee 10 - AI expert). Both users and experts emphasised the importance of long-term awareness building efforts to encourage more pro-environmental behaviour. Notably, despite being aware of the environmental impact, users often remain passive in adjusting their behaviour when using the GenAI tool. As one user stated, *"No, for sure I thought about the environmental impact, but not that it is a recurring theme when I use it."* (Interviewee 6 – GenAI user). Describing a pattern of automatic prompting behaviour and presence of unreflective usage. One interviewee was critical of this tendency, stating: *"Or people who keep repeating until they get the perfect answer, while I think, yes, it's nice if you like it, but if you have 90%, you can also adjust the last two words yourself. So that's also one thing, it doesn't have to take over everything, just use it as a support tool. But make sure to keep thinking critically yourself; after all, we're all educated people."* This behaviour may be explained by the tools' affordances, such as the ease of access, immediate output, and user-friendly interfaces, which invite habitual use. Hirvonen et al. (2024) warns about the environmental costs associated with these affordances of energy-intensive AI systems. Rethinking these design features may be key to fostering more sustainable GenAI interaction.

Overall, this synthesis provides valuable insight into current patterns of pro-environmental behaviour among GenAI users, as well as the perspectives of AI experts. It highlights the complex interplay between awareness, intention, and action, while also drawing attention to the influence of habitual or automatic prompting behaviour. These dynamics underscore the importance of addressing both cognitive and behavioural factors when promoting environmentally sustainable use of GenAI tools.

3.1.5. Factors enabling pro-environmental behaviour

The original codes, capturing both barriers and enablers, from Table 3.1 and Table 3.2 were translated into factors that enable pro-environmental behaviour, each assigned a corresponding ID code. Enablers were directly reformulated into enabling factors. Barriers, on the other hand, were interpreted as missing capabilities or obstacles and were rephrased into enabling factors that could help overcome them. For example, the original codes *Aware of environmental impact* from GenAI user interviewees (enabler) and *No awareness* from AI expert interviewees (barrier) were combined into the enabling factor CP2: Creating awareness of the environmental impact of using a GenAI tool.

This translation process enabled a structured interpretation of the interview data, linking the perspectives of both GenAI users and AI experts to enablers of pro-environmental behaviour within organisations. The factors are discussed according to the categories of the COM-B model.

Capability Psychological

Table 3.3: Factors enabling pro-environmental behaviour - Capability Psychological

Interview group	Original code	ID	Factor
GenAI user	Actionable knowledge gap	CP 1	Improving practical knowledge about how to act pro-environmental
AI Expert	Actionable knowledge gap		
GenAI user	Aware of environmental impact	CP 2	Creating awareness of the environmental impact of using a GenAI tool
AI expert	No awareness		
GenAI user	Knowledge about task based GenAI selection	CP 3	Improving practical knowledge about the selection of a GenAI model based on the task and needed performance for that task
AI expert	Performance based GenAI selection		
GenAI user	Knowledge about prompt engineering	CP 4	Improving practical knowledge about prompt crafting to achieve task efficiency
AI expert	Getting the most value creation out of one prompt		
GenAI user	Lack of knowledge about energy trade-offs between tools	CP 5	Improving knowledge about the energy consumption trade off between GenAI and alternative digital tools
AI expert	Lack of knowledge about the underlying processes and related costs of prompting	CP 6	Improving knowledge about the underlying processes and related costs when sending a prompt
	Use where it adds value	CP 7	Improving to reflect on whether GenAI use adds meaningful value

Seven enabling factors under psychological capability reflect the internal capacity of individuals to participate in the use of pro-environmental GenAI. These seven enabling factors are clustered and discussed into three domains: environmental understanding and knowledge (CP2, CP5, CP6), practical skills for sustainable use (CP1, CP3, CP4), and strategic reflection on necessity (CP7).

Under environmental understanding, GenAI users expressed a need for clearer insight into the energy consumption trade-offs between GenAI and alternative digital tools (CP5). GenAI experts highlighted the importance of gaining a deeper understanding of the underlying processes and associated costs involved in sending a prompt (CP6). Both users and experts emphasized the need to raise general awareness about the environmental impact of GenAI use (CP2).

Practical knowledge focuses on guidance on how to operate GenAI tools in a pro-environmental way (CP1). As one GenAI user asked: *"How can you actually use it in a more environmentally conscious way?"*

(Interviewee 5 – GenAI user). An AI experts (Interviewee 2) similarly noted: *"Do you want to be environmentally conscious?" 100% will say yes. Total agreement. But if you then ask, "How are you going to do that with AI?", they won't know. "Should I still use it at all? Or should I not?" I don't think they know."* Highlighting a common uncertainty and lack of practical knowledge about how to act sustainably in the context of GenAI.

Addressing this actionable knowledge gap includes, for example, the ability to select an appropriate GenAI model based on the task and required performance (CP3), as well as having the skills to craft effective and efficient prompts (CP4). Writing better prompts not only reduces unnecessary computational load, but also enhances the relevance and overall value of the generated responses.

Taking this a step further, AI experts reflected on the importance of questioning whether GenAI use is truly valuable in a given context. One AI expert (Interviewee 1) made a comparison to common energy-saving behaviour at home: *"Only use where it truly adds value: It's now normal not to leave your lights on at home when you go out. How do we make it normal for me not to use technology in ways that aren't necessary, and therefore use energy needlessly?".* This leads to the final enabling factor of developing the capability to assess when GenAI use adds meaningful value (CP7). It emphasizes strategic use, where users can reflect in advance on whether GenAI is genuinely needed and necessary.

Motivation Automatic

Table 3.4: Factors enabling pro-environmental behaviour - Motivation Automatic

Interview group	Original code	ID	Factor
GenAI user	Feeling of guilt upon seeing emissions	MA 1	Triggering emotional responses through the feedback on emissions
	Presence of automatic prompting behaviour	MA 2	Disrupting habitual and automatic prompting behaviour
AI expert	Presence of non-purposeful usage	MA 3	Reducing unreflective and unnecessary GenAI use

Three enabling factors are classified as automatic motivation. These reflect the subconscious emotional and habitual drivers that influence pro-environmental behaviour when using GenAI tools. It reflects the affordance of GenAI may unintentionally foster habitual or non-purposeful use, making energy-intensive interactions more likely.

The first factor (MA1) concerns the emotional response triggered by environmental feedback. Some GenAI users reported a feeling of guilt when confronted with emissions data related to their actions (MA1).

Secondly, participants described automatic prompting behaviour, where prompts were generated out of routine (MA2). Participants described falling into repetitive interaction patterns. As one GenAI user (Interviewee 5) stated: *"Especially with that sparring over and over again. That I think, okay, I now realise I shouldn't just keep firing off questions."* This quote illustrates how the interaction design and perceived responsiveness of GenAI unintentionally encouraged excessive prompting. According to affordance theory in Human-Computer Interaction (HCI), affordances are not solely embedded in the material features of a tool, but emerge through the relational dynamics between the user and the system within a specific context (Kaptelinin & Nardi, 2012). Therefore, disrupting automatic prompting patterns and designing affordances that invite more sustainable use, may promote more sustainable GenAI use.

Lastly, AI experts noted the presence of non-purposeful and *"nonsense that gets generated"* (AI expert - Interviewee 5) (MA3). Addressing this factor means reducing unnecessary and unreflective GenAI use, resulting in less wasteful system interactions.

Motivation Reflective

Table 3.5: Factors enabling pro-environmental behaviour - Motivation Reflective

Interview group	Original code	ID	Factor
GenAI user AI expert	Speed must be maintained Speed must be maintained	MR 1	Ensuring the GenAI tool generates its output with speed
GenAI user	Accuracy and value creation can not be compromised	MR 2	Ensuring GenAI tool continue to deliver accurate and valuable outputs
	Convenience and ease must be maintained	MR 3	Maintaining ease and convenience in GenAI tool usage
	Compliance with organisational norms, policies and structures	MR 4	Ensuring alignment with organisational norms, policies and structures.
	Creating awareness on environmental impact	MR 5	Providing awareness of environmental impact of GenAI use
	Aware but inactive when using	MR 6	Supporting follow-through after awareness is established
	Feeling of personal ownership	MR 7	Encouraging a sense of personal responsibility for the environmental impact of one GenAI use
	Motivated by reward	MR 8	Using rewards to promote pro-environmental GenAI use
	Lack of clarity in the magnitude of the impact	MR 9	Providing clarity in the magnitude of GenAI's environmental impact
	Lack of insight in personal impact	MR 10	Providing information on one's individual contribution to GenAI environmental impact
	Lack of knowledge about environmental consequences	MR 11	Improving understanding of the environmental consequences of GenAI usage
	Lack of clear source level information	MR 12	Enhancing transparency about the energy source
	Clear, simple and accessible	MR 13	Ensuring clear, simple and accessible execution of pro-environmental GenAI interaction
	Perceived impact via cost cues	MR 14	Strengthening the perceived environmental impact of GenAI use through cost-related cues
	Preference for autonomy and self-directed motivation	MR 15	Providing autonomy and self-directed motivational cues
AI expert	Balanced use of technology adoption and sustainability	MR 16	Facilitating a balanced perspective on AI adoption and environmental sustainability

Reflective motivation plays a critical role in shaping whether GenAI users engage in environmentally conscious behaviour.

A theme in the interviews was the need to preserve the utilities of GenAI tools. Both GenAI users and AI experts strongly emphasised that sustainability efforts should not come at the cost of system performance. Speed (MR1), accuracy and value creation (MR2), and ease of use (MR3) were named as baseline expectations. If sustainable alternatives were perceived as slower, less accurate, or less convenient, participants indicated that they would be unlikely to engage with them. This illustrates a key tension: pro-environmental actions must be integrated in ways that align with existing expectations of tool speed, functionality, and usability.

The organisational context also played a role in shaping reflective motivation. Participants indicated that sustainability is more readily adopted when it aligns with organisational policies, norms, and structures (MR4). Users reported feeling more supported in making environmentally conscious decisions when sustainability is embedded within institutional frameworks.

GenAI users expressed uncertainty about how their individual actions connect to the environmental impact of GenAI. Several interviewees reported limited understanding of the broader environmental consequences of GenAI use (MR11), and little insight into their contribution (MR10). This knowledge gap was compounded by a general lack of clarity about the overall scale of GenAI's environmental footprint (MR9) and the intransparency of energy sources behind its operation (MR12). As one GenAI user (Interviewee 4) explained, *"But with sustainability, it's naturally something that doesn't personally affect you directly, it's usually about the long term and large groups of people. It can sometimes be difficult to motivate yourself because, on your own, you have so little impact."* Building users' confidence by helping them clearly understand the environmental consequences, overall magnitude, and their contribution can serve as a key enabler of sustainable behaviour. In this regard, cost-related cues (MR14) were mentioned by GenAI users that could strengthen the perceived environmental impact while using.

Other factors related to the extent to which sustainable behaviour feels feasible in practice. Participants emphasised that sustainability must be clear, simple, and easy to execute (MR13). When sustainable choices are easy to execute, individuals are more likely to participate in them.

Other enablers of reflective motivation included a sense of personal ownership and responsibility for environmental impact (MR7), as well as sensitivity to symbolic or social rewards (MR8). Users also expressed the importance of autonomy, supported by self-directed motivational cues (MR15), rather than being forced into rigid systems.

Finally, AI experts called for a balanced approach (MR16) that integrates sustainability without hindering innovation or wider adoption of GenAI tools.

Opportunity Physical

Table 3.6: Factors enabling pro-environmental behaviour - Opportunity Physical

Interview group	Original code	ID	Factor
GenAI user AI expert	Lack of tangibility Lack of embedded tangibility	OP 1	Providing tangibility of environmental impact
GenAI user	Lack of embedded transparency	OP 2	Providing transparency of environmental data
	Sustainability impact feedback	OP 3	Providing feedback on the environmental impact of GenAI use
	Low frequency of sustainability cues	OP 4	Increasing exposure to sustainability-related cues
	Accessible information about impact	OP 5	Improving accessibility of environmental impact information
AI expert	Incentives enhance sustainable options	OP 6	Incentivising pro-environmental behaviour
	Lack of measurability	OP 7	Improving the measurability of the environmental impact
	Showing visibly consequences	OP 8	Making the environmental consequences of GenAI usage visible
	Track and set baseline	OP 9	Establishing monitoring mechanisms and baseline metrics for GenAI usage

Nine enabling factors emerged under the category of opportunity physical, highlighting the external conditions that influence whether individuals are able to engage in pro-environmental behaviour when using GenAI tools. These factors extend beyond personal motivation or knowledge and instead focus on how system design, access to information, organisational structures, and environmental cues shape sustainable decision-making.

One of the most consistent insights from both GenAI users and AI experts was the lack of tangibility and visibility surrounding the environmental impact of GenAI use. Participants noted that sustainability often feels abstract and disconnected from everyday digital actions. As one GenAI user (Interviewee 7) put it: *"I know a prompt isn't good and that it does lead to high emissions, but I don't have a tangible sense of what that actually means."* This highlights the importance of making environmental consequences more concrete, accessible, and visible within the system. Strengthening tangibility (OP1), improving transparency around environmental data (OP2), enhancing accessibility of impact-related information (OP5), and making consequences visibly present during tool use (OP8) were identified as essential conditions to enable and encourage action.

The design of the GenAI interface itself also plays a pivotal role in shaping opportunity. Participants emphasised the importance of embedding sustainability directly into the user experience. This includes offering real-time feedback on environmental impact (OP3), increasing exposure to sustainability-related cues during interaction (OP4), and integrating reminders into routine use. As one GenAI user (Interviewee 4) explained *"When you use it, you could also be reminded of it. That it's built into the GenAI tool itself, rather than just being something you read about in separate articles. So that when you use it, you're actually made aware of it."* These kinds of embedded cues or reminders could make sustainability feel like a natural part of digital interaction.

In addition, incentives were seen as another enabler of sustainable GenAI use. AI experts noted that providing rewards for sustainable actions (OP6) could motivate users who may not be intrinsically driven by environmental values.

Lastly, the ability to track usage over time and establish baseline metrics (OP9) was considered valuable for reflection and behavioural regulation. This is closely related to the need to improve the measurability of GenAI's environmental impact (OP7), which participants viewed as essential for both accountability and progress tracking.

Opportunity Social

Table 3.7: Factors enabling pro-environmental behaviour - Opportunity Social

Interview group	Original code	ID	Factor
GenAI user	Innovation culture	OS 1	Balancing innovation culture and GenAI adoption with sustainability priorities
AI expert	Culture on adoption and innovation		
GenAI user	Leadership as social modelling	OS 2	Demonstrating pro-environmental behaviour through leadership
AI expert	Leadership		
GenAI user	Peer comparison	OS 3	Encouraging pro-environmental behaviour through social influence and peer comparison
AI expert	Peer pressure		
GenAI user AI expert	Social attention Social attention	OS 4	Increasing social attention
GenAI user	Working in team/group motivating	OS 5	Encouraging motivation through collaborative team settings
GenAI user	Conversation trigger reflection	OS 6	Stimulating reflection through conversations about pro-environmental usage
	Prefers personal local engagement	OS 7	Fostering local and personally engagement
AI expert	First user of GenAI	OS 8	Preserving of exploratory and experimentation usage
	Strategic priority over sustainability	OS 9	Embedding sustainability within strategic organisational priorities
	Helping each other	OS 10	Encouraging peer support in adopting pro-environmental GenAI practices

The social environment in which GenAI tools are developed and used plays a role in shaping the opportunity for pro-environmental behaviour. Ten enabling factors were identified under the category of social opportunity, reflecting the influence of culture, management, peer dynamics, and social discourse on sustainable decision-making.

A dominant theme that emerged was the tension between the innovation-driven culture of GenAI adoption and the slower integration of sustainability concerns. Both users and experts emphasised the importance of balancing innovation with environmental responsibility (OS1). Many interviewees acknowledged that GenAI is still in an exploratory phase, and that imposing strict sustainability measures too early could potentially inhibit experimentation and adoption. Some AI experts pointed out that GenAI users are first movers, pioneering the use of the tools (OS8), and emphasise the culture on adoption.

Leadership (management) influence was also identified as an enabler of behavioural change. Visible engagement of role models in pro-environmental behaviour could powerfully shape organisational norms and expectations (OS2)

Social influence also emerged as an enabler. Interviewees noted that peer comparison and social pressure (OS3) affected their behaviour, particularly in team-based environments. As Interviewee 9 (GenAI user) stated: *"I would be more aware of whether I'm above or below the average, or average with my employees."* This is further supported by increasing social attention (OS 4), both mentioned by GenAI users and experts.

Observing colleagues making sustainable choices or receiving recognition for environmentally responsible behaviour was both found to encourage action. Additionally, peer support (OS10), where colleagues assist one another in adopting more sustainable practices, was seen as motivating. A sense of proximity also played a role in encouraging pro-environmental behaviour. Participants described how discussions around sustainability often led to self-reflection and more mindful use of GenAI tools (OS6). Team-based nature of work environments (OS5) supported these practices, where users stated they felt more motivated in collective settings where environmental goals are openly discussed and shared. This further reflects the importance of personal and local engagement (OS7), where sustainability efforts are more meaningful when connected to the user's immediate context. As Interviewee 3 (GenAI user) explained in response to a broad corporate message: *"Yes, I skip that a bit because that's often for a very broad audience."*

Lastly, ensuring that the intervention aligns with the organisation's strategic priorities (OS10) is essential for the feasibility of interventions that embed pro-environmental behaviour.

3.2. Conclusion

To better understand GenAI usage and what drives pro-environmental behaviour, semi-structured interviews with both GenAI users and AI experts were conducted. These revealed a wide range of factors that could influence pro-environmental GenAI use, categorised using the COM-B model.

The analysis of GenAI usage patterns revealed notable differences in user behaviour. While some users are aware of the environmental impact and take measures such as optimising prompts or avoiding unnecessary usage, others exhibit habitual prompting behaviour and lack a consistent environmental mindset. A key finding is the actionable knowledge gap: many users understand what constitutes environmentally preferable behaviour but struggle to apply it due to limited understanding or guidance. Experts note a widespread unawareness across the user base and emphasise the need for sustained awareness-building over the long term. These insights inform the design of behavioural interventions and serve as a key foundation for identifying user personas in 5.

Table 3.3 outlines the psychological capability factors that enable pro-environmental behaviour in GenAI use. From a capability standpoint, users need not only general awareness of GenAI's environmental impact but also actionable knowledge on how to act sustainably. This includes improving users' environmental understanding, practical skills, and decision-making. Users need greater knowledge of the energy impact of GenAI, along with hands-on knowledge such as prompt engineering, model selection, and tips for efficient use. Crucially, developing the ability to assess whether GenAI is the right tool for a given task can foster more environmentally conscious usage.

In terms of motivation, both automatic (Table 3.4) and reflective (Table 3.5 drivers play a crucial role in shaping sustainable GenAI use. Emotional responses, such as guilt triggered by emissions feedback, can encourage more mindful behaviour. In contrast, habitual prompting patterns and non-purposeful use present challenges that require disruption. Reflective motivation is shaped by users' personal values, awareness levels, and perceived behavioural control. Many users expressed uncertainty about the impact and effectiveness of adjusting their behaviour towards more sustainable practices. Furthermore, ensuring that sustainability efforts preserve GenAI's core utilities (speed, ease of use, and accuracy) is seen as essential. Motivation can be further strengthened through rewards, social norms, visible feedback, and long-term awareness-building.

Tables 3.6 and 3.7) Highlight the external factors within the physical and social environment that influence pro-environmental behaviour. It underscores the importance of both system-level and social enablers in supporting environmentally sustainable GenAI use. Physically, interface designs that embed sustainability cues and feedback on usage impact tangibly and transparently can shape user behaviour. Organisational structures also matter: management that shows leadership and models pro-environmental behaviour, peer support, and a workplace culture where sustainability is part of everyday conversations can create a social environment needed for long-term change.

Particularly, AI experts stressed that sustainability must be balanced with innovation and adoption. Early adopters need room to experiment, and overly rigid policies could hinder this progress. Nevertheless, the inclusion of sustainability in strategic priorities and organisational norms is essential for embedding responsible GenAI use as standard practice over time.

In conclusion, a range of enabling factors, across capability, opportunity, and motivation, have been identified as essential for promoting environmentally sustainable GenAI usage. These insights will inform the elicitation of requirements for interventions that support the embeddedness of environmentally sustainable GenAI usage.

4

Requirements for interventions to embed environmental sustainability in GenAI usage

This chapter answers SQ3: *What are the requirements for interventions that support the embeddedness of environmentally sustainable Generative Artificial Intelligence usage within organisations?*. It defines the requirements for an artefact aimed at integrating environmental sustainability into GenAI use, shifting from "what enables pro-environmental behaviour" to "what the system must do to support that behaviour." The chapter first outlines the artefact and then translates enabling factors from Chapter 3 into low-level requirements. These requirements were validated through brainstorming sessions with professionals, resulting in a final set of high-level functional and non-functional requirements. These high-level functional and non-functional requirements are intended to guide the development of interventions.

4.1. Outlining the artefact

To bridge the gap between the identified problem and a potential solution, researchers define a set of requirements that guide the design and development of the artefact (Johannesson & Perjons, 2021). In this study, the problem is represented by the lack of embeddedness of environmental sustainability in the current integration of GenAI usage. Presenting a missed opportunity that requires targeted improvement (Johannesson & Perjons, 2021).

This DSR-activity defines the type of artefact to be designed in order to address the identified problem. The artefact developed in this research comprises a set of interventions aimed at embedding environmental sustainability within GenAI usage. These interventions are designed to align with organisational practices and user behaviours, ensuring that environmental sustainability is systematically integrated into the interaction between users and GenAI tools.

These interventions are directly informed by the enabling factors identified through interviews with GenAI users and AI experts, as presented in Chapter 3. Each requirement remains traceable and linked to the relevant enabling factors categorised in the COM-B model. By translating these empirical findings into practical guidance, the interventions provide a foundation for organisations to implement context-appropriate strategies for behavioural change.

A set of targeted interventions is particularly appropriate in this context, as different types of GenAI usage are outlined in Chapter 3, Subsection 3.1.4. Therefore, the artefact is specified as a set of interventions tailored to different user groups. In the following section, the requirements for these interventions are defined to give shape to the artefact. According to Johannesson and Perjons (2021), "a requirement is a statement, made by a stakeholder of a practice, that a property of an artefact is desirable" (p.107).

4.2. Requirements elicitation

This section discusses the requirements elicitation process and the methods used to define the requirements for the artefact outlined in Section 4.1. In principle, any research method can be applied to elicit requirements (Johannesson & Perjons, 2021).

The initial set of requirements was derived from the enabling factors of pro-environmental behaviour identified using the COM-B model in Chapter 3. This resulted in a list of low-level requirements, which were categorised into two main groups: functional and non-functional requirements.

Functional requirements specify the core functions that the designed artefact must perform (Johannesson & Perjons, 2021), enabling the embeddedness of sustainable practices in GenAI usage. Non-functional requirements address the structure and context in which the designed artefact operates (Johannesson & Perjons, 2021). These can be divided into two subcategories: structural requirements, which relate to the internal architecture or design constraints of the artefact, and environmental requirements, which describe the external conditions under which the artefact must function.

Subsequently, the initial low-level requirements were validated and refined through iterative brainstorming sessions with professionals. This process resulted in a comprehensive list of high-level functional and non-functional requirements, which serves as the foundation for the next phase of designing the artefact. These requirements represent the properties of the artefact from the perspective of enabling environmentally sustainable GenAI use. Figure 4.1 presents an overview of the process resulting in the high-level requirements and design principles.

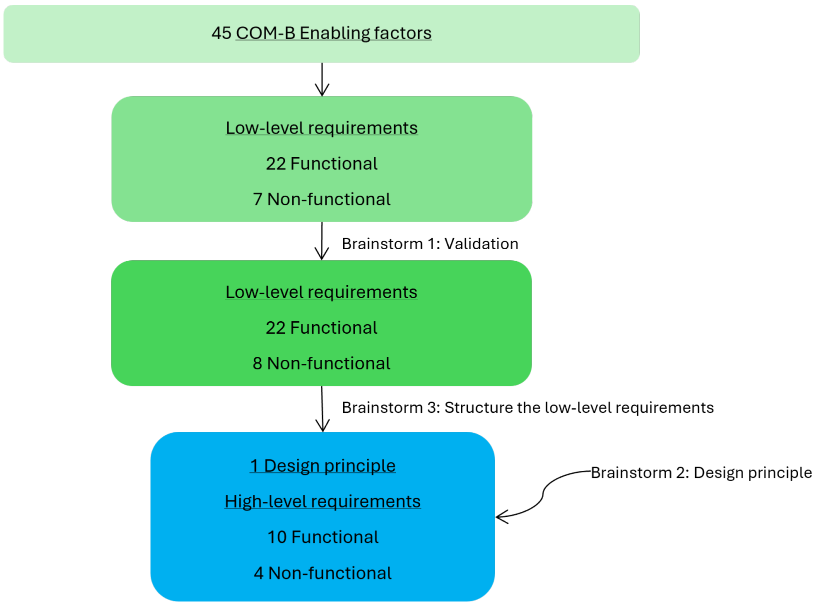

Figure 4.1: Process overview diagram

4.2.1. Method 1: Interviews

The first set of low-level requirements is derived from the enabling factors from Chapter 3 identified through interviews, structured in the COM-B model. An overview of the complete list of low-level requirements is provided in Table C.1 (Appendix C), with the sources of the enabling factors and related COM-B category.

The requirement elicitation process followed a systematic, three-step approach:

1. **Translate individual enabling factors into requirements**: For each enabling factor identified, a corresponding requirement was formulated. Each requirement was designed with the aim of enabling sustainability practices.
2. **Check for overlap:** After formulating a requirement, it was assessed to determine whether it also addresses other related enabling factors. This step helped consolidate and refine the requirements,

ensuring they were not redundant and that multiple enabling factors could be supported by a single requirement where appropriate.

3. **Repeat for all enabling factors:** The process continued iteratively by moving to the next enabling factor and repeating steps 1 and 2. This ensured that every relevant insight from the interviews was considered and translated into at least one actionable requirement.

An example is given to illustrate the requirement elicitation process. Starting from *CP1: Improving practical knowledge about how to act pro-environmental*, the initial requirement was formulated as: *"The intervention shall provide practical knowledge on how to act pro-environmental."* Secondly, during the assessment for overlap, it was identified that related enabling factors, *CP3: Improving practical knowledge about the selection of a GenAI model based on the task and required performance*, and *CP4: Improving practical knowledge about prompt crafting to achieve task efficiency*, represented more specific aspects of this general need. As a result, the original requirement was refined into two distinct low-level functional requirements:

- *F1.01 The intervention shall provide practical guidance on prompt crafting to achieve task efficiency* (COM-B sources: CP1 & CP4).
- *F1.02 The intervention shall provide practical guidance on model selection through task-based comparison and required performance* (COM-B sources: CP1 & CP3).

It is important to note that the requirements derived from the elicitation process are formulated at a low-level, as these are more specific, detailed and concrete (Johannesson & Perjons, 2021). This resulted in a list of 22 functional and 7 non-functional low-level requirements.

While the COM-B model guided the identification of behavioural needs, the resulting requirements are not strictly categorised by COM-B domains. This reflects the multifunctional nature of intervention features, which often address multiple behavioural components simultaneously.

4.2.2. Method 2: brainstorming sessions

To refine and discuss the previously elicited low-level requirements, a series of brainstorming sessions was held with professionals from different domains. The professionals were selected based on their expertise in organisational structures, AI integration, and intervention design. In these areas, deeper insight was needed to ensure the requirements were both contextually relevant and practically implementable.

The first session involved a participant with an organisational perspective, offering insights into how requirements align with internal structures and processes. The second session involved a professional with in-depth knowledge of GenAI and its deployment within organisations. The third professional has expertise in artefact design, offering a fresh perspective on the elicited requirements relevant to the design of interventions.

The sessions lasted between 30 minutes and one hour and addressed the following topics:

- The artefact to be designed
- The list of identified low-level requirements
- The central research question: *"What are the requirements for interventions that support the embeddedness of environmentally sustainable GenAI usage within organisations?"*
- The results on current patterns in GenAI usage through the lens of pro-environmental behaviour

Each brainstorming session was unstructured and resulted in either the validation of existing requirements, the addition of new requirements, or the formulation of a design principle. The sessions produced different outcomes, reflecting the varied expertise of the experts involved. Brainstorming session 1 resulted in validation of several requirements and the formulation of a new one, Table 4.1 gives an overview. The second brainstorming session emphasised a design principle. The third brainstorming session highlighted the need to cluster low-level requirements into broader, high-level requirements to support the design process.

Together, the interviews and brainstorming sessions resulted in the formulation of 14 high-level functional and non-functional requirements, supported by 30 low-level requirements and one design principle. Each brainstorming session is briefly discussed in the following paragraphs.

brainstorming session 1 - organisational stakeholder perspective

In this brainstorming session, several requirements were validated. For example, B1.04: *"People don't feel the impact personally. Unless you make it bigger, part of a larger story."* validated requirement 1.09: *The intervention shall reinforce user responsibility for the environmental impact of their actions.* Also, other requirements were validated during this session. Furthermore, a new important requirement emerged in this interview and is formulated in a new non-functional requirement 3.05: *The intervention shall be embedded in an environment that enables monitoring, data usage, and evaluation mechanisms to assess sustainability performance.* This is based on insights from the interview, which highlighted the importance of data usage and management. The interviewer stressed the importance of effective data management to enable better control over usage. These insights underscore the necessity of embedding the intervention within an organisational infrastructure that supports continuous monitoring, data utilisation, and evaluation.

Table 4.1: List of requirements elicited from brainstorming sessions 1

ID	Brainstorm	Validated/New requirements
B1.01	*"We're very much in a phase of: how do we get people to use AI daily? That's our main goal now."*	Validated 3.02: The intervention shall communicate sustainability in a way that complements AI adoption and the exploratory phase.
B1.02	*"Now it's invisible. You don't see the impact. There's no pain point."*	Validated 1.16: The intervention shall ensure that environmental information is transparent and accessible.
B1.03	*"If people saw a visual of their daily AI related CO_2 emissions, just like in those mobility apps that track car emissions, it could have an impact. Maybe. If I saw that every half-baked prompt adds up, maybe I'd think twice."*	Validated 1.12: The intervention shall inform users about their individual contribution to the environmental impact of Gen AI usage.
B1.04	*"This: people don't feel the impact personally. Unless you make it bigger, part of a larger story."*	Validated 1.09: The intervention shall reinforce user responsibility for the environmental impact of their actions
B1.05	*"Think the biggest opportunity now lies in data usage and management. So not always going for "search everything," but optimizing that process. Who are the heavy users? Are there "super users"? What are they doing? There might be a good reason, that's fine, but we want to understand what's happening. Should we replicate it? Offer another solution?"*	3.05: Provide mechanisms to support monitoring, data usage and evaluation mechanism on system level for management and assess sustainability performance.

brainstorming session 2 - AI adoption expert perspective

During the second brainstorming session, one insight emerged that critically influences the interpretation of requirements and shaping of the artefact. This insight is best captured as design principles, providing essential direction for the next phase of artefact development, and gives guidance on how the artefact should be shaped to effectively support its purpose. Emphasis was placed on recognising the diversity of GenAI users. This led to a discussion of different GenAI user types and the adoption of a user-informed approach. This insight comes together in the following design principle: *The design of the artefact should adopt a user-informed approach to accommodate diverse GenAI user roles, believes and behaviours.*

This design principle will guide the next phase of the research (Chapter **??**), which focuses on designing the artefact. In this phase, three different personas are identified and described in Section 5.1.1.

brainstorming session 3 - Design expert perspective

In this brainstorming session, we explored the low-level requirements in greater depth. The design expert emphasised the importance of balancing detailed requirements with design flexibility, noting that too many specific requirements can constrain creativity and limit the range of possible design solutions.

The 30 low-level requirements specified in Table C.1 (Appendix C) are highly specific and actionable. However, for the design phase, it is beneficial to formulate overarching high-level requirements that provide broader guidance (Johannesson & Perjons, 2021). Therefore, all low-level requirements were reviewed and clustered into high-level requirements that reflect common themes and design intentions. In this structure, low-level requirements are phrased as *"The intervention shall..."*, whereas high-level requirements are formulated as *"The intervention should..."*. An overview of the high- and low-level requirements is provided in Table C.2 (Appendix C). It provides insights into the high-level requirements and their corresponding low-level requirements, clarifying in more detail what the high-level requirements mean for environmentally sustainable GenAI usage.

For example, the high-level requirement FR01: *The intervention should provide practical guidance on pro-environmental behaviour*, groups together three low-level requirements 1.01 *The intervention shall provide practical guidance on prompt crafting to achieve task efficiency*, 1.02 *The intervention shall provide practical guidance in model selection by task-based comparison and required performance for that task.* and 1.06 *The intervention shall support reflecting on the necessity of using Gen AI for a specific task.*

4.2.3. Final list of requirements and design principle

Table 4.2 gives a comprehensive list of the 14 high-level requirements and serves as a foundation for guiding the design of the interventions. These requirements address various points of influence and aim to support environmental sustainability in both individual GenAI use and broader organisational practices. Notably, for more detailed information on each high-level requirement, Table C.2 in Appendix C provides an overview of the corresponding low-level requirements.

Table 4.2: List of high-level requirements

Requirement category	ID	Requirement
FUNCTIONAL	FR01	The intervention should provide practical guidance on pro-environmental behaviour.
	FR02	The intervention should raise user awareness of GenAI's environmental impact, including both the magnitude and consequences.
	FR03	The intervention should share information about the environmental impacts of GenAI.
	FR04	The intervention should provide sustainability feedback on GenAI usage.
	FR05	The intervention should support control with ongoing management.
	FR06	The intervention should present environmental information transparently and tangibly.
	FR07	The intervention should ensure that pro-environmental GenAI use is accessible, simple and easy to perform.
	FR08	The intervention should interrupt habitual and automatic prompt interactions.
	FR09	The intervention should strengthen social influence and group-based norms to reinforce sustainable GenAI usage.
	FR010	The intervention should foster collective engagement with environmental sustainability and GenAI.
NON-FUNCTIONAL (structural)	NFR01	The intervention should maintain utilities of high level of speed, accuracy and convenience.
NON-FUNCTIONAL (environmental)	NFR02	The intervention should support integration into existing organisational structures and align with the sustainability goals.
	NFR03	The intervention should communicate sustainability in a way that complements GenAI adoption and experimentation, supported by management.
	NFR04	The intervention should be embedded in an environment that enables monitoring, data usage, and evaluation mechanisms to assess sustainability performance.

The functional requirements (FR01–FR010) reflect user-centred goals and system-level enablers. They begin with the need to provide practical guidance on pro-environmental behaviour (FR01), helping users make informed, sustainable choices in their GenAI interactions. Equally critical is raising user awareness of GenAI's environmental impact (FR02), which focuses on increasing users' cognitive and emotional understanding of how their actions contribute to environmental consequences. This includes fostering recognition of the magnitude of GenAI's emissions and encouraging users to reflect on the broader implications of their usage. Building on this, interventions should share information about environmental impacts (FR03), emphasising transparent communication of underlying processes, energy consumption trade-offs, and individual contributions. While FR02 centres on building awareness and stimulating broader concern, FR03 is oriented toward providing more detailed information that helps users understand the environmental dimensions of GenAI usage.

To facilitate ongoing engagement, FR05 calls for control and management mechanisms that enable users to monitor their own performance on sustainability. Transparent and tangible presentation of environmental information (FR06) ensures that sustainability impacts are made visible and understandable for users. FR07 highlights the need for accessibility and ease of use, ensuring that pro-environmental actions remain simple. Furthermore, FR08 focuses on interrupting habitual and automatic prompt interactions, reducing non-purposeful use, and encouraging user reflection. Social dynamics are emphasised in FR09 and FR010, which aim to strengthen peer influence and group norms and to foster collective engagement around environmentally sustainable GenAI use.

Complementing these functional aims are four categories of non-functional requirements. Structurally, NFR01 stresses the importance of maintaining high levels of speed, accuracy, and convenience to avoid compromising its core utilities and values. Contextually, NFR02 emphasises integration with existing organisational structures and alignment with sustainability goals, while NFR03 underlines the need for communication of sustainability that complements GenAI adoption and experimentation, supported by management. Finally, NFR04 calls for embedding interventions in an environment that enables monitoring, data use, and evaluation mechanisms to track sustainability performance effectively.

One design principle was formulated based on brainstorming session 2, as outlined in Table 4.3, emphasising the use of a user-informed approach.

Table 4.3: Design principle

ID	Design principle
B2.01	The design of the artefact should adopt a user-informed approach to accommodate diverse GenAI user roles, believes and behaviours.

Together, the high-level requirements and the design principle provide a foundation for informing the design of a set of targeted interventions that embed environmental sustainability into GenAI usage.

4.3. Conclusion

This chapter defined the requirements that shape the foundation for designing targeted interventions to support the embeddedness of environmentally sustainable GenAI usage within organisations.

A structured and iterative process of requirements elicitation was described. Drawing on insight from semi-structured interviews with GenAI users and experts, the process translated enabling factors of pro-environmental behaviour into a set of low-level functional and non-functional requirements. These initial low-level requirements were validated through brainstorming sessions with professionals, contributing to their contextual relevance. Informed by organisational, adoption, and design perspectives, this approach led to the identification of 14 high-level requirements and 1 design principle. These high-level requirements bring together the detailed insights from the low-level requirements in a clearer and more manageable way, still allowing room for flexibility in the design phase.

The functional requirements focus on supporting GenAI users with practical guidance, raising environmental awareness, and providing transparent and tangible feedback. They also stress user control and ensuring sustainable use remains simple and accessible, while fostering social influence and collective engagement within organisations.

The non-functional requirements emphasise seamless integration into organisational structures, alignment with sustainability goals, and maintaining core utilities of GenAI. They also highlight the need for environments that support monitoring and evaluating sustainability outcomes.

The next chapter will build on these requirements by translating them into concrete design interventions. Furthermore, the design principle of adopting a user-informed approach will guide the design phase.

5 Design of the artefact

Building on the high-level requirements and design principle identified in the previous chapter, this chapter develops the interventions. The design principle and high-level requirements will be used to answer *SQ4: What interventions support the embeddedness of environmentally sustainable Generative Artificial Intelligence usage within organisations?*. First, based on the design principle of a user-informed approach, different personas are identified to inform targeted interventions. These personas are derived from the current GenAI usage patterns described in Chapter 3 and Section 3.1.4. Next, the behaviour change theories Affordance Theory, the Theory of Planned Behaviour (TPB), and Nudge Theory are introduced to inform the design of the interventions. This leads to the formulation of three targeted interventions, aligned with the requirements and design principle.

5.1. Personas

To achieve a user-centred approach to intervention design, the development of personas is used. Understanding different user types through personas is a widely used technique in design practice (Hao, 2019). Personas play a crucial role in supporting user-centred design (Pruitt & Adlin, 2006). As Adlin and Pruitt (2010) argue, the use of personas is a method for making assumptions and knowledge about users explicit, enabling focus and generating interest. They define personas as "a memorable, engaging, and actionable image that serves as a design target" (p.1).

In the field of pro-environmental behaviour, personas are recognised as strategic tools for exploring environmental attitudes and behaviours and influencing sustainable practices (Ayoola et al., 2024; Carey et al., 2019). The development of environmental personas allows for the identification of distinct user clusters based on sustainability-related values, attitudes, and intentions (Höpfl et al., 2024). Tailored interventions informed by these personas can more effectively promote sustainable behaviour by addressing the specific motivations and challenges of each user group.

5.1.1. Identification of the personas

Höpfl et al. (2024) employed thematic analysis in identifying three primary themes influencing sustainable behaviour: prerequisites, facilitators, and barriers. The cumulative effect determines the likelihood of an individual engaging in sustainable actions (Höpfl et al., 2024).

The prerequisites for sustainability include an understanding of sustainability, self-efficacy, and the presence of sustainable attitudes and values. These elements have been discussed in Chapter 3 and Section 3.1.4 in understanding current GenAI usage. Based on this chapter, three key personas have been identified to inform the intervention design. These personas reflect the prerequisites of sustainable GenAI usage, with distinct behaviours, motivations, and challenges users face in adopting pro-environmental GenAI practices. The three personas identified are: the aware but uncertain, the externally motivated, and the unaware user, each highlighting specific barriers and facilitators.

The unaware user

This persona is unaware of the environmental impact of GenAI tools and tends to engage with them automatically. Interviewee 1 (AI expert) noted that most GenAI users are *"Not knowing the impact. If you're looking purely at sustainability, that's a big one. I don't think people are aware. That's a key issue."*

These users are driven by the ease of use and habitual behaviour that GenAI tools provide, and they often do not reflect on the environmental costs of their actions. Raising awareness and creating feedback mechanisms for reflection are important facilitators. As one user explained, *"Especially with that sparring over and over again. That I think, okay, I now realise I shouldn't just keep firing off questions"* (Interviewee 5 - GenAI user).

Barriers

- Lacks awareness of the environmental impact of GenAI
- Driven by automatic prompting behaviour and ease of use
- Engages with GenAI frequently and with minimal reflection

Facilitators

- Create general awareness about environmental impact
- Create feedback mechanism for reflection

The externally motivated user

This persona shows low intrinsic motivation to act sustainably and believes that environmental responsibility lies with the organisation. Interviewee 1 (GenAI user) stated, *"So even though climate is not number one on my priority list, I do think about it, mainly because it gets attention from the environment, from society, and that influences you to adopt certain behaviours."* These users rely on organisational signals to guide their actions and tend to engage with sustainable practices when embedded in workplace culture. They value convenience and performance, as Interviewee 8 (GenAI user) noted, responsibility lies with the organisation, as you cannot count on personal behaviours: *"Because I think the more responsibility you place on the user, the less is actually going to happen. At least not with the average user."*

Barriers

- Exhibits low intrinsic environmental motivation
- Believes environmental responsibility lies with the organisation

Facilitators

- Responds positively to sustainable practices when embedded in workplace culture and organisational practices
- Relies on organisational signals rather than acting independently
- Values convenience and performance

The aware but uncertain user

This persona is aware of the environmental impact of GenAI tools, as reflected by statements as *"We now have a lot of AI, and linked to that, many data centres, but they require an enormous amount of energy. The sustainability aspect of AI use has always really interested me. That's why I've read more about it over time"* (Interviewee 7 - GenAI user). Despite holding environmental values and the intention to act sustainably, they struggle to translate these intentions into action. In addition, they seek to understand the effectiveness of their actions. As Interviewee 4 (GenAI user) is seeking *"on the one hand information about what the consequences are. And on the other hand, practical tips on how to use it."*. The gap between their intention and practical applications indicates the presence of the intention-behaviour gap (Pekaar & Demerouti, 2023; Zee et al., 2025).

Barriers

- Held back by low perceived control and effectiveness in their belief in the impact of their actions
- Unsure how to act pro-environmentally
- Presence of intention–behaviour gap

Facilitators

- Holds strong environmental values and a sense of personal ownership, with the intention to act pro-environmentally
- Actively seeks practical tips & guidance
- Aware of the environmental impact of GenAI tools

5.2. Interventions

This section introduces three user-centred intervention packages, based on the identified personas, relevant behavioural theories and associated requirements.

To overcome barriers of the user-persona's three behavioural theories were applied: Nudging Theory, the Theory of Planned Behaviour (TPB), and Affordance Theory. In designing the interventions, requirements were strategically selected based on their relevance to the target user persona and behavioural theories.

Nudging Theory

Nudging Theory, introduced by Thaler and Sunstein (2008) refers to subtle modifications in the choice architecture that steer behaviour predictably without restricting options. Nudges have been widely used to promote sustainable behaviours in areas such as waste reduction, energy conservation, and sustainable consumption (Wee et al., 2021).
Both antecedent interventions and consequence interventions are recognised as effective nudging strategies for reducing energy consumption. Commitment and goal-setting have been shown to be effective nudges for energy conservation (Agarwal et al., 2017). Similarly, real-time information, such as feedback on energy consumption, has proven effective in raising awareness and motivating energy-saving behaviour (Cappa et al., 2020). Consequence-based interventions in the form of monetary rewards and incentives can also be used to promote energy conservation (Agarwal et al., 2017).
Nudging strategies can bridge the intention–behaviour gap (further explained in TPB), particularly when users rely on automated responses (Zee et al., 2025). Further effective nudging techniques, categorized by Wee et al. (2021), include: prompting, which provides non-personalized information at key moments; proximity, which makes sustainable choices easily accessible; priming, which uses subtle environmental cues to influence decisions; labelling, which offers clear and transparent information about environmental impact; and functional design, which shapes interfaces to encourage eco-friendly behaviours.
Furthermore, to ensure effectiveness, it is necessary to personalise nudges to fit the reaction of the specific user (Karlsen & Andersen, 2019). It is also recommended to apply a combination of different nudging strategies within a single setting to enhance their overall impact (Wee et al., 2021).
The above information has been translated into input for the design of the sustainable prompt builder, monthly feedback and impact estimator widget interventions.

Applications in interventions:

- Sustainable prompt builder: Provides practical support and nudges during prompt creation (priming and proximity).
- Monthly feedback: Delivers consequence-based nudges through feedback, incentives, and goal setting.
- Impact estimator widget: Utilises labelling to provide clear and transparent information on individual emissions.

Theory of Planned Behaviour (TPB)

The Theory of Planned Behaviour by Ajzen (1991) explains intention to certain behaviour through three constructs: (1) attitude towards the behaviour, (2) subjective norms, and (3) perceived behavioural control. In the context of environmental sustainability, it is expected that employees who value sustainability positively, who perceive that their social and professional environment supports sustainable behaviour, and those who feel capable of engaging in sustainable practices are more likely to develop intentions to act sustainably. Several studies support the significance of these behavioural predictors for pro-environmental behaviour (Arya & Chaturvedi, 2020; Katz et al., 2022; Pekaar & Demerouti, 2023).

However, a limitation of the TPB explains the recognised intention–behaviour gap, the discrepancy between intended and actual behaviour (Pekaar & Demerouti, 2023; Zee et al., 2025). Factors such as lack of resources, skills, organisational support, and environmental barriers contribute to this gap (Pekaar & Demerouti, 2023). Moreover, low perceived behavioural control leads to weaker translation of intentions into behaviour, exacerbating the intention–behaviour gap (Hagger et al., 2022). Therefore, interventions that enhance users' sense of control and align with organisational norms can help bridge the intention–behaviour gap. As noted earlier, nudging strategies can also support users in overcoming this barrier (Zee et al., 2025). Moreover, job crafting, integrating sustainability goals into daily tasks, can further strengthen the link between sustainability intentions and actions, even when these goals are not part of one's job description (Pekaar & Demerouti, 2023).

The above information has been translated into input for the design of the monitoring dashboard and green tips rotation interventions.

Applications in interventions:

- Monitoring dashboard: enhances perceived control and normative alignment by visibility of organisational signals.
- Green tips rotation: enhances perceived behavioural control with tips and attitude by creating awareness.

Affordance Theory

Affordance Theory examines the possibilities for action that emerge from the relationship between users, technologies, and their social context (Evans et al., 2017; Hirvonen et al., 2024; Kaptelinin & Nardi, 2012). It focuses on the actual and perceived properties of an object that determine how it can possibly be used (Hirvonen et al., 2024). It identifies four phases: existence, perception, actualisation, and effect (Pozzi et al., 2014). In the AI context, Leonardi (2011) emphasises how AI transforms work and organisations by offering new capabilities and potential actions. Importantly, sustainability perspectives highlight how AI systems create affordances that influence energy use and broader environmental impacts (Hirvonen et al., 2024). In GenAI, perceived affordances, as ease of prompt generation or resource-intensive models, can both enable or constrain sustainable practices in daily operations.

The above information has been translated into input for the design of the energy-efficient default intervention.

Applications in intervention:

- Energy-efficient defaults: defaulting to lightweight models encourages energy-efficient use by making it the path of least resistance.

Each of these theories helps to inform the design of interventions that target the behaviours and barriers of the personas outlined in the previous section.

5.2.1. Intervention package - unaware user: Collective sustainability

This intervention package targets the unaware user. These users are driven by automatic behaviour, lack awareness, and engage without any reflection on their use. The intervention focuses, therefore, on increasing awareness about environmental impact and creating more feedback for reflection.

The intervention package consists of:

- Monthly feedback, providing feedback incentive, target-setting and social comparison (linked to Nudging theory),
- Green tips rotation, focused on creating awareness.

Monthly feedback

To increase the reflection on GenAI use of the unaware user, feedback mechanism can help. Consequence-based nudges such as feedback and incentives have proven effective in promoting pro-environmental behaviour (Agarwal et al., 2017; Cappa et al., 2020). Furthermore, feedback mechanisms combined with target-setting are more impactful than purely informational strategies for shifting attitudes and behaviour (Young et al., 2015).

This intervention is guided by the following functional requirements to foster feedback and reflection:

- FR02 The intervention should raise user awareness of Gen AI's environmental impact, including both the magnitude and consequences.
- FR04 The intervention should provide sustainability feedback on Gen AI usage.
- FR09 The intervention should strengthen social influence and group-based norms to reinforce sustainable Gen AI usage.
- FR010 The intervention should foster collective engagement with environmental sustainability and Gen AI.

Users receive data on their prompt-related emissions every month, benchmarked against the average emissions of their team or department. They can compare their own performance with that of their team. For example: *"Your total CO_2 emission for month X is X kg, which is X% [less/more] than the average of your team. Do you want tips to reduce your CO_2 emissions?"*

Users above average receive a tip button that offers suggestions to reduce emissions. Users who are below average are encouraged to share their best practices with the team, supporting peer learning and norm reinforcement.

The system includes goal-setting features, allowing users to set personal emission targets. Users can track their progress toward these goals each month and monitor whether they are improving compared to their team's average emissions. Additionally, top performers, those who reached the goal, are highlighted. Recognition can take the form of a symbolic reward.

Green tips rotation

This intervention focuses on creating general awareness while providing users with actionable tips to reduce emissions. The green tips rotation are subtle modification in the choice architecture, and can effectively steer behaviour predictably without restricting options (Thaler & Sunstein, 2008).

This component is guided by the following functional requirements to create awareness:

- FR01 The intervention should provide practical guidance on pro-environmental behaviour.
- FR02 The intervention should raise user awareness of GenAI's environmental impact.
- FR03 The intervention should share information about the environmental impacts of GenAI.
- FR08 The intervention should interrupt habitual and automatic prompt interactions.

Each session introduces a bite-sized sustainability tip on the initial setup screen. For example: *"Did you know? Shorter prompts use fewer tokens, lowering your carbon footprint. / More efficient prompts mean fewer interactions, reducing your carbon footprint. "* These tips provide users with simple and actionable advice to help reduce their environmental impact.

These tips are grounded in evidence that reducing token count and using simpler models lowers energy consumption and emissions (Dauner & Socher, 2025).

In addition, the tips can also appear to users' consideration of future consequences. Arya and Chaturvedi (2020) extend TPB by introducing the concept of consideration of future consequences. Employees who reflect on the long-term environmental impact of their actions show greater involvement in sustainable behaviours.

5.2.2. Intervention package - externally motivated user: Sustainable by default

This intervention package targets externally motivated users, who rely on organisational signals rather than acting independently.

The package consists of two interventions:

- A monitoring dashboard, which increases the visibility of organisational signals (supported by TPB constructs of perceived control and normative alignment), and
- Energy-efficient defaults, which reduce the threshold for sustainable action (linked to Affordance Theory)

Together, these features support pro-environmental behaviour by embedding sustainability directly into the system's architecture.

Monitoring dashboard

As this user group is not internally motivated and has no attitude towards sustainable behaviours. Strong institutional support (e.g., organisational culture) and leadership commitment are key influencers of employees' attitudes toward sustainable behaviour (Camacho et al., 2024; Kim & Kim, 2024). Transparency can shift attitudes toward sustainability by demonstrating the organisation's commitment to these goals. As a result, this can influence positive attitudes, perceived normative support, and a sense of control over their actions (TPB), thereby increasing the likelihood of engaging in pro-environmental behaviour (Arya & Chaturvedi, 2020; Katz et al., 2022; Pekaar & Demerouti, 2023; Pizarro, n.d.).

The following requirements guided this intervention to enhance normative alignment:

- FR03 The intervention should share information about the environmental impacts of Gen AI.
- FR05 The intervention should support control with ongoing management.
- FR06 The intervention should present environmental information transparently and tangibly.
- FR07 The intervention should ensure that pro-environmental GenAI use is accessible, simple and easy to perform.
- FR08 The intervention should interrupt habitual and automatic prompt interactions.

The Monitoring dashboard empowers employees to track their emissions, visualise their contributions to sustainability, understand the energy sources related to GenAI usage, and view company-wide emissions and sustainability goals.

Components of the dashboard include:

- Personal CO_2 emissions with user threshold: Employees can track their individual emissions and compare them against a predefined threshold, helping them manage their environmental impact. This feature enhances users' sense of control, while the threshold ensures alignment with the company's sustainability goals. When users approach the limit, they can request tips to reduce their emissions before any restrictions are applied.
- Tangible comparisons of emissions: Provides relatable comparisons to increase tangibility and responsibility, such as: *"The CO_2 emissions from your GenAI usage this month are equivalent to driving X km in a petrol car"* or *"This month, you saved the equivalent of X trees in CO_2 emissions compared to last month."*
- Energy source information: Displays the carbon intensity of the electricity grid, which reflects the amount of CO_2 emitted per kilowatt-hour (gCO_2/kWh) used to power GenAI interactions. This value is primarily determined by the current energy mix, whether electricity is generated from fossil fuels or from low-emission sources.
- Company-wide emissions and targets: Shows the organisation's overall emissions and progress toward collective sustainability goals, fostering a sense of shared responsibility. For example: *"The total CO_2 emissions this month are X kg, which is [more/less] than last month."*

The dashboard responds by providing visibility and organisational backing for sustainability efforts with company-wide emissions and targets and personal CO_2 emissions and thresholds, aligning users' actions with organisational goals and leadership priorities. The dashboard, through its usage thresholds, helps communicate the organisational attitude toward sustainability and facilitates management communication by prioritising organisational goals.

Energy-efficient defaults

The externally motivated user tends to follow the path of least resistance. In this context, the system's default settings create affordances that subtly guide users toward more sustainable actions, without requiring conscious effort or intrinsic motivation.

Therefore, the following requirement guided this intervention to create the path of least resistance:

- FR07 The intervention should ensure that pro-environmental GenAI use is accessible, simple, and easy to perform.

The feature of this intervention is the use of lightweight models by default, with more resource-intensive models being activated only when explicitly chosen by the user.

This approach shapes users' behaviour by presenting eco-friendly options as the default, which encourages users to select them more frequently. In contrast, using more resource-intensive models requires deliberate action, further reinforcing sustainable behaviour. Since the default setting aligns with sustainability goals, users are guided toward making energy-efficient decisions without additional effort. In this way, the system creates an environment where sustainability becomes the path of least resistance, motivating users to internalise and adopt more sustainable practices over time.

An example of how this can be implemented in model architecture is the Mixture-of-Experts (MoE) approach, outlined in 3 Section 2.1. Depending on the specific task, the system activates only components necessary to generate the requested output. By selectively utilising parts of the model and avoiding unnecessary data processing, GenAI can optimise energy consumption without compromising performance (Han et al., 2024). This allows lightweight models to handle routine tasks, while more resource-intensive models are only engaged when truly required.

5.2.3. Intervention package - aware but uncertain user: Sustainability guidance

This intervention package targets the aware but uncertain user, who holds pro-environmental intentions but lacks guidance and perceived behavioural control and effectiveness in their GenAI interactions. These users are motivated but unsure how to act effectively. The components are designed to address strategies that target the intention–behaviour gap. To address the intention–behaviour gap, nudging strategies can be effective, especially when users make automated responses (Zee et al., 2025). As well, job crafting can strengthen the link between sustainability intentions into action (Pekaar & Demerouti, 2023).

The intervention package consists of:

- Sustainable prompt builder, providing practical support and nudging during prompt creation (linked to TPB and nudging theory; priming and proximity, and job crafting),
- Impact estimator widget, which offers feedback per prompt to increase insight into individual contribution (linked to nudging theory; labelling).

Sustainable prompt builder

The Sustainable prompt builder is designed to address the intention–behaviour gap by offering practical guidance. In addition, it applies job-crafting principles by finding opportunities within their workflow to act sustainably.

The following requirement guided the design of this component to provide practical support:

- FR01 The intervention should provide practical guidance on pro-environmental behaviour.
- FR04 The intervention should provide sustainability feedback on Gen AI usage.
- FR07 The intervention should ensure that pro-environmental GenAI use is accessible, simple and easy to perform.
- FR08 The intervention should interrupt habitual and automatic prompt interactions.

The component offers feedback and suggests more efficient and lower-impact alternative prompts. It rephrases prompts and provides suggestions, such as requesting less information when unnecessary or being more concise in the question to get to the targeted answer more quickly (reducing back-and-forth prompting). This makes it easier for users to reduce their environmental impact while learning by doing.

In doing so, it nudges users by utilising proximity, making sustainable choices more accessible and visible. In addition, it uses priming, subtly guiding users toward more sustainable choices through suggestions that align with eco-friendly practices. This encourages pro-environmental behaviour without explicitly restricting other options.

To integrate sustainability into job crafting, the system personalises prompt suggestions based on the user's job responsibilities. During the initial setup, the system provides examples of the most suitable and frequently used prompts for the user's tasks. Over time, the system learns the user's most common tasks and adapts its suggestions accordingly. By personalising these nudges to fit the user's specific behaviour, the system ensures greater effectiveness in promoting sustainable actions (Karlsen & Andersen, 2019).

Impact estimator widget

Next to the lack of practical guidance, the aware but uncertain user also experiences a low perceived behavioural effectiveness. The Impact Estimator Widget utilises the nudging technique of labelling by providing clear and transparent information on the individual emissions.

The following requirement guided this intervention to provide tangible and transparent information:

- FR02 The intervention should raise user awareness of Gen AI's environmental impact, including both the magnitude and consequences.
- FR03 The intervention should share information about the environmental impacts of Gen AI.
- FR04 The intervention should provide sustainability feedback on Gen AI usage.
- FR06 The intervention should present environmental information transparently and tangible.

The widget shows estimates of emissions per prompt. It uses a colour-coded system (green, yellow, red) to visually indicate the environmental impact of each individual prompt. Green represents low emissions, yellow indicates moderate emissions, and red signals high emissions. This visual feedback helps users quickly assess the environmental impact of their choices for each prompt. When a prompt is marked red, the system provides a tips button to reduce emissions.

5.2.4. The functional requirement mapped to user personas

Figure 5.1 visualises how the functional requirements are distributed across the intervention goals for the three identified user personas. The heat map reveals overlaps and divergences in the requirements that support specific behavioural objectives. It ensures that the intervention design is tailored to the distinct facilitators and barriers of each persona.

Moreover, it highlights opportunities for overlapping areas where a single intervention component (functional requirement) could serve multiple user groups. The heat map serves as a guide for prioritisation of features and integrating them into organisational workflows.

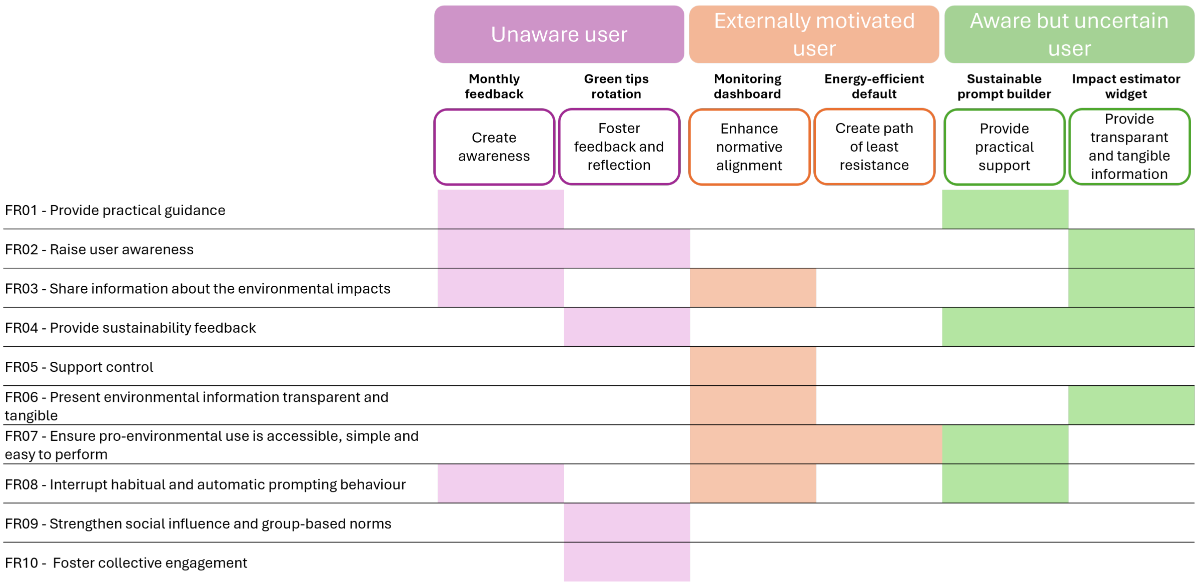

Figure 5.1: Functional requirement mapped to user personas

5.3. Conclusion

This chapter presented three intervention packages aimed at promoting environmentally sustainable use of GenAI within organisations, tailored to the needs of different user groups. The interventions were developed based on the design principle, theories, and high-level functional requirements identified earlier in Chapter 4. Each intervention addresses specific user needs and barriers, ensuring that sustainability goals are embedded in the GenAI usage patterns of different personas.

The first intervention package, collective sustainability, addresses unaware users by delivering monthly emissions feedback combined with goal-setting and symbolic rewards. This encourages reflection and engagement through social influence. Additionally, the green tips rotation, through subtle interface modifications, creates general awareness and motivates users to adopt pro-environmental practices.

The second intervention package, sustainable by default, focuses on externally motivated users by embedding energy-efficient model settings as defaults and offering a monitoring dashboard with a usage threshold. This intervention aligns users' actions with organisational sustainability goals, while minimising the effort required to make pro-environmental choices.

The third intervention package, Sustainability guidance, targets users who are aware of sustainability but uncertain about how to act pro-environmentally, seeking guidance. By providing feedback on prompts and suggesting lower-impact prompt alternatives, this intervention helps with practical guidance on prompt crafting. Moreover, personalised prompt suggestions are provided based on the user's job and tasks. Additionally, as the aware but uncertain user experiences low perceived behavioural effectiveness, the Impact Estimator Widget directly targets this barrier by providing transparent and tangible information on the environmental impact of their prompt. Together with the Sustainable Prompt Builder, this intervention empowers users with practical guidance and helps them understand the individual contribution of their actions.

In the following chapter, these interventions will be evaluated based on functional and non-functional requirements, testing their feasibility and effectiveness in real-world settings.

6 Evaluation

As outlined in the previous chapter, six interventions were developed to support environmentally sustainable GenAI usage among different user groups. This chapter evaluates these interventions by answering *SQ5: To what extent do the interventions support the embeddedness of environmentally sustainable Generative Artificial Intelligence usage within organisations?* To address this sub-question, both functional and non-functional requirements were assessed.

The functional requirements are evaluated through a survey among GenAI users, asking whether they perceived the interventions meet the associated requirements and whether the intervention would reinforce pro-environmental behaviour. This provides insights into their desirability and potential to stimulate pro-environmental behaviour. The non-functional requirements are assessed during semi-structured interviews with two AI experts, focusing on organisational alignment and technical feasibility. Together, these evaluations offer insight into what extent the intervention supports the embeddedness of environmentally sustainable GenAI usage within organisations.

6.1. Evaluation methodology

Following the DSR framework (Johannesson & Perjons, 2021), the interventions were evaluated against the functional and non-functional requirements defined in Chapter 4. A dual strategy was adopted: a survey with GenAI users assessed functional requirements, while semi-structured interviews with AI experts explored organisational alignment and technical feasibility.

6.1.1. Evaluation context

The interventions were designed to embed environmental sustainability into GenAI usage by addressing the functional and non-functional requirements defined earlier. The evaluation focused on three aspects: (1) assessing whether the interventions fulfilled the practical needs and stimulate pro-environmental behaviour (functional requirements), (2) examining their alignment with organisational context (non-functional requirements), and (3) evaluating their technical feasibility, essential for successful implementation.

Two groups participated in the evaluation. The first group consists of GenAI users, specifically the same participants from the earlier stage of this research who took part in the interviews during SQ2 to identify enabling factors for pro-environmental behaviour. This group assesses the functional requirements (1) through a survey. The second group comprised AI experts with expertise in GenAI and organisational strategy. They evaluated the non-functional requirements (2) and provided insights into technical feasibility (3). This was achieved through semi-structured interviews. This combined perspective ensured a holistic evaluation of the interventions' potential to drive sustainable practices.

6.1.2. Evaluation goals and strategy

The functional requirements were evaluated through a survey conducted among GenAI users. The participants of the survey were categorised into three user groups, unaware users, conscious but uncertain users, and externally motivated users, based on their earlier responses to the question: *"Have you ever thought about the environmental impact of using GenAI tools?"* An overview of the categorisation of the GenAI users can be found in Table D.1 in Appendix D. This categorisation enabled a targeted assessment of whether the intervention packages (sustainability guidance, sustainable by default, collective sustainability) met the corresponding functional requirement for each user group. In addition, it allowed for exploring their willingness to engage in pro-environmental behaviour when introduced to the interventions.

The non-functional requirements were assessed through semi-structured interviews with two AI experts (see Table D.2 in Appendix D). AI experts were chosen based on the same three criteria earlier in the research: (1) professional experience in deployment or governance of GenAI tools, (2) social recognition in the field, and (3) minimum of three years work experience in the field of data, AI or digital transformation. These interviews examined the interventions' alignment with organisational practices and their technical feasibility. Although technical feasibility was not explicitly part of the original non-functional requirements, it was included in the evaluation due to its critical role in ensuring implementation of the interventions.

This combined approach ensured the evaluation captured insights relevant to both individual user adoption and the broader organisational integration of environmentally sustainable GenAI usage.

6.1.3. Evaluation design

The evaluation was conducted ex-ante, assessing the interventions based on anticipated user and expert perceptions prior to implementation. It is important to note that *NFR01 – The intervention should maintain high levels of speed, accuracy, and convenience* was not evaluated directly. As a baseline expectation tied to the underlying GenAI technology, it remains crucial for user acceptance but lies beyond the scope of this study's intervention design validation.

Survey

The survey was created using Microsoft Forms and distributed among the different identified GenAI user groups, who participated in the earlier stages of the research. In-depth information on the survey text and explanation can be found in Appendix D Section D.2.1. Each intervention was presented with a brief description and a visualisation. For each intervention, participants were asked: *"Please indicate whether you believe this intervention component offers the following function or value."* Each functional requirement associated with the intervention was listed, and respondents could respond with [Yes] or [No].

Furthermore, participants were also asked to rate the perceived behavioural impact of the intervention using the question: *"To what extent do you think this intervention component would influence you to act more sustainably when using GenAI?"* Responses were collected on a 5-point Likert-scale: [Not at all (1), Slightly (2), Moderately (3), Mostly (4), Very much(5)]. The Likert scale allowed for the summation of subjective Likert-type responses to create a quantifiable score representing an overall attitude for interpretation (Koo & Yang, 2025). This approach provides a comprehensive measure of the attitude towards pro-environmental behaviour.

Each user group received the survey corresponding to the two interventions included in the intervention package, specifically tailored to their profile (unaware users, conscious but uncertain users, and externally motivated users).

Semi-structured Interviews

The participants received the interview questions in advance, along with an Informed Consent Form that they were asked to review, sign, and return prior to the interview. Participation was entirely voluntary. The respondents had the freedom to decline participation, ask questions at any point, and decide whether to allow audio recording of the interview and use of quotations in the research. The interviews were conducted in person, and each session lasted approximately 30 to 60 minutes.

The semi-structured interviews focused on evaluating the non-functional requirements and technical feasibility of all six interventions. Each intervention was presented on paper with a description and visualisation. Participants were invited first to record their answers ([Yes] or [No]) on paper, which then served as a basis for an open discussion.

The discussion was guided by the following questions:

- *Do you think this intervention fits with existing organisational norms and policies and aligns with sustainability goals?*
- *Do you think this intervention communicates sustainability in a way that complements GenAI adoption and experimentation?*
- *Do you think this intervention could be monitored to assess its sustainability performance?*
- *Do you think this intervention is technically feasible within the current GenAI infrastructure?*

The interviews were recorded and transcribed to allow analysis of the responses regarding organisational alignment and technical feasibility.

6.2. Evaluation results

Both surveys and semi-structured interviews gave insightful information in fulfilling the functional and non-functional requirements for each of the six interventions.

Table 6.1 presents an overview of the functional requirements, mapped to their associated interventions and whether they met the requirements according to the survey. A requirement was considered fulfilled when >50% of the respondents answered *Yes*. Table 6.3 gives an overview of the fulfilment of non-functional requirements, according the AI expert.

The following paragraphs present and discuss the results of the survey and semi-structured interviews, reasoned from the perspective of the functional and non-functional requirements. In contrast, Appendix D, Section D.3, provides a detailed overview of the results structured by intervention package. For each intervention, Section D.3 presents the corresponding survey results and a comprehensive summary of requirement fulfilment and technical feasibility, offering insight into the overall effectiveness and implementation potential of each intervention. Subsection D.3.1 views the outcomes of the collective sustainability package and its associated requirements. Subsection D.3.3 presents the findings for the sustainability guidance package, while Subsection D.3.2 covers the results for the sustainable by default package.

6.2.1. Functional requirements

First, the results of fulfilling the functional requirements presented in Table 6.1 are discussed. Subsequently, the perceived influence on pro-environmental behaviour based on the summative score, as shown in Table 6.2, is discussed referring back to the theoretical foundations of the interventions.

Table 6.1: Functional requirements evaluation by GenAI users

Functional Requirement	Intervention	Fulfilled
FR01 – The intervention should provide practical guidance on pro-environmental behaviour	Sustainable prompt builder Green tips rotation	Yes Yes
FR02 – The intervention should raise user awareness of GenAI's environmental impact, including both the magnitude and consequences	Impact estimator widget Monthly feedback Green tips rotation	Yes Yes Yes
FR03 – The intervention should share information about the environmental impacts of GenAI	Monitoring dashboard Impact estimator widget Green tips rotation	Yes Yes Yes
FR04 – The intervention should provide sustainability feedback on GenAI usage	Sustainable prompt builder Impact estimator widget Monthly feedback	No Yes Yes
FR05 – The intervention should support control with ongoing management	Monitoring dashboard	Yes
FR06 – The intervention should present environmental information transparently and tangibly	Monitoring dashboard Impact estimator widget	Yes Yes
FR07 – The intervention should ensure that pro-environmental GenAI use is accessible, simple, and easy to perform	Monitoring dashboard Energy-Efficient Defaults Sustainable prompt builder	No No Yes
FR08 – The intervention should interrupt habitual and automatic prompt interactions	Monitoring dashboard Sustainable prompt builder Green tips rotation	No Yes Yes
FR09 – The intervention should strengthen social influence and group-based norms to reinforce sustainable GenAI usage	Monthly feedback	Yes
FR10 – The intervention should foster collective engagement with environmental sustainability and GenAI	Monthly feedback	Yes

The first high-level functional requirement (FR01), providing practical guidance, is addressed by the green tips rotation and the sustainable prompt builder. According to the survey results, this requirement is fulfilled in both interventions. Similarly, the functional requirement of raising user awareness (FR02) is fulfilled by the impact estimator widget, monthly feedback, and green tips rotation, as these interventions communicate both the magnitude and consequences of GenAI's environmental impact. FR03, sharing information about the environmental impacts, is also fulfilled by the monitoring dashboard, impact estimator widget, and green tips rotation.

FR04, providing sustainability feedback, is not fulfilled by the sustainable prompt builder. This may be because the feedback in the sustainable prompt builder is not directly emission-related but rather supportive in nature. The Monitoring dashboard fulfils FR05 by supporting control with ongoing management. Additionally, both the monitoring dashboard and impact estimator widget succeed in making environmental information transparent and tangible (FR06) through clear visualisations.

FR07, which requires that pro-environmental behaviour is easy, accessible, and simple to perform, turned out to be difficult to meet. Neither the monitoring dashboard nor the energy-efficient defaults fulfilled this requirement, likely because they require additional user effort or operate outside the primary interaction flow. In contrast, the sustainable prompt builder supports easy adoption of sustainable behaviour by being directly embedded in the prompting process.

For FR08, which focuses on interrupting habitual and automatic prompt interactions, the monitoring dashboard also did not meet the requirement, as it operates in a separate interface rather than within the prompting environment. By comparison, the sustainable prompt builder and green tips rotation met this requirement by embedding pro-environmental cues directly into the user workflow.

Finally, the monthly feedback intervention appears to strengthen both social influence (FR09) and collective engagement (FR10), as it provides recurring, comparative feedback that encourages reflection and discussion within teams.

In addition to assessing the fulfilment of the requirements, participants were asked to rate the perceived influence of each intervention component on their pro-environmental behaviour. Table 6.2 summarises these summative scores based on the responses on the Likert scale, grouped by user persona.

Table 6.2: Intervention summative scores

User Group	Component	Score
Externally motivated	Monitoring dashboard	2
	Energy-Efficient Default	3
Aware but uncertain	Sustainable prompt builder	3
	Impact estimator widget	4
Unaware	Monthly feedback	4
	Green tips rotation	3

The monitoring dashboard is intended to motivate externally motivated users towards more pro-environmental behaviour by providing institutional support and demonstrating organisational commitment. However, these features do not appear to directly guide users to act sustainably (*Sligthly* (score = 2)). The TPB constructs of normative alignment and perceived control may not be sufficient for this user group. While organisational signals aim to shape attitudes and norms, they do not directly trigger pro-environmental behaviour.

In contrast, the energy-efficient defaults, the sustainable prompt builder, and the green tips rotation *Moderately* (score = 3) support moderately pro-environmental behaviour. The energy-efficient defaults, guided by Affordance Theory, are partially effective; however, not all users actively change their behaviour. The sustainable prompt builder combines nudging techniques (proximity and priming) with TPB's focus on practical guidance to address the intention–behaviour gap for aware but uncertain users. This approach shows partial effectiveness but lacks sufficient salience to produce stronger behavioural shifts. Similarly, the green tips rotation, which applies nudging, lacks reinforcement and appears too subtle to drive significant pro-environmental behavioural change among unaware users.

The monthly feedback and impact estimator widget stands out as more influential, with respondents indicating they would *Mostly* (score = 4) be influenced to act more sustainably. The social influence and collective engagement mechanisms in the monthly feedback appear to have a strong impact on shaping pro-environmental behaviour. Likewise, the impact estimator widget strengthens perceived behavioural effectiveness by providing clear information on environmental impact. The nudging technique of labelling reinforces its role as a driver of pro-environmental behaviour.

6.2.2. Non-functional requirements

The non-functional requirements are discussed below. In addition, the technical feasibility of each intervention has been evaluated. The results are presented in the following Table 6.3.

Table 6.3: Non-functional requirements evaluation by experts

Non-Functional Requirement	Intervention	Expert 1	Expert 2
NFR02 – The intervention should support integration into existing organisational structures and align with the sustainability goals.	Green tips rotation	Yes	Yes
	Monthly feedback with Reward	Yes	Yes
	Energy-Efficient Default	Yes	Yes
	Monitoring dashboard	Yes	Yes
	Impact Estimator	No	Yes
	Sustainable prompt builder	Yes	Yes
NFR03 – The intervention should communicate sustainability in a way that complements GenAI adoption and experimentation, supported by management.	Green tips rotation	Yes	Yes
	Monthly feedback with Reward	Yes	Yes
	Energy-Efficient Default	Yes	Yes
	Monitoring dashboard	No	No
	Impact Estimator	No	Yes
	Sustainable prompt builder	No	Yes
NFR04 – The intervention should be embedded in an environment that enables monitoring, data usage, and evaluation mechanisms to assess sustainability performance	Green tips rotation	Yes	No
	Monthly feedback with Reward	Yes	Yes
	Energy-Efficient Default	Yes	Yes
	Monitoring dashboard	Yes	No
	Impact Estimator	Yes	No
	Sustainable prompt builder	Yes	Yes
The intervention should be technical feasible	Green tips rotation	Yes	Yes
	Monthly feedback with Reward	Yes	No
	Energy-Efficient Default	Yes	Yes
	Monitoring dashboard	Yes	Yes
	Impact Estimator	Yes	No
	Sustainable prompt builder	Yes	Yes

Almost all interventions in this research align with the company's existing organisational norms and policies and support its sustainability goals (NFR02). However, both experts raised concerns regarding whether the impact estimator widget might incur additional compute costs and related CO_2 emissions per prompt, potentially undermining the sustainability goals. As expert 2 noted: *"you naturally increase compute usage."*

Similar concerns apply to the sustainable prompt builder. Although it fulfilled all the requirements according expert 2. He is questioning the overall benefit: *"You can build this, but then you'd first need to build an intermediate step where an LLM says: "Do you think this is an efficient prompt, yes or no?" Well, I think it could have been a better, more efficient prompt. But then you're already consuming compute, and you hope that the second prompt is so much more efficient that it cancels out the first one. Well. . . I think that's quite a gamble."* Doubting whether the achieved sufficient prompt offset the computational costs of generating suggestions. However, expert 1 suggested a longer-term perspective, arguing that *"in the long run this will lead to savings,"* as the intervention may promote user education and more efficient prompting over time.

However, expert 2 came up with another idea while discussing the sustainable prompt builder. He mentioned that instead of feedback within the interface of the prompt builder, it can include periodic analysis of the prompt history. This would involve running monthly evaluations of logged prompt data and providing users with practical tips for improving their prompting efficiency. The results would be presented in a monthly report based on the history and this analysis.

Regarding NFR03, the intervention should communicate sustainability in a way that complements GenAI adoption and experimentation, and both interviews indicated disagreement about the monitoring dashboard on this requirement. As expert 2 said: *"It depends a bit on how you set the threshold, but if people are really enthusiastic and they get cut off, and after 20 days they're not allowed to use it for 10 more days, that doesn't seem smart to me."* Indicating the monitoring dashboard undermining experimentation and adoption of GenAI tools. Similarly, expert 1 noted that the impact estimator and sustainable prompt builder could hinder GenAI adoption and experimentation.

Regarding NFR04, which concerns whether the interventions enable monitoring and evaluation of sustainability performance, the interviews highlighted two important implications.

First, for intervention as the green tips rotation, it may be feasible to evaluate sustainability performance at the cohort level. Usage patterns could be analysed over time to identify shifts in pro-environmental behaviour following implementation. However, directly linking these changes to individual actions remains challenging, as external factors may also influence user behaviour. As expert 2 noted: *"I think at the individual level it's a lot harder to establish the correlation between 'they saw those tips' and 'they therefore became more efficient or not.' I don't rule it out, but I think it's more indirect. There are people who just use standard practices; when a pop-up appears, one person looks at it, the other doesn't. Or maybe in parallel, they've figured something out themselves. So I think that correlation is harder."* This observation underscores the difficulty of monitoring individual behavioural change related to specific interventions.

Second, in terms of company-wide monitoring for the monitoring dashboard, feasibility is limited by the lack of direct CO_2 emissions data from Application Programming Interface (API) providers. When using APIs offered by cloud hyperscalers, only proxy metrics (as token counts, model types, or duration) are available. The relationship with CO_2 emissions has not been established. Making it also difficult for the impact estimator to give an indication of the CO_2 related to a prompt. As expert 2 explained: *"Whether a company emits less CO_2, or whether an individual emits less CO_2, I think for none of these things we have the tools today to really do that properly. But if you say, 'we'll use some proxy indicators for that,' then it is possible."*

While most interventions are technically feasible, challenges remain for the monthly feedback with reward and the impact estimator widget. Both rely on CO_2 emissions data, which can only be approximated using proxy indicators, questioning the reliability. As expert 2 pointed out: *"The difficulty lies in CO_2 emissions. How evidence-based these estimates are is highly questionable."* The technical challenge stems from the absence of direct energy or emissions data and the uncertainty in translating usage metrics into accurate environmental impact estimates. This concern was emphasised further: *"How is it going to do that? So how efficiently can you do that, and how reliably can you do that?"*

Nevertheless, proxy indicators such as compute time, token usage, or reasoning iterations could serve as alternatives: *"But if you say, 'we'll use some proxy indicators for that,' then it is possible."*

Table 6.4 provides a comprehensive overview of identified challenges and opportunities for each non-functional requirement and technical feasibility.

Table 6.4: Challenges and opportunities per non-functional requirement and technical feasibility

Non-functional requirement / Technical Feasibility	Challenges	Opportunities
NFR02 – The intervention should support integration into existing organisational structures and align with the sustainability goals.	The Impact Estimator and Sustainable prompt builder may not fully align, as the computations of the interventions could increase energy use, undermining sustainability objectives. Risk of additional computing contradicting organisational sustainability goals.	Replace real-time feedback with periodic analysis of prompt history, providing monthly reports with practical tips for improving prompt efficiency.
NFR03 – The intervention should communicate sustainability in a way that complements GenAI adoption and experimentation, supported by management.	Hard usage thresholds in the Monitoring dashboard risk discouraging experimentation and frustrating users. Impact Estimator and Sustainable prompt builder undermining experimentation.	Use departmental key performance indicators (KPIs) to track progress. Replace hard thresholds with softer visual nudges.
NFR04 – The intervention should be embedded in an environment that enables monitoring, data usage, and evaluation mechanisms to assess sustainability performance	Directly linking individual behaviour affected by the intervention to CO_2 reductions is challenging. Organisation-wide CO_2 monitoring is constrained by the lack of direct emissions data from hyperscale providers.	Evaluate behavioural changes at the cohort or organisational level to identify trends. Use proxy indicators (token usage) for approximate sustainability monitoring.
The intervention should be technically feasible	CO_2 feedback in the monthly feedback and impact Estimator is difficult due to lack of direct energy or emissions data. Translating usage metrics (token counts, model types, compute time) into reliable CO_2 estimates remains highly uncertain.	Use proxy metrics visualised with intuitive symbols (leaves, scores, or traffic lights).

6.3. Conclusion

This chapter evaluated the six interventions by validating their functional requirements, non-functional requirements, and technical feasibility. The functional requirements, defined as the desired properties of the interventions, were assessed through surveys to determine whether the intervention fulfilled these criteria. Additionally, the survey explored whether GenAI users perceived the interventions as influencing their behaviour towards more pro-environmental. The non-functional requirements and technical feasibility were examined through semi-structured interviews with experts, which revealed both challenges and opportunities related to organisational contextual fit and technical implementation.

The survey results for the functional requirements indicate that interventions embedded directly within the user workflow (e.g., sustainable prompt builder, green tips rotation, impact estimator) were more likely to fulfil requirements linked to behavioural change. In contrast, interventions that operated in separate interfaces or required additional user effort (e.g., monitoring dashboard, energy-efficient defaults) often struggled to meet requirements related to accessibility, ease of use, and habit disruption. This suggests that integration into the existing workflow interface is critical for interrupting automatic prompting behaviour and ensuring that sustainable practices are accessible, simple, and easy to perform.

According to the perceived behavioural effectiveness question "To what extent do you think this intervention component would influence you to act more sustainably when using GenAI?" the monitoring dashboard was rated the least effective, with respondents indicating it would only *Slightly* (score = 2) influence their pro-environmental behaviour. This suggests that the TPB construct of normative alignment and perceived control does not directly trigger pro-environmental behaviour for externally motivated user. In contrast, social influence and collective engagement mechanisms in the monthly feedback and the nudging technique of labelling in the impact estimator widget are stronger drivers of pro-environmental behaviour, with a summative score of 4, *Mostly*.

The semi-structured interviews revealed that most interventions align with existing organisational structures and sustainability goals (NFR02), although concerns were raised that additional compute usage could undermine these objectives. Communicating sustainability in a way that complements GenAI adoption (NFR03) also proved challenging for the monitoring dashboard, as strict usage thresholds may discourage experimentation. For enabling monitoring and evaluation (NFR04), direct measurement of individual-level behavioural change was considered difficult, particularly for the green tips rotation, due to the indirect link between exposure and behavioural outcomes. At the organisational level, CO_2 monitoring is constrained by the lack of direct emissions data from cloud hyperscaler providers. Nevertheless, proxy indicators such as token usage, compute time, or model type were suggested as alternatives for assessing sustainability performance. This limitation also affects technical feasibility: while all interventions are technically possible to develop, the CO_2 feedback in the monthly feedback and impact estimator remains uncertain due to the absence of direct emissions data from hyperscaler APIs and the reliance on proxy metrics.

To what extent the interventions support the embeddedness of environmentally sustainable GenAI usage does not have a single definitive answer; however, the evaluation revealed encouraging insights across multiple dimensions. Most interventions largely fulfilled their functional requirements, with only small refinements needed to enhance their effectiveness. They also demonstrated strong alignment with organisational structures and sustainability goals, and technical feasibility was generally high. While the absence of direct CO_2 emissions data poses a challenge for monitoring and certain feedback-based interventions, workable solutions using proxy indicators present opportunities.

Based on the combined fulfilment of requirements and perceived behavioural impact, as shown in Appendix D Tables D.4, D.6, and D.8, the monthly feedback and green tips rotation interventions stand out as having the greatest potential for further development and implementation. Both met most of their requirements and were perceived as effective in encouraging pro-environmental behaviour, providing a strong foundation for embedding sustainability into daily GenAI use.

7
Framework and implementation strategy

The previous chapters have applied the DSR methodology to design and evaluate six targeted interventions aimed at fostering pro-environmental behaviour among three distinct user groups.

This chapter bridges the gap between theory and practice by presenting both a user-informed framework, decision tree and a comprehensive implementation strategy. It offers practical recommendations and a structured roadmap for organisations seeking to promote pro-environmental behaviour in the workplace. The user-informed framework represents the core output of this research and highlights the shared functional and non-functional requirements (FR/NFR) across the defined personas. While the framework focuses on embedding environmentally responsible practices into GenAI usage to support long-term sustainability outcomes, the implementation strategy complements this by outlining how targeted interventions can be introduced and embedded in professional practice.

7.1. Framework

This section introduces the user-informed integration framework for environmentally sustainable GenAI use, as illustrated in Figure 7.1. The framework is primarily intended for transformation managers, AI teams, sustainability leads, and other professionals seeking practical guidance on how to embed environmental sustainability into the day-to-day use of GenAI tools within organisations.

It aims to bridge the gap between the design of behavioural interventions and their real-world implementation by translating theoretical constructs and user-centred insights into actionable guidance. The framework is grounded in the findings of this research and incorporates behavioural personas and their corresponding intervention packages. These packages are linked to functional requirements that address the specific behavioural barriers associated with each persona. Finally, the framework defines the broader contextual conditions, non-functional requirements that reflect the organisational, communicative, and technical prerequisites for successful adoption.

Rather than prescribing a one-size-fits-all solution, the framework helps organisations to tailor interventions based on user characteristics. In doing so, it supports the integration of pro-environmental practices into the GenAI tool, aligning with organisational structures, sustainability objectives, and everyday usage patterns.

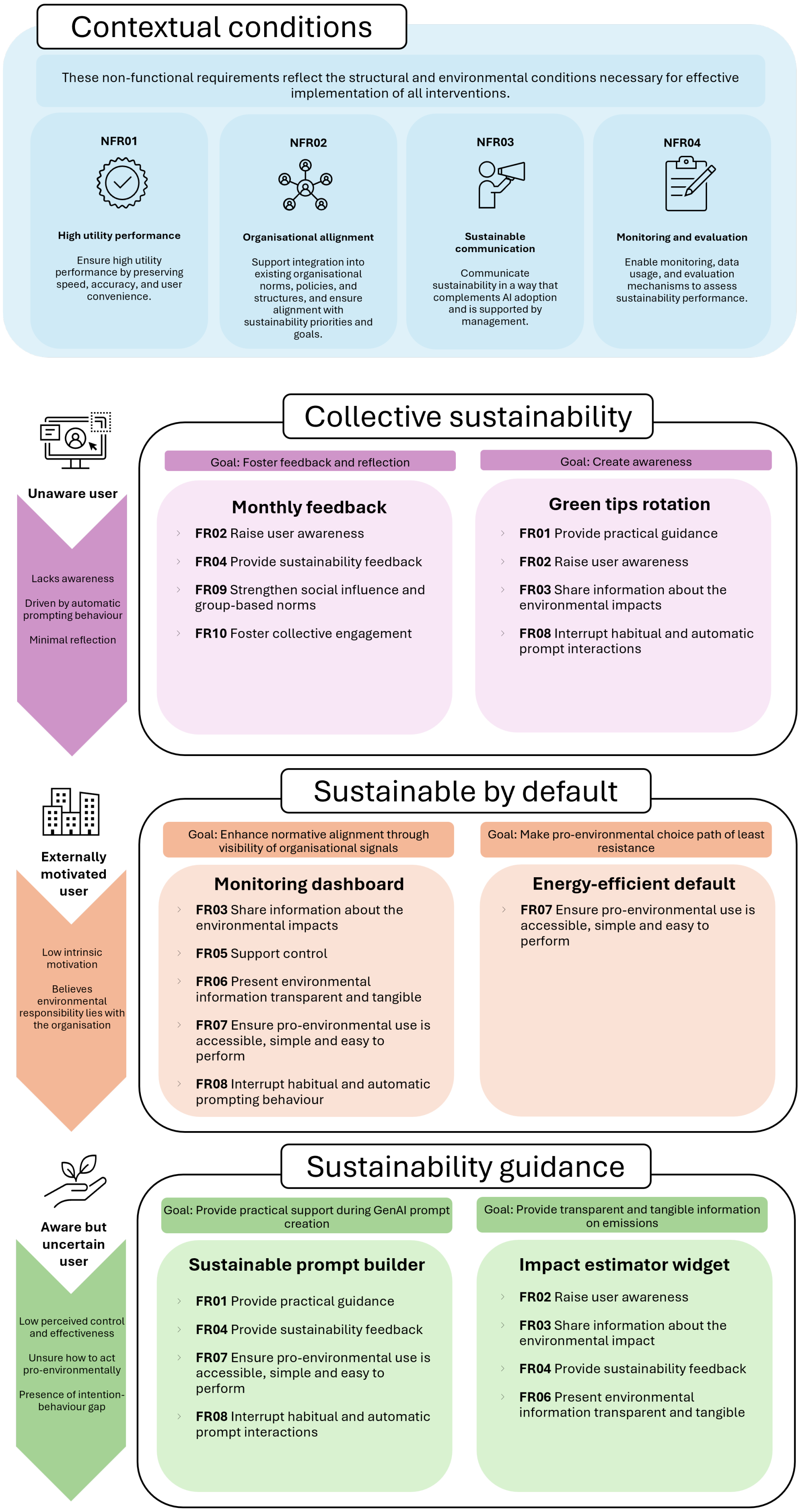

Figure 7.1: User-informed integration framework for environmentally sustainable GenAI use (own work)

The user-informed integration framework for environmentally sustainable GenAI use consists of four building blocks.

- **Non-functional requirements (NFRs)**: These define the contextual (environmental and structural) conditions under which the interventions must operate effectively. This includes maintaining high utility performance, aligning with organisational goals, maintaining usability, and enabling monitoring and evaluation.
- **Personas**: Three behavioural personas represent distinct user types within organisations, each facing specific barriers to environmentally sustainable GenAI use. These include the *aware but uncertain*, the *externally motivated user*, and the *unaware user*.
- **Intervention packages**: Based on the personas and requirements, three tailored intervention packages were designed: *sustainability guidance*, *sustainable by default*, and *collective sustainability*. Each package contains two interventions with a specific goal that addresses the behavioural needs of the corresponding persona group.
- **Functional requirements (FRs)**: These outline what the intervention should do to support pro-environmental behaviour and to address the behavioural barriers at the persona level, such as providing feedback, offering practical guidance, or presenting environmental information.

The user-informed integration framework for environmentally sustainable GenAI use provides organisations with structured guidance for embedding environmental sustainability into the daily use of GenAI tools. It serves multiple purposes.

First, it offers organisations a lens for identifying the different GenAI user types they may have. The three personas each represent behavioural needs and barriers users may face when it comes to using GenAI tools sustainably. By acknowledging this behavioural diversity, the framework enables organisations to map existing GenAI usage patterns and determine the specific goals for which interventions are needed to overcome those barriers.

Second, the framework functions as a practical design tool. It links each persona to a tailored intervention package, each with two specific goals, corresponding interventions, and an associated set of functional requirements. This ensures that the interventions are targeted, goal-oriented, and behaviourally aligned. For example, *the aware but uncertain* users experience low perceived control and effectiveness. The goal in this case is to provide transparent and tangible information on emissions through the *impact estimator widget*. This intervention addresses the following functional requirements: FR02 (Raise user awareness), FR03 (Share information about the environmental impact), FR04 (Provide sustainability feedback), and FR06 (Present environmental information transparently and tangibly).

This modular structure supports implementations, allowing organisations to select interventions that are most appropriate for their users. In addition to functional design, the framework also defines the contextual conditions under which interventions must operate. These non-functional requirements describe the broader structural and environmental environment in which the interventions must function. They ensure that interventions are not isolated fixes but are embedded within a system that supports long-term behavioural change.

The framework serves as a structured support tool for decision-making. It guides organisations in translating environmental sustainability ambitions into concrete, actionable steps. It helps practitioners make informed and evidence-based choices on how to integrate sustainable practices into everyday GenAI use.

Taken together, the framework delivers a methodologically grounded and behaviourally informed approach to concrete intervention choices and embedding environmental sustainability in GenAI usage. To make the framework more practical, a decision tree has been developed to guide decision-makers in selecting targeted interventions for environmentally sustainable GenAI usage (Figure 7.2). The decision tree aligns with the axes of the framework.

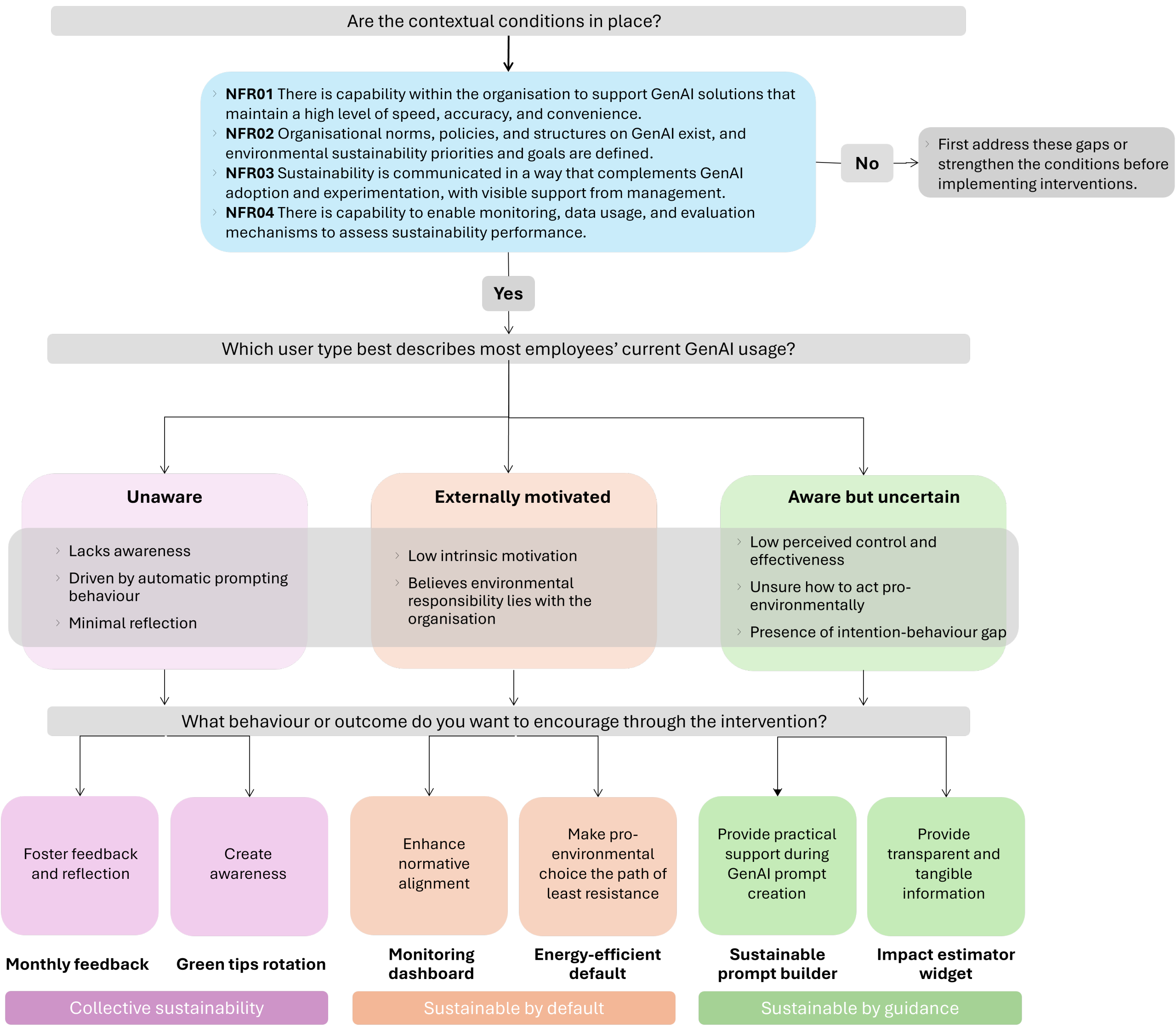

Figure 7.2: Decision tree environmental sustainably GenAI interventions (own work)

7.2. Implementation strategy

To move from a chosen intervention or set of interventions from the decision tree, this section presents an implementation strategy for organisations seeking to embed these into their GenAI workflows. The strategy is designed to help sustainability leads, AI teams, and transformation managers translate behavioural insights into scalable, actionable steps.

In literature, Kurt Lewin's Change Management Model (Burnes, 2019), with its three phases of unfreeze, change, and refreeze, and Kotter (2012) 8-Step Model are two foundational frameworks for managing organisational change. Both models emphasise the importance of creating a climate for change, engaging and enabling the organisation, and implementing and sustaining the change. The implementation strategy presented in Figure 7.3 draws inspiration from both these models but is specifically tailored to the integration of environmental sustainability in GenAI use. It combines elements of behavioural change, governance alignment, and capability building to ensure that environmental sustainable GenAI practices are not only introduced, but also embedded into daily organisational processes.

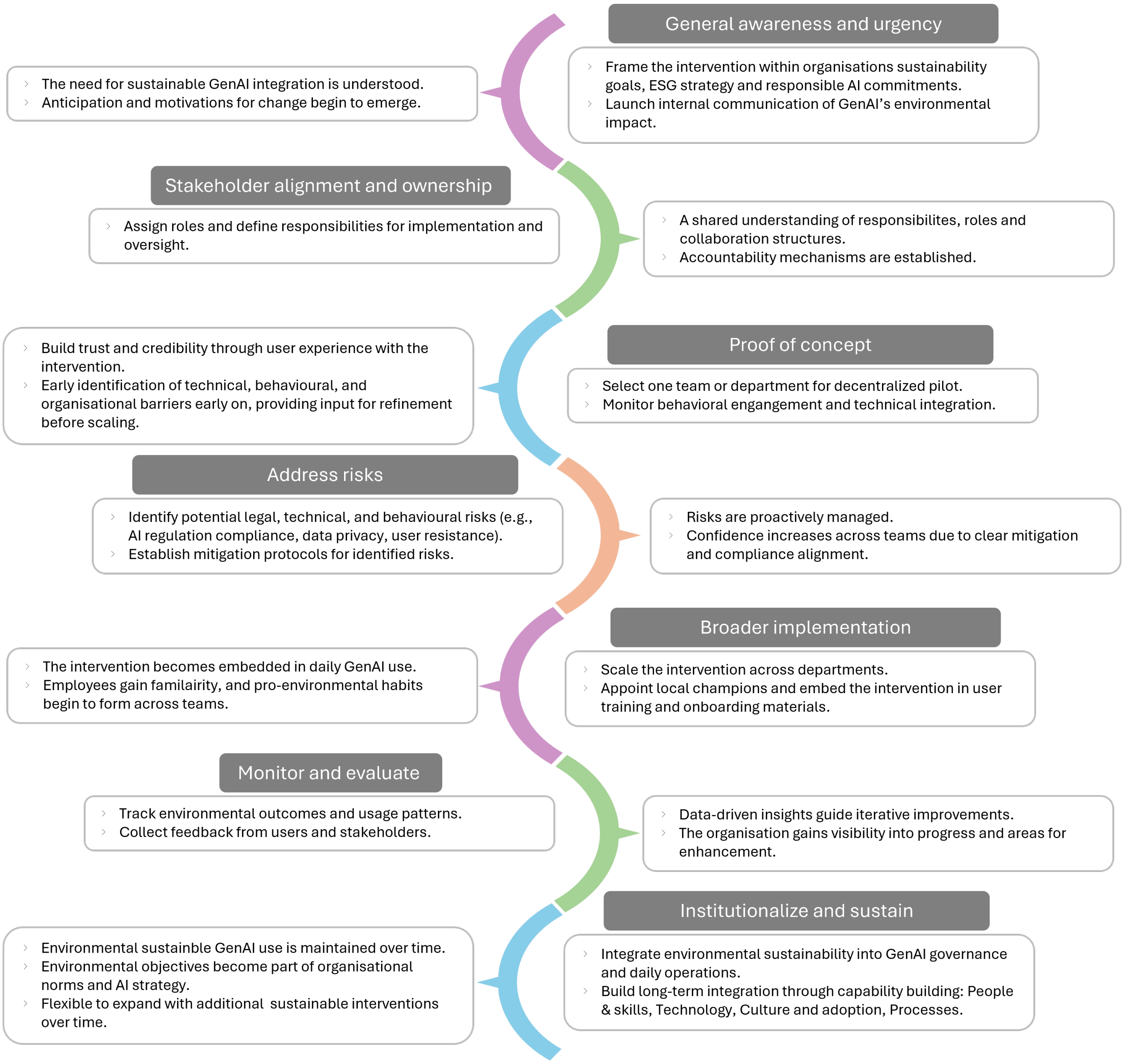

Figure 7.3: Implementation strategy (own work)

The implementation process starts by creating general awareness and a shared sense of urgency across the organisation. The intervention should be introduced through targeted internal communication that raises awareness of the environmental impact of GenAI use. Framing the intervention as part of the organisation's broader sustainability goals and responsible AI strategy helps establish relevance and alignment. This phase is critical for building a sense of urgency and commitment before the technical or behavioural changes are introduced. In parallel, it is important to define clear roles and responsibilities by identifying key internal stakeholders, as compliance officers, internal champions, sustainability leads and a technical team. Clearly define who is responsible for behavioural enablement, system integration, performance tracking, and policy alignment. Cross-functional governance is essential to embed the intervention across both behavioural and operational layers.

The next step involves launching a proof of concept (PoC). This phase begins with the rollout of the intervention within a single department or team to test its performance in a real-world setting. This allows teams to experiment with the intervention, adapt it to their context, and provide users with time to become familiar with the changes. It's also an opportunity to evaluate how well the intervention integrates with existing GenAI tools and workflows. Any lessons learned during this pilot phase provide valuable input for refinement and help assess whether the organisation is ready for a broader implementation. At this point, it becomes essential to identify and address potential risks before scaling. These risks may include handling large volumes of user data, regulatory compliance (e.g., with the EU AI Act), employee resistance, and operational complexity. Risk ownership should be clearly assigned (legal, compliance, or IT departments), and mitigation protocols should be established to ensure a secure implementation.

After establishing urgency, assigning clear roles, completing a decentralised pilot, and identifying key risks, the intervention can be scaled across departments. At this stage, the intervention becomes embedded in daily GenAI use, and pro-environmental behaviour begins to form across teams. Scaling efforts can be supported by appointing local champions and by integrating the intervention into user training programmes and onboarding materials. Following implementation, it is essential to monitor and evaluate the impact of the interventions. This involves assessing environmental outcomes or behavioural changes as a direct result of the intervention. This evaluation process should be continuous and inform iterative improvements.

The final step focuses on embedding environmentally sustainable GenAI use into the organisation's core to ensure long-term impact. The intervention must shift from a temporary initiative to an institutionalised practice. This requires building enduring capabilities that position environmental sustainability as a structural component of GenAI usage. In doing so, the organisation also ensures flexibility to expand with additional or alternative environmentally sustainable interventions as employee maturity in GenAI use evolves.

The capabilities are developed across four key domains:

- **People & skills:** Equip teams with the knowledge and skills to design, implement, and maintain environmentally sustainable GenAI practices. This includes targeted training for AI developers, sustainability leads, and end-users to foster a shared understanding of environmental goals and their role in achieving them.
- **Technology:** Integrate sustainability indicators and feedback mechanisms into the GenAI infrastructure. Assign responsibility to technical teams for embedding, monitoring, and iterating on sustainability performance within GenAI tools.
- **Culture & adoption:** Promote a culture in which sustainable GenAI practices are recognised, rewarded, and normalised. Celebrate internal champions and embed pro-environmental usage norms into onboarding materials and internal communication strategies.
- **Process & governance:** Align governance structures by incorporating environmental sustainability into AI policies, decision-making protocols, and key performance indicators (KPIs). This ensures that environmental criteria are consistently considered in future GenAI usage.

7.3. Conclusion

This chapter presented a theoretically grounded, user-informed integration framework with a decision tree, and a complementary implementation strategy for embedding environmentally sustainable GenAI use within organisations. The framework translates the core output of the research and gives behavioural insight into practical guidance by linking three distinct user personas to tailored intervention packages and their corresponding functional and non-functional requirements.

The implementation strategy provides a step-by-step roadmap to how these interventions can be introduced in practice. It offers concrete guidance on how to create urgency, assign ownership, pilot interventions, and ultimately institutionalise environmentally sustainable GenAI practices.

Together, the framework, decision tree and strategy enable organisations to systematically embed environmental sustainability into GenAI use.

8

Discussion

This chapter discusses the main findings of the research and situates them within the broader academic and practical discourse on environmentally sustainable AI. It also outlines the limitations of the study and proposes directions for future research.

8.1. Research implications

The research implications are discussed from both an academic and a practical perspective. The following section first elaborates on the theoretical contributions of the study, before moving on to outline its practical relevance.

8.1.1. Theoretical implications

This research contributes to the academic understanding of environmentally sustainable AI by shifting the focus from upstream technical interventions to user behaviour within organisational GenAI use. While prior literature has focused on upstream emissions, such as those from model training, hardware optimisation, and energy-aware algorithms (Järvenpää et al., 2024; Kaack et al., 2022; Tabbakh et al., 2024; Verdecchia et al., 2023), this study responds to concerns raised by de Vries (2023) by emphasising that the inference phase, remains under explored despite its growing share of AI's environmental footprint. Recent warnings that frequent, large-scale GenAI interactions could generate significant environmental by Kaack et al.; Robbins and van Wynsberghe (2022, 2022) are addressed in this research through six targeted interventions.

This study addresses the gap by operationalising the calls of Tabbakh et al. (2024) and Kunkel et al. (2023) to integrate environmental sustainability into practice, specifically by tackling this challenge at the point of user interaction with GenAI tools. This approach aligns with the human-centred AI framework proposed by Torkamaan et al. (2024), which goes beyond a technology-focused view by also considering user-, human-, and future-centred perspectives. They argue that AI should be judged not just on technical performance (accuracy), but also on factors such as user experience. In line with this, this research shows that understanding user motivations and perceptions is key to making GenAI use more sustainable.

For example, the interviews revealed barriers to pro-environmental behaviour, including low perceived impact, lack of guidance and automatic prompting behaviour. These findings demonstrate that habitual interactions carry material CO_2 consequences, which can be shaped through behavioural interventions. The identification of three user personas, unaware, externally motivated, and aware but uncertain, along with their preferences and interaction patterns with the system, formed the basis for a user-centred approach to environmentally sustainable design.

The importance of affordances in supporting behaviour change, as discussed in Evans et al.; Hirvonen et al.; Kaptelinin and Nardi (2017, 2024, 2012), is confirmed by this research. The survey results for the functional requirements indicate that interventions embedded directly within the user workflow (e.g., sustainable prompt builder, green tips rotation, impact estimator) were more likely to fulfil requirements linked to behavioural change. In contrast, interventions operating in separate interfaces or requiring additional user effort (e.g., monitoring dashboard, energy-efficient defaults) were less effective in meeting requirements related to accessibility, ease of use, and habit disruption. This suggests that integration into existing workflows is critical for interrupting automatic prompting behaviour and supporting sustained change, underlining the importance of affordance.

In addition, this research demonstrates that external signals and social structures in the monthly feedback play a role in shaping sustainable GenAI use, particularly for unaware users. This validates the relevance of social norms and feedback loops as theorised in TPB (Ajzen, 1991). Users exposed to monthly feedback reported a higher likelihood of adapting their behaviour, supporting the view that social influence and collective engagement mechanisms are important drivers of pro-environmental behaviour.

Consistent with prior behavioural research, this research finds that even users with strong pro-environmental intentions often fail to act sustainably, illustrating the well-documented intention–behaviour gap in environmental contexts (Pekaar & Demerouti, 2023; Zee et al., 2025). In line with Thaler and Sunstein (2008), the findings show that this gap can be closed through targeted nudging strategies such as labelling and proximity approaches that also proved effective in the present research. For example, providing transparent and tangible information on environmental emissions, combined with proximity-based practical support during GenAI prompt creation, emerged as key enablers for translating intention into behaviour.

The TPB suggests that constructs such as normative alignment and perceived behavioural control are sufficient to drive pro-environmental behaviour (Arya & Chaturvedi, 2020; Katz et al., 2022; Pekaar & Demerouti, 2023). However, this research nuances that claim in the context of GenAI use: for externally motivated users, simply strengthening normative alignment did not influence pro-environmental behaviour.

This research supports the idea that interaction design can either enable or inhibit pro-environmental behaviour. By embedding the behavioural change theories within a socio-technical perspective, this research offers a new conceptual lens for AI sustainability. Rather than focusing on the technology-centric, the research shows how individual behaviour, system design, and organisational culture interact to shape environmental impact. The proposed interventions, as the impact estimators, sustainable prompt builder, monitoring dashboard, energy-efficient default, monthly feedback and rotating tips, serve as practical tools for embedding sustainability into daily AI interactions. Making the practical application in industry clear in embedding sustainable AI practices into organisational processes (Kunkel et al., 2023; Tabbakh et al., 2024; Verdecchia et al., 2023).

The contextual conditions identified in this research also help explain why the shift to environmental sustainability can be challenging for organisations. Consistent with findings in the literature (Castellanos-Nieves & García-Forte, 2023; Schwartz et al., 2020; Verdecchia et al., 2023), this research confirms the importance of balancing high utility performance of speed, accuracy, and convenience, with sustainability goals. Communicating sustainability in a way that complements GenAI adoption and experimentation is essential, especially in early adoption phases when maintaining space for innovation is crucial. At present, the use of GenAI tools often incurs no visible operational costs, suggesting that organisations may act only when environmental and financial consequences become more tangible.

Finally, the research highlights technical challenges in monitoring and evaluating sustainability performance. This research reveals that monitoring and evaluation mechanisms for assessing sustainability performance or displaying CO_2 feedback are hindered by a lack of direct data from hyperscale providers and unreliable CO_2 estimates. This finding resonates with the broader difficulty of assessing AI's environmental impact, where differences in scope and system boundaries make it challenging to establish consistent evaluation standards (de Vries, 2023; Eilam et al., 2023).

In sum, this research deepens theoretical understanding by integrating behavioural change theories with a user-centric approach to GenAI sustainability. It shifts the focus from green infrastructure to green interaction, moving from academic discourse to practical, actionable organisational interventions. These insights lay the foundation for a new strand of research on human–AI interaction for environmental sustainability, one that is informed by actual user behaviour and designed to enable enduring, scalable transformation.

8.1.2. Practical implications

The findings of this research provide several actionable directions for organisations seeking to embed environmental sustainability into GenAI use. From a broader perspective, the user-informed framework and accompanying decision tree can serve as a practical guide for decision-making on how to embed pro-environmental behaviour in GenAI usage. The interventions are tailored to distinct user personas, highlighting that different user groups face different barriers to pro-environmental behaviour. Unaware users benefit most from feedback loops and social norm cues; externally motivated users respond to organisational signals and default settings; and conscious but uncertain users require transparent emissions data and practical guidance.

The evaluation of the interventions provided further insight into their effectiveness. More specifically, intervention features integrated directly into the existing user workflow, such as the sustainable prompt builder and green tips rotation proved more effective in disrupting habitual prompting behaviour than tool as the monitoring dashboard located in a separate interface. Furthermore, nudging strategies, such as labelling the environmental impact of prompts and providing proximity-based practical guidance, can help close the intention–behaviour gap for aware but uncertain users. The monthly feedback mechanism, leveraging social influence and collective engagement, also emerged as a strong driver of pro-environmental behaviour.

Importantly, during the evaluation, technical challenges emerged around the monitoring of CO_2, hindered by the lack of transparency in the AI industry and its systems. Such transparency is crucial for organisations to gain insight into their sustainability performance and to drive change towards more sustainable practices. While proxy-based monitoring can serve as an interim solution, this research underscores the urgency for the wider industry to make CO_2 emissions data openly available, or for regulation to mandate such disclosure as a prerequisite for environmental accountability.

It should be noted, however, that the framework was developed and validated within the context of a single organisation. The generalisability of the findings is therefore influenced by the organisational culture, GenAI maturity, and sustainability ambitions of the case organisation. Applying the framework in different sectors or types of organisations may require contextual adjustments to the personas or intervention design.

Furthermore, the desirability and behavioural impact of the interventions were tested with a relatively small subset of respondents, meaning that the results provide initial indications rather than definitive evidence of effectiveness. Broader testing across diverse organisational settings and larger user samples will be required to validate the framework and refine its applicability across different industries and contexts.

8.2. Limitations

During the research, many design choices were made that introduced limitations impacting the outcomes and generalizability of this research. Reflecting on these limitations is important to understand the shortcomings.

Fast-evolving nature of AI

This research focused on targeting the inference phase, exploring how behavioural interventions could embed environmental sustainability into daily usage. However, given the combination of the DSR approach, which required substantial time and resources, and the fast pace of AI advancement, there is a risk that the interventions may become obsolete and not represent the area of greatest environmental impact within the lifecycle of GenAI tools. The fast-evolving nature of the GenAI field introduces developments as agent-based architectures (where multiple models interact simultaneously) or Retrieval-Augmented Generation (RAG-ing) into organisational contexts. These developments may significantly influence CO_2 emissions in ways that surpass user-related factors like model choice, prompt length, or frequency of prompting. These emerging technology changes alter the relative importance of user behaviour as a driver of emissions. Nevertheless, by focusing on GenAI usage, this research contributes to raising awareness of the role users can play in supporting environmental goals, even if the overall impact may be smaller compared to upstream technical developments.

Testing of maintaining utilities of high level of speed, accuracy and convenience

A key limitation is the inability to test non-functional requirement NFR01, which focuses on preserving essential GenAI utilities (performance, speed, and convenience) while embedding sustainability. Evaluating potential trade-offs between environmental benefits and user experience requires technical implementation and real-world testing, which were beyond the scope of this ex-ante evaluation. As a result, the impact of proposed interventions on these core utilities remains unaddressed. Moreover, this research did not examine how users might weigh these utilities against potential sustainability gains.

Limited evaluation phase

The evaluation of the interventions was constrained by a limited number of respondents, which affects the strength and generalisability of the findings. In the survey evaluation, testing with a larger group of participants could provide more reliable outcomes and stronger evidence about which behavioural theories and interventions are most effective for different user groups in the context of GenAI tools. Furthermore, the inclusion of only two experts in the validation phase provided limited feedback, restricting the ability to capture a broader range of organisational perspectives.

Secondly, full development and technical integration of the interventions were not feasible within the scope of this project. The evaluation phase leaves room for further development, iteration, and refinement of the intervention set before broader implementation.

Generalisability

The approach was conducted solely within a single organisation and was not evaluated with employees (GenAI users) from other organisations or sectors. As a result, the variability in expertise, background, and personal preferences was not fully assessed. This is likely to influence the outcomes of interventions and their adoption. Furthermore, it limits the generalisability of the findings across different organisational settings.

8.3. Future research

This research has laid the groundwork for embedding environmental sustainability into organisational GenAI usage through targeted interventions. However, several areas require further research to strengthen, validate, and extend these findings. The future research directions presented here are linked to the discussed limitations of this research.

Exploring the broader impact of GenAI tools

While this research focused on user interactions with GenAI tools, future research could investigate other AI-related developments that may contribute to emissions in ways that go beyond behaviour-related factors such as prompt frequency or model selection.

For example, it could explore the environmental impacts of agent-based architectures (where multiple models interact simultaneously) or Retrieval-Augmented Generation (RAG) systems. These architectures could be assessed for their potential emissions in a use case. Additionally, formulate potential barriers to environmental impact and inform policy development. Such research would provide organisations with valuable insights for prioritising sustainability measures, navigating recent AI developments and mitigating potential costs.

Testing trade-offs with core utilities: speed, accuracy, and convenience

The environmental sustainability interventions may influence the core utilities of GenAI tools, speed, accuracy, and convenience, which were not assessed in this research. Future research should explore how organisations can balance these competing priorities.

One method to apply is the Best-Worst-Method, where participants are asked to rank trade-offs between sustainability and utility dimensions in realistic usage scenarios. For example, users could evaluate whether a slight delay in response time is acceptable in exchange for lower CO_2 emissions. This approach could provide empirical data on user tolerance for sustainability-related trade-offs and guide organisations in prioritising features during implementation.

Extensive evaluation

Evaluating the interventions with a larger and diverse group of participants from different organisations, expertise levels, and organisational roles is essential. This would provide deeper insights into the interventions' perceived usefulness and their ability to stimulate pro-environmental behaviour in GenAI usage across a variety of contexts. It would also strengthen the generalisability of the results and offer more robust evidence regarding both the adaptability of the interventions and the validity of their theoretical foundations.

Lastly, the development and integration of the set of interventions leaves room for further refinement of the interventions. Future research should focus on refining the interventions in collaboration with diverse user groups and testing them across multiple organisational environments. This would help assess to which extent the framework and its underlying behavioural design can be generalised.

Regulatory considerations

An important factor in the research was finding a balance between adoption and sustainability. Preserving space for innovation and experimentation has been seen crucial, particularly during the early adoption phase. At present, the use of GenAI tools does not directly translate into visible operational costs, suggesting that companies may only take action when environmental and financial consequences become more apparent. This suggests the importance of regulatory mechanisms. as Future research could explore how regulatory systems, for example, subsidies, can be designed to support the adoption and scaling of environmental sustainability initiatives in AI systems. As the current AI Act does not explicitly address environmental impact, such measures may be necessary to close this regulatory gap. This is especially necessary as organisations prioritise innovation and experimentation to become first movers in the field, often placing sustainability lower on the agenda.

Future studies could also advocate for more transparent emissions reporting from hyper scalers, potentially influencing industry standards or policy. These improvements would enable organisations to implement reliable monitoring systems, which are critical for broader sustainability strategies.

9 Conclusion

In this final chapter, we reflect on the Design Science Research by Johannesson and Perjons (2021) undertaken in this thesis and synthesise the insights gained throughout the research. Firstly, we reflect on the research sub-questions, showing how each contributed to answering the main research question and addressing the identified academic gap. We then elaborate on the societal and academic contributions of the research. Finally, we discuss limitations and propose future research directions to further advance the field of environmentally sustainable GenAI usage.

9.1. Answering the research question

The central research question guiding this thesis was *"How can organisations integrate environmental sustainability within the use of Generative Artificial Intelligence through targeted interventions?"* To answer this question, the DSR process was followed, from problem investigation to evaluation of the designed artefact. The output of every sub-question served as input for the following formulated sub-question. The response to the main research questions encompasses the insights from each sub-question. All the research questions are discussed, following in answering the main research question.

9.1.1. The sub-questions

SQ1: What are the current environmentally sustainable initiatives in the operational phase of generative Artificial Intelligence?

This research originated from the intersection of two pressing topics: environmental sustainability and artificial intelligence (AI), driven to explore ways to mitigate the negative sustainability impacts of AI on the environment. Early in the process, it became evident that environmental sustainability remains insufficiently embedded within organisational AI practices. Despite growing awareness of AI's environmental footprint, sustainable AI adoption is hindered by underdeveloped policy frameworks, fragmented metrics, and unclear roles for disciplines and stakeholders. Combined with concerns about technological lock-in and high-emission trajectories, these challenges raise a critical question of how organisations can take ownership of embedding environmental sustainability in their AI practices.

To address this, a literature review was conducted on sustainability initiatives in the operational phase of AI. The review identified several technical measures, mostly focused on the training phase. Additionally, it examined the determinants of CO_2 emissions during GenAI's operational phase, including electricity carbon intensity, model complexity, inference time, hardware efficiency, prompt length, and overall usage scale. Particular attention was drawn to the inference phase. While a single query may consume 0.43 Wh, the number of queries executed daily results in a substantial environmental impact and overall usage scale.

These findings underscored the need for and decision to further research focusing on the usage phase of GenAI. The absence of actionable, organisation-driven interventions for embedding environmental sustainability into everyday AI use highlights a critical opportunity for innovation. Addressing this gap became the foundation for the intervention designs developed in this thesis.

SQ2: What factors enable environmentally sustainable Generative Artificial Intelligence usage within organisations?
Building on the insights from the literature review, the research turned to focus on the AI usage phase, with the objective of embedding environmental sustainability into daily organisational practices and ensuring responsible use of GenAI.

To understand the factors that enable environmentally sustainable GenAI usage, semi-structured interviews were held with both GenAI users and AI experts. The enabling factors were categorised using the COM-B behaviour change model by Michie et al. (2011): capability, opportunity, and motivation. The COM-B model was chosen because of its broad application in studies on behavioural change and pro-environmental behaviour.

From a capability perspective (Table 3.3), GenAI users emphasised not only the need for general awareness of GenAI's environmental impact but also practical knowledge and guidance. This includes understanding the energy implications of GenAI, developing practical skills such as prompt efficiency and model selection, and critically assessing the value of using GenAI in a given context. AI experts noted that users often lack insight into underlying processes and associated environmental costs; improving this knowledge can facilitate pro-environmental behaviour.

In terms of motivation (Table 3.4), interviews revealed that many users engage in automatic prompting behaviour without reflection. However, emissions feedback could serve as a trigger for more mindful usage. Reducing unreflective and unnecessary GenAI use is seen as a critical enabler for pro-environmental behaviour. Maintaining GenAI's core utilities (speed, accuracy, ease of use) is also essential to avoid resistance. Reflective motivation (Table 3.5) is influenced by feelings of personal responsibility, perceived behavioural control, and clarity regarding individual impact. Further strengthening motivation requires visible feedback, improved understanding of environmental consequences, and clear, accessible means of executing pro-environmental GenAI interactions.

Opportunity factors highlighted the importance of supportive physical (Table 3.6) and social environments (Table 3.7). Interviews highlighted the importance of interface designs that embed transparency and tangibility, as users currently have no sense of the consequences and magnitude of their impact when prompting. Furthermore, organisational management, peer support, and a culture that normalises environmental sustainability have been revealed to be seen as potential drivers for environmental sustainable use.

In addition to these insights, experts warned that sustainability must be balanced with innovation. While early adopters require space to experiment, embedding sustainability in strategic priorities and organisational norms is essential to making pro-environmental GenAI use a default practice over time.

These insights, viewed through the lens of enabling factors, provide a promising foundation for designing interventions that promote environmentally sustainable GenAI usage within organisations.

SQ3: What are the requirements for interventions that support the embeddedness of environmentally sustainable Generative Artificial Intelligence usage within organisations?
Based on the enabling factors identified in the interviews, we defined the artefact to be designed. These factors were translated into functional and non-functional requirements for the interventions. Brainstorm sessions were held with professionals from different fields, including organisational strategy, AI adoption, and design. These sessions validated the identified requirements and underscored the importance of different user personas in design science. In the third session, the low-level requirements were examined in greater depth. With input from a design professional, the focus shifted towards formulating overarching high-level requirements, as the extensive set of detailed low-level requirements risked limiting flexibility in the design phase. The final set of 14 high-level requirements (Table 4.2) served as the guiding framework for intervention design.

While the detailed low-level requirements were not used directly in the intervention design, they remain valuable for organisations seeking more specific guidance when implementing certain requirements. Table C.2 provides an overview of the high-level requirements alongside their corresponding low-level requirements.

SQ4: What interventions support the embeddedness of environmentally sustainable Generative Artificial Intelligence usage within organisations?
With the set of 14 high-level requirements and one design principle, the next step is the design of targeted interventions. Translating the requirements into concrete designs.

Different user profiles were identified; the externally motivated user, the unaware user, and the aware but uncertain user. Each user group highlights distinct barriers and facilitators. The analysis of behavioural theories such as Nudging, Affordance Theory, and the Theory of Planned Behaviour informed tailored strategies to overcome specific barriers, aligned with the identified personas. This guided the association of requirements and the development of the interventions.

Three intervention packages were developed: sustainable by default, sustainability guidance, and collective sustainability. Sustainable by default, designed for the externally motivated user, applies affordance theory through default settings and provides a monitoring dashboard with usage thresholds to steer pro-environmental behaviour. Sustainability guidance, targeting the aware but uncertain user, combines the theory of planned behaviour and nudging techniques to offer personalised feedback and lower-impact prompt suggestions. Tools such as the impact estimator widget and sustainable prompt builder enhance perceived behavioural control and effectiveness. Collective sustainability, aimed at the unaware user, leverages social norms and automatic motivation through nudges, including symbolic rewards in the monthly feedback. The green tips rotation further raises awareness among unaware users and fosters collective responsibility.

Together, these interventions target different user groups, collectively supporting the embeddedness of environmentally sustainable GenAI usage.

SQ5: To what extent do the interventions support the embeddedness of environmentally sustainable Generative Artificial Intelligence usage within organisations?
The evaluation of the designed interventions was conducted ex-ante, assessing them based on anticipated user and expert perceptions before implementation, and was carried out within a single consulting company. Two complementary methods were used: surveys gathered user insights on functional performance and behavioural reinforcement, while interviews explored organisational integration and technical feasibility.

The functional requirement validation showed that most interventions successfully met their intended goals, demonstrating strong potential to meaningfully embed environmentally sustainable GenAI usage. The interventions provide practical guidance (FR01), raise awareness (FR02), share information about environmental impacts (FR03) transparently and tangibly (FR06), support control through ongoing management (FR05), strengthen social influence (FR09), and foster collective engagement (FR10).

The functional requirement validation also revealed opportunities for refinement: the sustainable prompt builder lacked direct feedback (FR04), the monitoring dashboard and energy-efficient defaults were not sufficiently simple or seamless for users (FR07), and the monitoring dashboard did not actively disrupt habitual prompting behaviour (FR08). Addressing these refinements would further strengthen the overall impact of the interventions. In contrast, the sustainable prompt builder, green tips rotation, and impact estimator did meet these requirements; potentially, because they are integrated directly into the user workflow. Interventions embedded in the primary interaction flow are more likely to interrupt behaviour and are seen as more accessible than tools such as the monitoring dashboard or energy-efficient defaults, which operate outside the main user interface.

The monitoring dashboard is intended to motivate externally motivated users towards more pro-environmental behaviour by providing institutional support and demonstrating organisational commitment. However, these features do not appear to directly guide users to act sustainably (*Sligthly* (score = 2)). The TPB constructs of normative alignment and perceived control may not be sufficient for this user group. However, the monthly feedback and impact estimator widget stands out as influential, with respondents indicating they would *Mostly* (score = 4) be influenced to act more sustainably. The social influence and collective engagement mechanisms in the monthly feedback appear to have a strong impact on shaping pro-environmental behaviour. Likewise, the impact estimator widget strengthens perceived behavioural effectiveness by providing clear information on environmental impact. The nudging technique of labelling reinforces its role as a driver of pro-environmental behaviour.

The semi-structured interviews revealed some challenges in fulfilling the functional requirements. Concerns were raised about the additional compute usage of interventions, which could potentially undermine alignment with organisational sustainability goals. Communicating sustainability in a way that complements GenAI adoption potentially poses challenges for the monitoring dashboard, as strict usage thresholds risk discouraging experimentation. Monitoring and evaluation mechanisms to assess sustainability performance could be difficult on individual-level behaviour, and, because of a lack of direct CO_2 data from cloud providers. While all interventions are technically feasible to develop, real-time CO_2 feedback (featured in some interventions) remains uncertain due to the absence of direct emissions data from hyperscaler APIs. However, proxy metrics such as token usage, compute time, or model type offer solutions.

Answering the question of whether the interventions support the embeddedness of environmentally sustainable GenAI usage within organisations, the evaluation provides strong evidence of their potential. Most interventions fulfil the majority of their functional requirements, directly addressing key needs such as providing practical guidance, raising awareness, enabling transparent impact communication, and fostering social influence and collective engagement. Notably, the monthly feedback and impact estimator widget achieved high behavioural impact scores and fulfilled all their functional requirements, showing strong potential for ready implementation. Although barriers remain, such as additional compute usage and the lack of direct CO_2 data, proxy-based monitoring and feedback methods offer practical ways forward. With targeted refinements, these interventions can form a strong foundation for embedding environmental sustainability into daily GenAI use and inspiring broader organisational change.

9.1.2. Main research question

To answer the main research question:

How can organisations integrate environmental sustainability within the use of Generative Artificial Intelligence through targeted interventions?

This research project has developed and validated a set of persona-driven interventions to address the environmental impact of GenAI usage in organisational contexts. The Design Science Research (DSR) methodology by Johannesson and Perjons (2021) guided this process, enabling a structured approach to problem investigation, artefact design, and evaluation. This methodology enabled the collection of qualitative insights from both GenAI users and AI experts, offering an understanding of attitudes, behaviours, and current practices in interacting sustainably with GenAI tools.

Firstly, this study revealed insights into the integration of environmental sustainability within the use of GenAI in organisations. The development of the set of high- and low-level requirements provided detailed and practical guidelines for embedding environmental sustainability into daily GenAI interactions.

Secondly, it emphasised the importance of focusing on different user groups, as they exhibit diverse patterns of GenAI usage and varying levels of environmental awareness. The research defines three user personas: the unaware user, the conscious but uncertain user, and the externally motivated user, each with distinct barriers and facilitators to pro-environmental action.

The resulting intervention packages, sustainable by default, sustainability guidance, and collective sustainability, successfully align these user personas with behavioural change theories (Nudging, TPB, and Affordance Theory) to address their specific barriers. The behavioural change theories informed the intervention design and guided the selection of functional requirements essential to their effectiveness, making each package tailored to both the user persona and the identified functional and non-functional requirements.

The collective Sustainability package targets the unaware user and includes:

- The monthly feedback with the goal of fostering reflection and motivation through consequence-based nudges such as feedback, incentives, and goal-setting.
- The green tips rotation with the goal of enhancing perceived behavioural control (TPB) and positive attitudes by providing guidance and sharing environmental information.

The sustainable by default package targets the externally motivated user and includes:

- The monitoring dashboard to promote normative alignment through visibility of organisational signals.
- The energy-efficient defaults with the goal of making the pro-environmental choice the path of least resistance, inspired by Affordance Theory.

The sustainability guidance package targets the aware but uncertain user, overcoming the intention–behaviour gap with the Nudging theory, and includes:

- The sustainable prompt builder with the goal of providing practical support during GenAI prompt creation through nudging strategies such as priming and proximity.
- The impact estimator widget with the goal of offering transparent and tangible information on emissions, inspired by the nudging technique of labelling.

Although the development and integration of the interventions was not feasible within this project. The evaluation results show great potential. The monthly feedback and green tips rotation was found to have the greatest potential for further refinement and implementation, as it fulfilled most of its requirements and reinforced pro-environmental behaviour. Behavioural strategies as social influence and collective engagement mechanisms and the nudging labelling and proximity technique can be effective in influencing pro-environmental interaction with GenAI tools.

From the structural and environmental conditions (non-functional requirements), several challenges and opportunities emerged. For example, concerns were raised about the potential additional compute usage of some interventions. In particular, communicating sustainability in a way that supports GenAI adoption may pose difficulties for the monitoring dashboard, since strict usage thresholds could discourage experimentation. Moreover, monitoring and evaluating sustainability performance is challenging, both in assessing individual-level behaviour and due to the absence of direct CO_2 data from cloud providers. Although all interventions are technically feasible to develop, providing real-time CO_2 feedback—as envisioned in some concepts—remains uncertain because hyperscaler APIs do not currently provide direct emissions data. However, proxy metrics such as token usage, compute time, or model type can offer practical alternatives.

Overall, the set of interventions developed in this research represents a substantial step toward embedding environmental sustainability in GenAI usage. They are tailored to distinct user personas, grounded in behavioural change theory, and supported by functional and non-functional requirements that ensure both behavioural impact and organisational fit. By addressing structural and environmental challenges and continuing to refine design, these interventions hold strong potential to foster the responsible use of GenAI in daily workflows. Together, they provide a robust foundation for shaping environmentally sustainable GenAI practices and driving lasting organisational change.

9.2. Academic contribution

This research highlights the complex implementation of environmental sustainability into GenAI usage within organisations. By developing and demonstrating practical interventions, this thesis contributes to the ongoing discourse on the responsible and environmentally sustainable use of GenAI tools.

The literature review revealed that while significant progress has been made in sustainable initiatives in the upstream, with optimising model architectures and sustainable algorithms, environmental sustainability remains insufficiently embedded in organisational AI practices. Moreover, strategies targeting the usage phase of AI are largely absent in existing research. This gap is especially relevant given that the inference phase, due to the large and growing number of daily queries, is projected to result in substantial environmental impacts.

This thesis contributes to addressing this academic gap by focusing on enabling factors that support environmentally sustainable GenAI usage within organisations. Through empirical research, including interviews with both GenAI users and AI experts, these factors were systematically identified and categorised using the COM-B behaviour change model by (Michie et al., 2011). This approach extends current theoretical frameworks by integrating behavioural science into the design of organisational interventions for sustainable GenAI usage. Furthermore, the academic contribution of this research lies in the development of a comprehensive set of high-level and low-level requirements for embedding environmental sustainability practices into GenAI usage. While the high-level requirements offer general principles to guide intervention design, the low-level requirements offer detailed and actionable guidance for organisations seeking to implement granular measures.

The interventions developed in this thesis address user behaviour and organisational structures, demonstrating how socio-technical perspectives can enable more responsible and sustainable use of GenAI systems. Their evaluation provided insights into the application of behavioural strategies, such as nudging, affordances, and the Theory of Planned Behaviour (TPB), in the context of user interaction with GenAI tools. While prior research has applied these behavioural theories to promote pro-environmental behaviour in other domains, this thesis extends their application to the specific context of GenAI tools. Additionally, by engaging experts in the evaluation process, organisational and technical opportunities and challenges for implementation were identified and discussed.

In sum, this study advances the state of the art by integrating behavioural science, sustainability principles, and systems engineering into practical interventions for environmentally sustainable GenAI usage. It offers both theoretical contributions and practical tools, such as the user-informed framework and decision tree, for organisations aiming to reduce emissions associated with GenAI. By addressing the interaction between user behaviour, organisational structures, and technical constraints, this thesis provides a foundation for future research on the organisational embedding of environmental responsibility in GenAI.

9.3. Societal contribution

This research addresses the growing societal challenge of mitigating the environmental impact of AI, particularly in the operational phase where GenAI tools are increasingly integrated into organisational workflows. While public and academic attention has largely focused on the energy demands of training large models, the inference phase (with cumulative add-ups in daily use) poses an equally significant and under-acknowledged source of emissions. As GenAI becomes a general tool in knowledge work, organisations have both the opportunity and responsibility to embed environmental sustainability into everyday AI use.

The high- and low-level requirements developed in this study provide a valuable framework for organisations seeking to understand what is needed to support pro-environmental behaviour in GenAI usage. These requirements are highly informative and offer detailed guidance on how to enable employees to use GenAI tools in an environmentally sustainable way. Taking it a step further, the designing and validating of the targeted interventions, demonstrates how sustainability can be operationalised at the point of user interaction. The interventions target the behavioural dimensions of environmental sustainability towards GenAI use. For instance, sustainable by default reduces user effort by embedding environmentally by lower impact settings, sustainability guidance empowers users with feedback and practical tools to make low-impact choices, and collective sustainability fosters a culture of shared accountability through social influence and visible impact metrics. Together, this work raises awareness by demonstrating that everyday AI interactions carry environmental costs and can be mitigated through small but cumulative changes in user behaviour.

While these interventions demonstrate potential, challenges remain. These include addressing the additional compute demands of feedback tools, ensuring the reliability of proxy metrics for emissions monitoring, and calling for greater industry transparency in CO_2 emissions. Nonetheless, this study provides a first practical foundation for organisations seeking to embed environmental sustainability into GenAI use and to take meaningful steps toward climate-conscious AI adoption.

9.4. Link to MSc program

In recent years, the rapid expansion of AI has transformed various industries, raising concerns about its large-scale adoption and associated energy consumption (Malik et al., 2024). The MSc program in Complex Systems Engineering and Management (CoSEM) at Delft University of Technology focuses on designing and implementing innovative solutions within socio-technical systems, taking into account the broader organisational, societal, and environmental context. The program equips students with the skills to navigate complex decision-making by integrating technology, stakeholder values, sustainability, human behaviour, and regulations.

This research aligns with the CoSEM approach by exploring the trade-offs between AI and environmental sustainability in the context of increasing adoption and long-term environmental impacts. By focusing on the usage phase of GenAI tools, it explores how behavioural interventions can support sustainability within organisations. Rather than targeting upstream technical optimisations, it emphasises the human and organisational dimensions of sustainable AI adoption. The interventions developed in this thesis address user behaviour and organisational structures, demonstrating how socio-technical perspectives can enable more responsible and sustainable use of GenAI systems.

Addressing the environmental impact of GenAI tools highlights the complexity of the problem. It calls for understanding user perceptions, competencies, and the institutional environment in which technologies are embedded. By integrating behavioural science with systems thinking, this research illustrates how practical interventions can influence daily workflows and organisational practices to reduce environmental impact.

Thus, this thesis reflects the CoSEM vision of tackling complex societal challenges by connecting technology, people, and institutions. It provides a concrete example of how systems engineering and management principles can be applied to promote environmental sustainability in evolving technological domains such as GenAI. As AI advances and its vast potential continues to grow, the integration of organisational compliance, societal implications, and sustainability objectives becomes essential to ensuring responsible and long-term AI adoption.

A

Embodied and operational emissions AI

A.1. The AI lifecycle

Understanding the lifecycle of AI is essential for assessing its environmental impact. Mapping this lifecycle clarifies the different phases and identifies which stages are directly within the organisation's influence or lie outside the system boundary. The lifecycle of AI systems requires significant computing power and energy consumption, which lead to substantial greenhouse gas emissions. This energy demand varies considerably depending on the algorithms used and the specific stages of an AI model's development and application (Kaack et al., 2022). To evaluate the sustainability of AI more accurately, it is essential to adopt a holistic perspective of the AI lifecycle. This approach also serves to clarify the scope and focus of this research.

Various studies offer insights into the compute-related environmental impacts of AI. A distinction is made between embodied and operational emissions, as illustrated in Figure A.1. Embodied emissions refer to the environmental costs associated with manufacturing, the supply chain, and the end-of-life phase of AI hardware and infrastructure. Operational emissions, on the other hand, arise during the use of AI systems, particularly in research & development, training & tuning, and search or inference. This study focuses specifically on operational emissions, those generated during the AI model's lifecycle. Embodied emissions are excluded from the scope, as they are beyond the direct influence of organisations deploying AI models. While still important, these emissions are generally determined by upstream supply chains and hardware manufacturers.

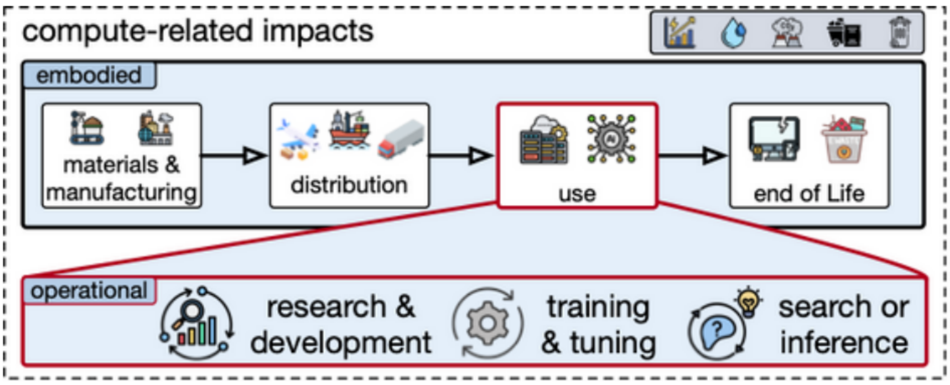

Figure A.1: Embodied and operational emissions. Adopted from Bashir et al. (2024).

A.2. The AI model lifecycle

Eilam et al. (2023) define the AI model lifecycle as an end-to-end process comprising data collection, model exploration and experimentation, training, distillation, fine-tuning, deployment, re-training, and inference. Alternatively, Kaack et al. (2022) propose a more concise classification, distinguishing between three main stages of the opearional phase of AI: model development tuning, and training, model deployment and model inference.

Development & Training: This phase involves the creation of AI models, including the design and construction of the model architecture (Eilam et al., 2023). It encompasses data preparation and management, followed by model exploration and experimentation, where different configurations and parameters are tested (Wu et al., 2022). Subsequently, the training process begin. A computationally intensive task in which the prepared data is used to teach the AI model to perform a specific function (Robbins & van Wynsberghe, 2022).

Deployment: This phase refers to the stage at which the AI model is integrated into real-world applications and systems, making it accessible for its intended use (Rohde et al., 2024). It includes the implementation of the trained model and its distribution across operational environments. Deployment can take place in various settings using different techniques, each of which may affect the carbon intensity of the AI workload (Dodge et al., 2022; Järvenpää et al., 2024).

Inference: Once the model is trained and deployed, it begins receiving input data for processing (Robbins & van Wynsberghe, 2022). This is the stage where the model is in use of the world (Kaack et al., 2022).

The boundaries between the phases of the AI model lifecycle are not clear-cut. The inference phase is closely tied to the deployment phase. Once a model is deployed and enters the inference stage, it is subject to ongoing evaluation, monitoring, and can be a feedback loop to the development team. This highlight that deployment and inference is not the end, but can lead backs to development/training improvements and leads to further fine-tuning or re-training. The MLOps cycle captures this iterative process, encompassing development and training, deployment, inference, and the monitoring necessary for model refinement (Mattoo, 2024).

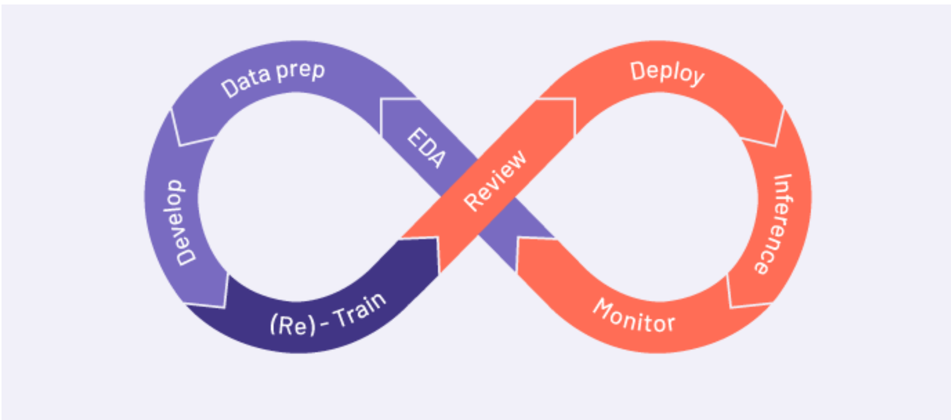

Figure A.2: MLOps Cycle. Adopted from (Mattoo, 2024).

B

Interviews

B.1. List of interviewees enabling factors pro-environmental behaviour

Table B.1: List of interviewees semi-structured interviews

Interviewee #	Role
	GenAI Users
1	Technology Transformation Consultant
2	Technology Transformation Consultant
3	Technology Transformation Consultant
4	Technology Transformation Consultant
5	Financial Technology Consultant
6	Technology Transformation Consultant
7	Technology Transformation Consultant
8	Compliance and Reporting Specialist
9	Data and AI Consultant
	AI Experts
1	Change Management Consultant (Focus on internal GenAI deployment)
2	Data and AI Consultant (AI cases for clients)
3	Data and AI Consultant (Focus on internal GenAI deployment)
4	Data and AI Consultant (Focus on internal GenAI deployment)
5	Strategy Consultant (Focus on internal GenAI deployment and client AI development and deployment)
6	Risk Consultant (Focus on environmental risks of AI)

B.2. Interview questions

Interview questions for GenAI users.

1. **Setting the context: Mapping use and awareness of environmental sustainability**
   (a) What are your main reasons for using Generative AI tools in your work? How frequently do you use them?
   (b) Have you ever thought about the environmental impact of using GenAI tools? If so, can you share any thoughts or reflections, and whether that has influenced how you use them?
   (c) How satisfied are you with the guidance or best practices for using GenAI tools in an environmentally sustainable way?

   (d) Would you like to use GenAI tools in a more environmental sustainable way?

2. **Behavioural and contextual motivators**
   (a) What internal factors (such as personal values, knowledge, or skills) affect how environmentally sustainable you use GenAI tools?
   (b) What external factors (such as organisational policies, peer influence, or industry standards) affect how environmentally sustainable you use GenAI tools?
   (c) Do you think your team or department could support behavioural changes to promote more environmentally sustainable use of GenAI tools?
   (d) Do you think environmental sustainability is part of your role or responsibility when using GenAI at work?

Interview question for AI experts.

1. **Setting the context: process of GenAI tools**
   (a) Can you describe the process for selecting, developing, and deploying generative AI tools?
   (b) In what ways, if any, does sustainability influence decisions around generative AI development or infrastructure?
   (c) Are there any sustainability initiatives, tools, metrics, or frameworks used during the development and deployment phases of generative AI? (e.g., model efficiency, monitoring tools, cloud optimization)
   (d) What about during the inference/user phase?
   (e) Who is responsible for managing or overseeing the sustainability impacts of generative AI tools?

2. **Sustainability integration**
   (a) What factors do you think influence whether sustainable practices are adopted during the inference phase?
   (b) What would influence how sustainably you use generative AI?
   (c) What are the main challenges in making the use of generative AI more sustainable? Why?
   (d) How do you balance other priorities (such as performance, speed, or accuracy) with sustainability concerns?

C

Requirement elicitation

C.1. Low-level requirements

Table C.1: List of low-level requirements (elicitated from the enabling factors)

Requirement category	ID	Description	Source COM
FUNCTIONAL	1.01	The intervention shall provide practical guidance/knowledge on prompt crafting to achieve task efficiency.	CP1, CP4
	1.02	The intervention shall provide practical guidance/knowledge in model selection by task-based comparison and required performance for that task.	CP1, CP3
	1.03	The intervention shall create awareness about the environmental impact of using Gen AI tools.	CP2, MR5
	1.04	The intervention shall inform about the energy consumption trade-off between Gen AI and alternative digital tools.	CP5
	1.05	The intervention shall inform about underlying processes, type of energy sources, and associated costs.	CP6, MR12
	1.06	The intervention shall support to reflect on the necessity of using Gen AI for a specific task.	CP7, MA3
	1.07	The intervention shall provide emissions-related feedback that encourages reflection.	MA1, OP3
	1.08	The intervention shall disrupt habitual and automatic prompt interaction.	MA2
	1.09	The intervention shall reinforce user responsibility for the environmental impact of their actions.	MR7
	1.10	The intervention shall use symbolic recognition to incentivize sustainable Gen AI use.	MR8, OP6
	1.11	The intervention shall communicate the overall magnitude and consequences of the environmental impact associated with GenAI usage.	MR9, MR11
	1.12	The intervention shall inform users about their individual contribution to the environmental impact of Gen AI usage.	MR10
	1.13	The intervention shall use autonomy-supportive and recurring sustainability cues to promote pro-environmental choices.	MR15, OP4, MR6
	1.14	The intervention shall support the continuity and reinforcement of pro-environmental behaviour over time.	MR21

Requirement category	ID	Description	Source COM
	1.15	The intervention shall provide tangible information on the environmental impact of Gen AI usage.	OP1, MR14
	1.16	The intervention shall ensure that environmental information is transparent and accessible.	OP2, OP5, OP8
	1.17	The intervention shall maintain control by enabling measurement, monitoring, and baseline metrics.	OP7, OP9
	1.18	The intervention shall allow peer comparison and support to promote sustainable social norms.	OS3, OS5, OS10
	1.19	The intervention shall promote social attention.	OS4
	1.20	The intervention shall stimulate conversations on sustainable Gen AI usage.	OS6
	1.21	The intervention shall adapt sustainability messaging based on user role or local context.	OS7
	1.22	The intervention shall ensure that pro-environmental actions is clear, simple and easy to perform.	MR13
NON-FUNCTIONAL (structural)	2.01	The intervention shall maintain a high level of responsiveness and speed in Gen AI interactions.	MR1
	2.02	The intervention shall maintain accuracy and valuable Gen AI outputs.	MR2
	2.03	The intervention shall preserve usability and maintain ease and convenience in Gen AI interaction.	MR3
NON-FUNCTIONAL (environmental)	3.01	The intervention shall align with the organisation's existing norms, policies, and structures.	MR4
	3.02	The intervention shall communicate sustainability in a way that complements AI adoption and and exploratory phase.	MR16, OS1, OS8
	3.03	The intervention shall be in alignment within the strategic organisational priorities.	OS9
	3.04	The intervention shall be implemented in an environment where management supports pro-environmental behaviour.	OS2
	3.05	The intervention shall be embedded in an environment that enables monitoring, data usage, and evaluation mechanisms to assess sustainability performance.	B1.06

C.2. High- and low-level requirements

Table C.2: List of high- and low-level requirements

Requirement category	ID	Requirement
FUNCTIONAL	FR01	*The intervention should provide practical guidance on pro-environmental behaviour.*
	1.01	The intervention shall provide practical guidance on prompt crafting to achieve task efficiency.
	1.02	The intervention shall provide practical guidance in model selection by task-based comparison and required performance for that task.
	1.06	The intervention shall support to reflect on the necessity of using Gen AI for a specific task.
	FR02	*The intervention should raise user awareness of Gen AI's environmental impact, including both the magnitude and consequences.*
	1.03	The intervention shall create awareness about the environmental impact of using Gen AI tools.
	1.11	The intervention shall communicate the overall magnitude and consequences of environmental impacts linked to Gen AI usage.
	FR03	*The intervention should share information about the environmental impacts of Gen AI.*
	1.04	The intervention shall inform about the energy consumption trade-off between Gen AI and alternative digital tools.
	1.05	The intervention shall inform about underlying processes, type of energy sources, and associated costs.
	1.12	The intervention shall inform users about their individual contribution to the environmental impact of Gen AI usage.
	FR04	*The intervention should provide sustainability feedback on Gen AI usage.*
	1.07	The intervention shall provide emissions-related feedback that encourages reflection.
	1.13	The intervention shall use autonomy-supportive and recurring sustainability cues to promote pro-environmental Gen AI use.
	1.21	The intervention shall adapt sustainability messaging based on user role or local context.
	FR05	*The intervention should support control with ongoing management.*
	1.09	The intervention shall reinforce user responsibility for the environmental impact of their actions.
	1.14	The intervention shall support the continuity and reinforcement of pro-environmental behaviour over time.
	1.17	The intervention shall maintain control by enabling measurement, monitoring, and baseline metrics.
	FR06	*The intervention should present environmental information transparent and tangible.*
	1.15	The intervention shall provide tangible information on the environmental impact of Gen AI usage.
	1.16	The intervention shall ensure that environmental information is transparent and accessible.
	FR07	*The intervention should ensure that pro-environmental GenAI use is accessible, simple andd easy to perform.*
	1.22	The intervention shall ensure that pro-environmental actions is accessible, simple and easy to perform.
	FR08	*The intervention should interrupt habitual and automatic prompt interactions.*

Requirement category	ID	Requirement
	1.08	The intervention shall disrupt habitual and automatic prompt interactions.
	FR09	*The intervention should strengthen social influence and group-based norms to reinforce sustainable Gen AI usage.*
	1.10	The intervention shall use symbolic recognition to incentivize sustainable Gen AI use.
	1.18	The intervention shall allow peer comparison and support to promote sustainable social norms.
	FR10	*The intervention should foster collective engagement with environmental sustainability and Gen AI.*
	1.19	The intervention shall promote social attention.
	1.20	The intervention shall stimulate conversations on sustainable Gen AI usage.
NON-FUNCTIONAL (structural)	NFR01	*The intervention should maintain utilities of high level of speed, accurate and convenience.*
	2.01	The intervention shall maintain a high level of responsiveness and speed in Gen AI interactions.
	2.02	The intervention shall maintain accuracy and valuable Gen AI outputs.
	2.03	The intervention shall preserve usability and maintain ease and convenience in Gen AI interaction.
NON-FUNCTIONAL (environmental)	NFR02	*The intervention should support integration into existing organisational structures and allign with the sustainability goals.*
	3.01	The intervention shall align with the organisation's existing norms, policies, and structures.
	3.03	The intervention shall be in alignment with the organisation's sustainability priorities and goals.
	NFR03	*The intervention should communicate sustainability in a way that complements GenAI adoption and experimentation, supported by management.*
	3.02	The intervention shall communicate sustainability in a way that complements AI adoption and and exploratory phase.
	3.04	The intervention shall be implemented in an environment where management supports pro-environmental behaviour.
	NFR04	*The intervention should be embedded in an environment that enables monitoring, data usage, and evaluation mechanisms to assess sustainability performance.*
	3.05	The intervention shall be embedded in an environment that enables monitoring, data usage, and evaluation mechanisms to assess sustainability performance.

D Evaluation

D.1. List of respondents evaluation

Table D.1: List of respondents survey - GenAI users

Interviewee #	Role
	Externally motivated users
GenAI user 1	Technology Transformation Consultant
GenAI user 6	Technology Transformation Consultant
	Unaware users
GenAI user 2	Technology Transformation Consultant
GenAI user 4	Technology Transformation Consultant
GenAI user 5	Financial Technology Consultant
	Aware users
GenAI user 3	Technology Transformation Consultant
GenAI user 7	Technology Transformation Consultant
GenAI user 8	Compliance and Reporting Specialist
GenAI user 9	Data and AI Consultant

Table D.2: List of interviewees semi-structured interviews - AI experts

Interviewee #	Role
	AI experts
1	Technology Transformation Consultant (Focus on internal GenAI deployment)
2	Technology Transformation Consultant (Focus on internal GenAI deployment)

D.2. Evaluation design

D.2.1. Survey design

Introductory Text

Thank you again for participating in my research on embedding environmental sustainability into GenAI usage. I appreciated your time and the insightful input you provided during the interviews.

Based on these interviews, I have developed targeted intervention concepts aimed at promoting more sustainable use of GenAI within organisations. A systems intervention refers to a strategic action (or set of actions) designed to influence a system to bring about a desired change (environmentally responsible use of GenAI). In this short survey, I would like to evaluate these interventions by reflecting on whether they align with practical needs. Your responses will help assess whether these interventions fulfill the key requirements identified.

Each intervention will be briefly presented and visualized. You will then be asked a series of short questions for each intervention. These questions focus on whether you believe the intervention would fulfill a set of predefined functional requirements. Since the interventions are evaluated ex-ante (they are not yet implemented), please answer based on your expectations of how the intervention would work in practice.

The survey is anonymous. By continuing, you give your consent to use your responses in the analysis of this research. Thank you again for your contribution!

D.2.2. Intervention description

Monitoring dashboard

This intervention includes a personal monthly usage threshold for each employee. The monitoring dashboard enables employees to track their emissions against this usage threshold, visualize their contributions to sustainability, understand the energy sources behind GenAI usage, and view company-wide emissions and sustainability goals.

Energy-efficient defaults

Lightweight GenAI models are set as the default option, while more energy-intensive models require an explicit selection and an additional action by the user.

Sustainable prompt builder

The widget displays real-time emission estimates per prompt using a colour-coded system (green, yellow, red) to visually indicate the environmental impact. Green represents low emissions, yellow indicates moderate emissions, and red signals high emissions. When a prompt is marked red, the system provides a "Tips" button with suggestions to reduce emissions.

Impact estimator

The widget displays real-time emission estimates per prompt using a colour-coded system (green, yellow, red) to visually indicate the environmental impact. Green represents low emissions, yellow indicates moderate emissions, and red signals high emissions. When a prompt is marked red, the system provides a "Tips" button with suggestions to reduce emissions.

Monthly feedback

Each month, users receive data on their prompt-related CO_2 emissions, benchmarked against the average of their team. They can set personal goals, track their progress, and receive tailored tips. When a user reaches their personal goal, they are recognized through symbolic rewards.

Green tips rotation

The green tips rotation are subtle modifications in the system interface. At the start of each session, users see a short sustainability tip. These tips offer simple and actionable advice to lower environmental impact.

D.3. Evaluation results

D.3.1. Results collective sustainability

Table D.3: Survey results for collective sustainability intervention package

Collective sustainability intervention package				
	Monthly feedback	#1	#2	#3
	Please indicate whether you believe this intervention component offers the following function or value:			
FR02	Does this intervention component raise awareness of the environmental impact of GenAI use?	Yes	Yes	Yes
FR04	Does this intervention component provide feedback on the environmental impact of your GenAI usage?	Yes	Yes	Yes
FR09	Does this intervention component strengthen social influence or group-based norms that support sustainable GenAI use?	Yes	Yes	Yes
FR10	Does this intervention component foster a sense of collective engagement with environmental sustainability in GenAI use?	Yes	Yes	Yes
	To what extent would this intervention influence you to act more sustainably?	Moderately	Mostly	Very much
	Green tips rotation	#1	#2	#3
	Please indicate whether you believe this intervention component offers the following function or value:			
FR01	Does this intervention component provide practical guidance on how to craft more sustainable and efficient GenAI prompts?	Yes	Yes	Yes
FR02	Does this intervention component raise awareness of the environmental impact of GenAI use?	Yes	Yes	Yes
FR03	Does this intervention component share relevant information about the environmental impacts of your GenAI usage?	Yes	Yes	No
FR08	Does this intervention component help interrupt habitual or automatic prompt behaviour during your GenAI usage?	Yes	Yes	Yes
	To what extent would this intervention influence you to act more sustainably?	Mostly	Mostly	Moderately

Table D.4: Fulfilment of requirements for collective sustainability intervention package

Requirement Type	ID	Monthly feedback	Green tips rotation
Functional	FR01	-	Yes
	FR02	Yes	Yes
	FR03	-	Yes
	FR04	Yes	-
	FR08	-	Yes
	FR09	Yes	-
	FR10	Yes	-
Non-functional	NFR02	Yes	Yes
	NFR03	Yes	Yes
	NFR04	Yes	No
	Technical feasibility	No	Yes
Summative Score		4	3

D.3.2. Results sustainable by default

Table D.5: Survey results for sustainable by default intervention package

Sustainable by default intervention package			
	Monitoring dashboard	#1	#2
	Please indicate whether you believe this intervention component offers the following function or value:		
FR03	Does this intervention component share relevant information about the environmental impact of using GenAI?	Yes	Yes
FR05	Does this intervention component help you monitor or manage your own environmental impact when using GenAI?	Yes	Yes
FR06	Does this intervention component present environmental information in a transparent and easy to understand way?	Yes	Yes
FR07	Does this intervention component make it easy and accessible to use GenAI in a more environmentally sustainable way?	No	Yes
FR08	Does this intervention component help interrupt habitual or automatic prompting behavior?	No	No
	To what extent do you think this intervention component would influence you to act more sustainably when using GenAI?	Slightly	Slightly
	Energy-efficient default	#1	#2
	Please indicate whether you believe this intervention component offers the following function or value:		
FR07	Does this intervention component make it easy and accessible to use GenAI in a more environmentally sustainable way?	No	Yes
	To what extent do you think this intervention component would influence you to act more sustainably when using GenAI?	Slightly	Mostly

Table D.6: Fulfilment of requirements for sustainable by default package

Requirement Type	**ID**	**Monitoring dashboard**	**Energy-efficient default**
Functional	FR03	Yes	-
	FR05	Yes	-
	FR06	Yes	-
	FR07	No	No
	FR08	No	-
Non-functional	NFR02	Yes	Yes
	NFR03	No	Yes
	NFR04	No	Yes
	Technical feasibility	Yes	Yes
Summative Score		2	3

D.3.3. Results sustainability guidance

Table D.7: Survey results for sustainability guidance intervention package

Sustainability guidance intervention package					
	Sustainable prompt builder	#1	#2	#3	#4
	Please indicate whether you believe this intervention component offers the following function or value:				
FR02	Does this intervention component raise awareness of the environmental impact of your GenAI use?	Yes	Yes	Yes	Yes
FR03	Does this intervention component share relevant information about the environmental impacts of your GenAI usage?	Yes	Yes	No	Yes
FR04	Does this intervention component provide emission-related feedback on your GenAI usage?	Yes	Yes	Yes	Yes
FR06	Does this intervention component present environmental information in a transparent and easy to understand way?	Yes	Yes	Yes	Yes
	To what extent do you think this intervention component would influence you to act more sustainably when using GenAI?	Mostly	Mostly	Mostly	Mostly
	Impact estimator	#1	#2	#3	#4
	Please indicate whether you believe this intervention component offers the following function or value:				
FR01	Does this intervention component provide you with practical guidance on how to craft more sustainable and efficient GenAI prompts?	Yes	Yes	Yes	Yes
FR04	Does this intervention component provide sustainability feedback on your GenAI usage?	No	Yes	No	No
FR07	Does this intervention component make it easy and accessible to act more sustainably when using GenAI?	Yes	No	Yes	Yes
FR08	Does this intervention component help interrupt habitual or automatic prompt behaviour during your GenAI usage?	Yes	Yes	Yes	Yes
	To what extent do you think this intervention component would influence you to act more sustainably when using GenAI?	Mostly	Slightly	Mostly	Moderately

Table D.8: Fulfilment of requirements for sustainability guidance package

Requirement Type	**ID**	**Sustainable prompt builder**	**Impact estimator**
Functional	FR01	Yes	-
	FR02	-	Yes
	FR03	-	Yes
	FR04	No	Yes
	FR06	-	Yes
	FR07	Yes	-
	FR08	Yes	-
Non-functional	NFR02	Yes	No
	NFR03	No	No
	NFR04	Yes	No
	Technical feasibility	Yes	No
Summative Score		3	4

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