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Navigating the Green AI Trade-off: A Qualitative Exploration of AI Practitioners' Cognitive Thresholds and the Role of Model Cards

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ABSTRACT:
The attainment of global sustainability targets has suffered a significant setback owing to the unprecedented growth in the adoption of artificial intelligence (AI) technologies both by the organization and the society at large. Earlier efforts to tame this threat have largely ignored the impact of human element in attainment of sustainable AI with preference for algorithm optimization and hardware efficiency. Green AI achievement is not immune to the multitude of daily AI model selection decisions made by AI practitioners and the continuous sustainability exclusion from these model selection criteria threatens an unavoidable surge in global carbon footprints. It is based on this background that the thesis seeks to answer two key questions, first, how do AI practitioners navigate the Green AI trade-off within their cognitive limits and secondly, how can Green AI model cards close the operationalization chasm that is the gap between awareness and action of Sustainable AI.

Thus, this thesis focuses on promotion of Green AI adoption AI practitioners by applying a dual synthesis of theory of bounded rationality and Diffusion of Innovation. The "how" of the problem is diagnosed by using the bounded rationality theory which provided explanation for the "satisficing" behaviors of AI practitioners due to information overload when making AI model selection decisions and the diffusion of innovation theory complemented the bounded rationality by providing the remedies for reversing the ugly trend through the redesigning of the decision making artefact that is the Green AI model card.

This study uses a qualitative approach by conducting a semi structured interview with eight purposively selected domain experts. First, the thesis established the current model selection practice among AI practitioners then proceeded to introduce the redesigned Green AI model card as a research stimulus to ascertain its effectiveness in bridging sustainability exclusion and finally the determination of impact of compatibility attribute in transforming sustainability into routine habits for practitioners. Reflexive thematic analysis of the data revealed three important findings to Green AI operationalization. First, practitioners "satisfice" without sustainability that is they select good enough AI models solely based on performance and accuracy related parameter. Second, contextualization and color coding of environmental metrics on the redesigned model cards enables practitioners to overcome their bounded awareness by triggering their system 1 thinking. Third, all the participants prioritize compatibility of Green AI model card to their existing workflow as a prerequisite for speedy adoption. The participants also inadvertently offered inductive themes which provide novel strategies for overcoming institutional barriers to sustainable AI adoptions, such recommendations include CSR Framing and updated regulations from policy makers to enforce compliance.

KEYWORDS: Green AI, Model Cards, Sustainability, Cognitive Threshold, Diffusion of Innovation, Bounded Rationality, AI Practitioners

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Abbreviations

AI: Artificial Intelligence
BR: Bounded Rationality
CO_2: Carbon Dioxide
CO_2eq: Carbon Dioxide Equivalent
CPU: Central Processing Unit
CSR: Corporate Social Responsibility
CTM: Cascading Threshold Model
DOI: Diffusion of Innovation
DSL: Domain-Specific Language
ESG: Environmental, Social, and Governance

GPT: Generative Pre-trained Transformer
IEA: International Energy Agency
kgCO_2e: Kilograms of Carbon Dioxide Equivalent
LAGSSE: Lean, Agile, and Green Sustainable Software Engineering
LLM: Large Language Model
MWh: Megawatt-hours
NeurIPS: Neural Information Processing Systems
SDG: Sustainable Development Goals
SOTA: State-of-the-Art
TWh: Terawatt-hours
YAML: Yet Another Markup Language

1 Introduction

1.1 The Green AI Imperative in 2026

Artificial intelligence (AI) has enjoyed tremendous acceptance in the industry with its tentacles spread across different organization functions. This acceptability surpasses the business arm alone even the populace at large has embraced this technology. However, this growth has not been without its consequence, the growth came with a significant price especially regarding the environmental cost of AI adoption which seems to have constantly kept pace with the technology growth itself. The energy and water demand to run AI technologies are enormous couple with the amount of carbon emission from its usage which all pose a threat to the attainment of carbon neutrality targets among countries globally especially if urgent action to reverse this adverse trend is not embarked upon soonest. Similarly, there is the unending race among the top AI companies to develop the state-of-the-art (SOTA) AI models, this contest makes the pursuit of achieving cutting-edge accuracy the sole objective of these organisations with minimal regard to the environmental implications of the resulting competition among the firms. This necessitate the development of the sustainable AI or Green AI field whose aim is to introduce environmental consciousness into the development of AI solutions away from the practice of accuracy at all costs, the so-called Red AI era (Schwartz et al., 2020, p. 55,56; Verdecchia et al., 2023, p. 101).

The topical issue of achieving sustainable AI cannot be overemphasized. One reason for this claim is the continuous investment devoted to the building of additional data centers globally, a need which arose from the desire to satisfy the energy greediness of AI technologies, for example, the electricity usage by data centers is projected to exceed more than twice the 2024 figure (415 terawatt-hours) by the end of this decade representing about 3% share of the global usage (IEA, 2025). To shed more light on this, the energy demand of individual model themselves are significantly huge, for instance, it would require 1287 mWh to train GPT 3 which represent a 25,000 times increase in training compute when compare with the previous version of GPT and its carbon emission is approximately 552 metric tons of $CO2$ (Patterson et al., 2022; Strubell et al., 2019).

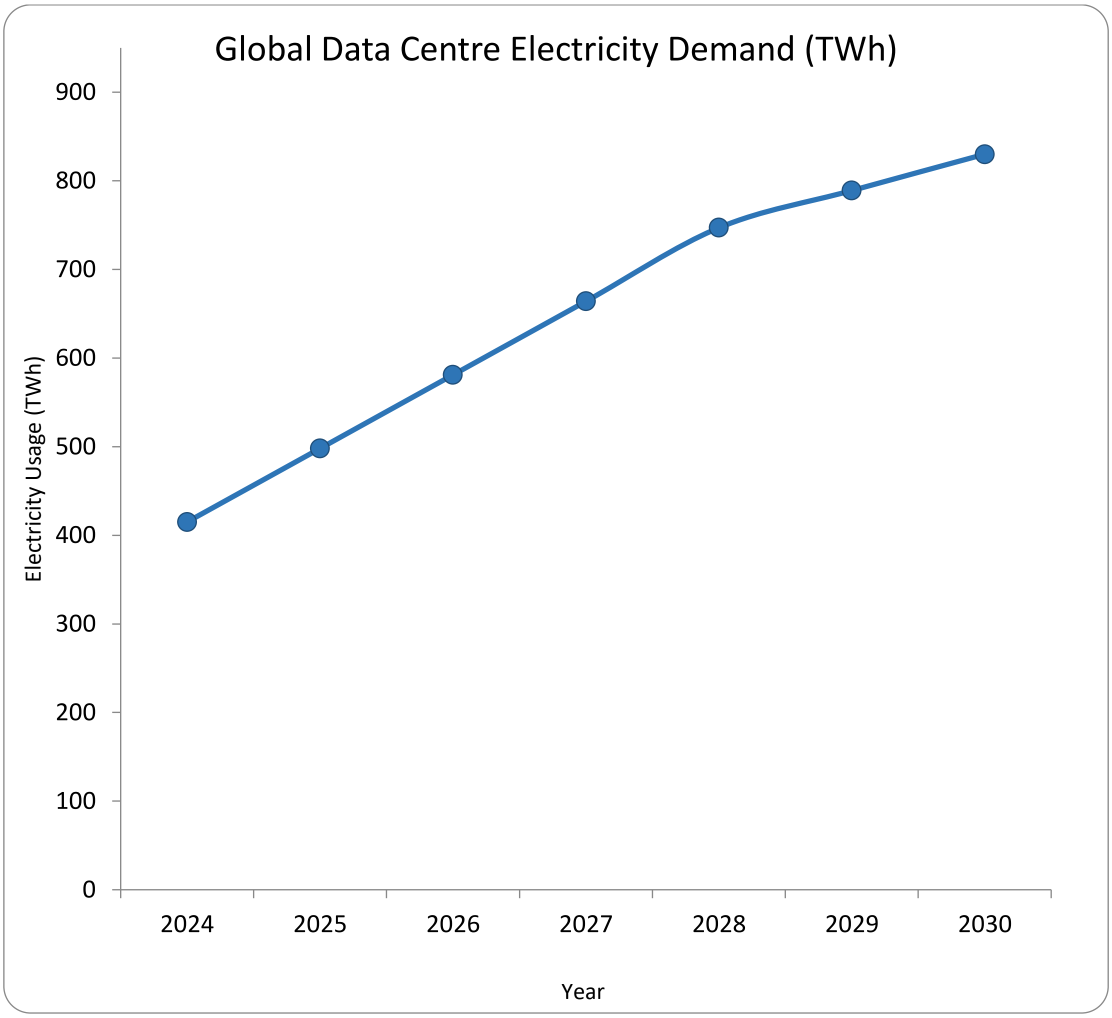

Figure 1: Projected global data centre electricity consumption, 2024–2030, showing more than doubling of demand driven by AI workloads (IEA, 2025).

Another source of concern around this technology is related to the continuous decline in openness among key AI players about the negative influence of their specific models on the environment. Survey revealed that openness declines by 18% in just one year that is between 2024 and 2025 which is disappointing when one considers the fact that investment in data centres during the same period continues to proliferate and this same increase in the number of data centres has translated to additional pressure on both the electricity grid and prices (Wan et al., 2025). It is unexpected that despite the improvement in awareness around sustainable AI, the desire to be open about statistics concerning AI models' environmental impact would still be lagging.

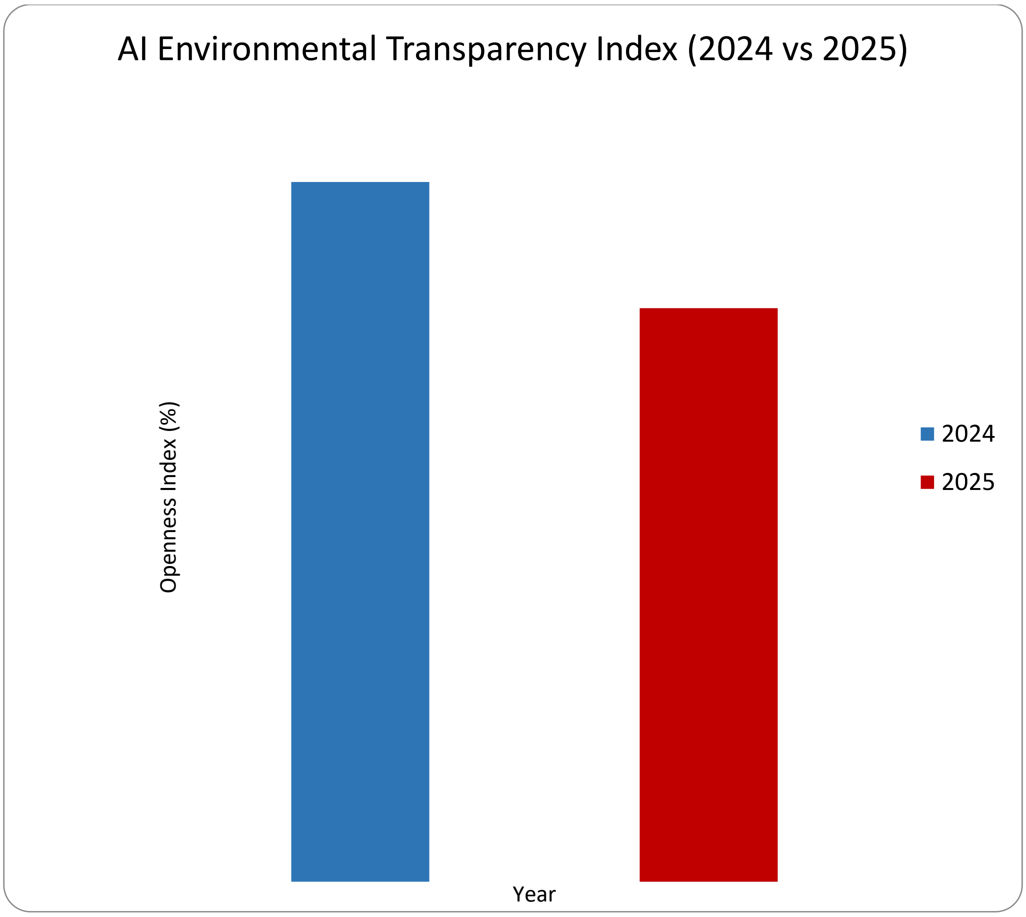

Figure 2: Year-over-year decline in transparency regarding AI environmental impact, recording an 18% reduction in openness between 2024 and 2025 (Wan et al., 2025).

Yet more recent findings show the possibility of achieving significant energy savings without significant impact on accuracy. For example, (Naser, 2023, p. 13) found opportunity for significant reduction in energy consumption between 23% to 99% by AI models provided users would employ specialize model for their tasks. These findings clearly demonstrate that the bigger is not always the better model and sometimes based on specific activity to be executed, a small model may be sufficient. Moreover, this finding was similar to earlier outcome of (A. E. I. Brownlee et al., 2021, p. 11,12) whereby they showed that a marginal sacrifice of 1.1% decline in accuracy could result massive energy savings up to 77%. Therefore, prioritizing more sustainable AI models does not usually involve forgoing accuracy.

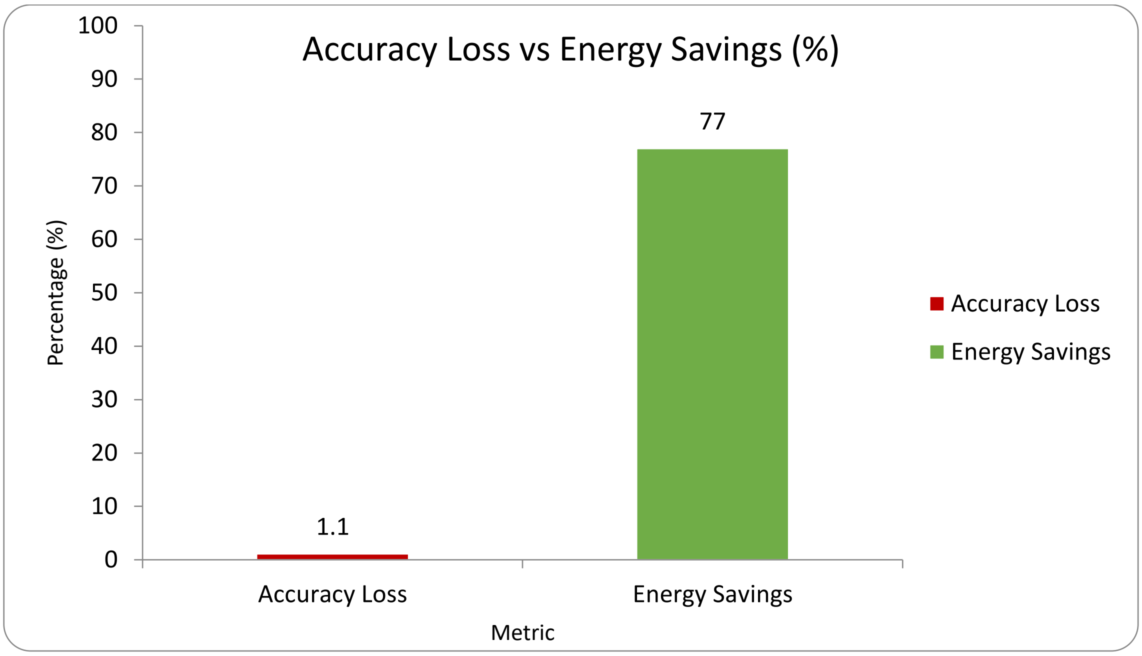

Figure 3: Trade-off between model accuracy loss and energy savings, demonstrating that a 1.1% accuracy reduction enables up to 77% energy savings (Brownlee et al., 2021).

The Green AI landscape is therefore defined by three interrelated themes. The current AI technologies continue to demand massive amount energy and investment while model sustainability transparency is on a downward spiral even though there are room for significant improvement. This therefore necessitate the need to investigate the reason sustainability is at the back foot despite the awareness and how to project it at the front burner of AI selection/ decision making.

1.2 The Operationalization Chasm

Although studies have shown AI practitioners familiarity with sustainable AI practices, this knowledge is yet to translate into action. The numerous research efforts into sustainable AI have yielded results by drawing the AI community attention to the environmental impacts of their model. Starting with the work of (Strubell et al., 2019) which provided the emission statistics associated with the training activities of different AI models and then proceeded to compared this figure with emission from other technologies that are familiar from our everyday life activities, for example, we can deduce from their work that a single LLM emit as much carbon emission as a single car in its entire lifetime, Schwartz et al.'s (2020) further amplify the conversation by providing Green AI principles to be followed by the research community, more so, (Verdecchia et al., 2023) discovers that sustainable AI has become one of the central theme in academic conferences and companies at the fore front of this AI race have signified their readiness to ensure reduction in carbon emission from their models.

On the contrary, the workflow for selecting AI models has remained unchanged despite the increase in the level of awareness around Green AI. For instance, although the process of conducting environmental impact assessment exercise typically requires the provision of inputs including carbon and water metrics, unfortunately this information are often not readily accessible to the model users although some actions have been taken in this regards by Hugging face through their AI energy score initiative the accessibility remains an issue (Jouneaux & Cabot, 2025, p. 3,5). One key answer to this challenge is the provision of a streamline workflow whereby the description of sustainability metrics through a medium such as the model card is promoted among decision makers in order to their action towards sustainable AI but studies in this area are still in their nascent stage (Jouneaux & Cabot, 2025, p. 1,7; Mitchell et al., 2019, p. 1)

It is therefore this gap between awareness and action that I labelled as operationalization chasm. This operationalism chasm exists for three major reasons, firstly, environmental considerations were treated as an afterthought while model accuracy remains the focal point of the selection criteria for AI models. This practice is synonymous with what is obtainable in the broad field of software engineering whereby functionality and time to market remain at the core of decision making (Zada et al., 2025, p. 1). Secondly, the absence of standardization of environmental impact metrics makes the process of embedding sustainability into the decision process a herculean task even for green oriented practitioners as comparison across different models is limited (Jouneaux & Cabot, 2025, p. 1,6). Finally, while tools exist for carbon emission estimation at the training phase and they are functional, there is lack of comprehensive tools that include both the training and the inference stage (Duran et al., 2024, p. 1,3).

An explanation for the occurrence of the operationalization chasm in Green AI is because of the disparity between the cognitive constraints of decision makers--the product managers responsible for making AI models decision and the format of the sustainability metrics available to them during the selection or development process. For example, a product manager may find environmental impact statistics in form of kilowatt per hour unrelatable unless a comparison to another familiar benchmark is provided. This is in alignment with (Simon, 1955, 1972) which posits that decision makers operate within bounded rationality which results in what the author termed satisficing, this means the process of opting for a good enough option rather than choosing the most optimal one. This implies that decision makers are bombarded with large volumes of information under a limited time to deliver on their responsibilities while there is a cap on the amount of information the brain can process per time. Moreover, when information is presented in a complex manner, there is tendency for it to fall below the cognitive threshold during decision making process even though the decision maker is aware of the importance of such information (Kahneman, 2011).

Bridging this chasm extends beyond applying a technical solution or employing a moral appeal. It requires the creation of a process that smooths the decision-making process by reducing the amount and complexity of information and presenting the same in an easy-to-understand approach to decision makers. Hence the desire to adopt a dual lens of bounded rationality and diffusion of innovation, the former explains the cognitive impediments and the latter identify the attributes of the tool to address the impediments.

1.3 Research Gap, Questions and Objectives

While Green AI has received considerable attention among researchers in recent times, the efforts have been concentrated on the narrowed aspect of enhancing technical efficiency. Although this approach has yielded diverse level of success ranging from 13% to 115% in energy savings much of this work has been done exclusive of the industry (Verdecchia et al., 2023, p. 2). Notwithstanding the gain of these previous works, the human or behavioral aspect of model selection remains unaddressed. Salient questions such as the reason product managers, despite the high awareness of the environmental impact of AI continue to favor the energy greedy models and whether intervention tools such as the sustainability model cards assist would translate to better inclusion of sustainability criteria in decision making.

Despite the importance of these questions, it has been ignored by Green AI literature. This is a topical issue that cut across different fields such as Sustainable AI and cognitive psychology. Moreover, the Green AI domain is ripe for the application of theories such as bounded rationality and diffusion of innovation to enable the closure of the current gap between knowledge of green principles and the application of same. Bounded rationality will amplify our understanding of the barrier inhibiting the adoption of sustainable AI while diffusion of innovation would highlight the attributes that sustainability tools specifically the model cards must possess to improve decision making.

The application of these theories has practical implications for Green AI adoption. Recent studies are recommending the use of sustainability model cards and benchmarking to improve AI energy efficiency but these interventions risk being inefficient, especially if the understanding of the cognitive barrier faced by the decision makers are omitted from the equation. For instance, providing raw figure of AI models environmental impacts could further exacerbate the potential for product managers to experience information overload. Excessive information has been shown to inhibit effective decision making (Chugh & Bazerman, 2007). Consequently, this theory employs a dual lens understanding of the combination of bounded rationality theory and diffusion of innovation to explain why adoption of Green AI remains low and how to upturn this trend.

Research Questions

The anchor thesis research questions goes thus:

i. How do AI Practitioners navigate the Green AI trade-off in their cognitive limits?

ii. How can Green AI Model Cards bridge the gap between awareness and action that exist in Sustainable AI domain?

Research Objective

i. To examine the complexity–cognition interaction in AI model selection.
ii. To assess the role of observability in overcoming bounded awareness.
iii. To determine bridging mechanisms for Green AI operationalisation

1.4 Definitions and Scope of Study

Green AI

Green AI is defined as the redefining of AI development goals inclusive of sustainability, it is a shift from the accuracy at all cost mindset towards the development of a more environmentally conscious AI and it entails evaluating the marginal accuracy improvement in AI development vis-à-vis the computational resources required to achieve same (Schwartz et al., 2020, p. 3). Green AI should not be confused with Green by AI whose focus is on the attainment of sustainability in other domains by relying on the potential of AI technology (Gutiérrez et al., 2025, p. 1). In this thesis, Green AI is limited to the daily micro decisions made by AI practitioners that include sustainability as against development of optimized algorithm to reduce AI carbon footprints.

Model Cards

Model Cards are “short documents accompanying trained machine learning models that provide benchmarked evaluation in a variety of conditions” (Mitchell et al., 2019, p. 220). This implies that every AI model is accompanied by documentation providing crucial information relating to its training and performance. Most model cards are exclusive of sustainability information, however recent efforts by Jouneaux and Cabot (2025) have provided framework for sustainability-oriented model cards. Earlier model cards are analyzed for their ineffectiveness in promoting sustainability and a redesigned Green AI model card was introduced to support decision making

Sustainability

Sustainability in this thesis is restricted solely to environmental sustainability and its application to AI technologies (Strubell et al., 2019; Patterson et al., 2022; IEA, 2025). The investigation is limited to the anticipated carbon emission at the inference stage of AI usage in the organization and other broad sustainability areas such as ethical AI are excluded.

Cognitive Threshold

Cognitive Threshold refers to the limit on human mental processing ability due to excessive information at their disposal. (Oladeji, 2026, p. 3) discovers that this limitation usually resulted in reliance on decision support tools. Kahneman (2011) dual processing theory divided cognitive information processing into two distinct systems including system 1 and system 2. Simon 1972 found that under time pressure and information overload, decision makers often defer to adoption of simple heuristics for decision making.

Diffusion of Innovation

Diffusion of Innovation theory introduces five main attributes that drives adoption of a new innovation. This thesis is restricted to three of the attributes including observability, complexity and compatibility and the application of these attributes to the redesigning of the model card to improve the visibility of environmental metrics, thereby leading to adoption of more sustainable AI models. Siyal et al. (2023) confirmed the significance of compatibility for technology adoption ($\beta = 0.287$, $p = 0.000$), while Bonisoli et al. (2024, p. 5) established observability as a prerequisite for adoption to occur.

Bounded Rationality

Bounded Rationality is a theory which states that the assumption that decision makers are rational decision makers is unfounded but rather they often “satisfice” due to unfeasibility of assessing all the criteria and options available at their disposal when making decision. Satisficing refers to the process of settling for the first option that meets predefined criteria which may not be the most optimal solution available (Simon, 1955, p. 114). Simon (1972, p. 163) further solidifies the satisficing behaviour through showing that decision makers rely on simple heuristics when faced with deluge of information Beil et al. (2025, p. 14) demonstrates that when task complexities vary across different phases of their execution, the quality of humans’ decisions suffers terribly. This thesis applies bounded rationality theory to understand the load pressure faced by AI practitioners and its relationship to sustainability exclusion from decision making.

AI Practitioners

AI Practitioners are organization employees saddled with the responsibility of selecting and deploying AI models in their respective organizations. The alternative title may include AI product managers, machine learning engineers, data scientists and other related portfolios associated with the development of AI products and solutions in the organization.

1.5 Structure of the study

This thesis is arranged in chronological order from chapter 1 to chapter 5. The thesis is divided into five chapters starting with introduction to findings and conclusions. In the first chapter, the urgency of action to address the gap between awareness of Green AI and implementation of the same was brought to the fore. The research questions and accompany objectives were stated and the current lacuna in the form of evaluation of human element role in attaining Green AI was discussed.

The second chapter addresses the extant literature on Green AI and the synthesis of the two dominant theories that guided the research. The chapter started by establishing the current situation of Green AI debate in the literature and then proceeded to discuss both the bounded rationality theory and diffusion of innovation theory and the fusion of the two to gain an in-depth understanding of the exclusion of sustainability from Green AI and ended with the presentation of the research framework.

The third chapter provided the research methodology and the philosophy underpinning this thesis. The thesis adopted the interpretivist approach where the researcher participated in deriving meaning from the interview process. The data was collected through semi structured interviews with eight AI practitioners with the use of Green AI model card to determine the potency of the artefact. Reflexive thematic analysis was employed for data analysis and interpretation.

Chapter 4 presents the findings organised around three themes: the complexity-cognition barrier, the observability-awareness bridge, and the compatibility-heuristics integration. It provides response to the research questions and ended with the development of the exploratory framework that guides the operationalization of Green AI.

The final chapter situates the findings among earlier research efforts in the field of Green Ai and goes ahead to provide the different identified participant threshold from the studies. Furthermore, it provided useful recommendations for diverse stakeholders in promoting sustainable inclusion in AI model selections. Literature Review

2 The Green AI Movement

2.1 Green AI Domain Literature

2.1.1 Defining the Movement

The origin of the Green AI field can be traced to the need to address the initial obsession with attaining topmost accuracy in different AI models. Thus, the resulting AI models were inefficient based on the production cost and efficiency. This informed the work of (Schwartz et al., 2020), where the authors classify the era in which accuracy was the defining objective as the “red AI era” and they advocated for the need for a shift to Green AI which entails introducing cost and efficiency as important factors to consider in AI research. This shift is essential otherwise the cost of AI development will keep ballooning especially as the red AI race has reached a point whereby the cost of high impact AI research is growing at a superior rate than Moore’s Law (Schwartz et al., 2020, p. 4). For example, in a span of only 8 years, the training cost for AI projects increased over 300,000 times which is visible in the accrued training cost for XLNet which was over $60,000 in 2012 and the cost to redevelop Alphago, the Go player AI algorithm in 2020 was placed at over $35m (Schwartz et al., 2020, p. 9). Schwartz et al., (2020, p. 3) defined Green AI as any AI developing endeavour that led to new result while taking abreast of other considerations including cost and resources consumed.

It is however important to distinguish between Green AI and Green by AI. The former is associated with the goal of energy optimization for AI while the latter involves how AI can facilitate sustainability (Gutiérrez et al., 2025, p. 1). Despite the urgency of shifting to Green AI, 27% of the paper published failed to account for the method employed to quantify energy use in their work (Gutiérrez et al., 2025, p. 12) even though it is feasible to do so. For instance, the estimated carbon dioxide equivalent (CO_2eq) from the newest set of large models (LLM) are in about 100s tonnes while a lower amount of about 2 tonnes CO_2 equivalent is required to be generated annually by one person to ensure global warming remains at below the target rate.

2.1.2 The Performance-Sustainability Synergy

The first chapter discusses the current operationalism chasm that exists in sustainable AI where there is disparity between awareness of sustainability and the corresponding action to address it. This chasm exists due to the assumption by practitioners that factoring sustainability into model selection decisions requires sacrificing accuracy but findings from the literature disputed this assumption. For example, a research endeavour to develop a simplified algorithm in the form of logistic regression resulted in improvement in sustainability without sacrificing accuracy. (Sworna et al., 2023) used logistic regression to attain a slight improvement in accuracy of 0.38% but this improvement is in addition to realization of other green benefits including overall reduction of CPU core hours and model size by 95.91% and 97.65% respectively with the training time also collapsing by 3 folds (Sworna et al., 2023, p. 5). Thus, the authors discovery shows the possibility of achieving a twin objective of sustainability and accuracy improvement at the same time and the is an accurate example of Green in AI, that is making AI more sustainable.

In another case, the use of data centralization strategies proved consequential for emission reduction. (Spillo et al., 2025) using an example of book recommendation task algorithm they developed showed that the algorithm resulted in significant reduction in emissions by 43.45% with a minimal decline in accuracy of 3.72% (Spillo et al., 2025, p. 9). Although accuracy declines in this instance, (A. E. I. Brownlee et al., 2021, p. 32) opined that in functionality or accuracy acceptable limit in machine learning algorithms should be set within a range of values and not viewed as a static target to be met.

Similarly, significant results have been achieved using EATL-A framework whose proponents are (Dwivedi & Islam, 2025). This framework ensures that sustainability is an integral part of the AI model training and that each training loop is optimized in real time depending on the feedback thereby allowing energy conservation (Dwivedi & Islam, 2025, p. 29) and this approach has translated to energy savings of 27% and reduced training time of 40%. This differs from the current AI model training practices whereby settings remain unchanged from the beginning to the end resulting in wastage. In the author's case, their sustainability adjusted framework has translated to improved energy savings of 27% with 94.5% accuracy (Dwivedi & Islam, 2025, p. 23)

2.1.3 The 2026 Landscape

The Green AI field has continued to receive recognition with its status being elevated from a mere concept to actual discipline. This is evident in the number of publications in this field which has grown from a mere 9 published papers in the year 2019 to 20 in the year 2020 after the seminal paper of Strubell et al. (2019), which calls the research community attention to the huge carbon footprint of the different AI models and provided a comparison table of their emissions against other relatable technologies. Other important milestones recorded in the field included expansion of the research topics to 13 and the research efforts in the field have yielded different results from a mere 13% at the lowest limit to the upper limit of 115% in energy savings (Verdecchia et al., 2023, p. 17).

Gogineni et al. (2025) broadened the sustainability lens beyond achieving sustainability in the training phase. They opined that earlier studies exclude the overall life cycle of the hardware employed for AI development and that the authors solely concentrated on the training phase even though sustainability is essential across board (Gogineni et al., 2025, p. 31) .

2.2 Model Cards as Transparency Mechanisms

The introduction of the model card in 2019 was a major milestone for AI documentation. Model cards are "short documents accompanying trained machine learning models that provide benchmarked evaluation in a variety of conditions" (Mitchell et al., 2019, p. 220). One expectation from its introduction is the possible impact of the model card availability on the decision-making practices of AI models and whether it would bring sustainability of AI to the front burner. However, the existence of the operationalism chasm identified in section 1.2 indicates that this has not happened and this section goes ahead to show that its ineffectiveness lies in its current structure, which is primarily checklist driven, this fit into what Zhou et al. (2026) regarded as a situation whereby the decision maker operating mostly under bounded rationality become overwhelm by the volume of information at their disposal.

The pioneering model card was introduced by Mitchell et al. (2019) with the purpose of promoting transparency in AI model reporting and the card was subdivided into nine unique categories with no dedicated section to environmental sustainability. Noticing this lacuna, Jouneaux & Cabot, (2025) proceeded to develop a modified “sustainability model card framework” whereby the provision of sustainability metrics is mandatory specifically energy consumption and carbon emission are required. In addition to these two fundamental metrics, they added the need to provide water consumption information into their model and ensure that the information requirement is inclusive of the inference phase which have been largely ignored in the previous Green AI research. However, their model card is still in the infancy stage, and its application is yet to be tested in the industry, and the checklist manner of their framework suggests that its adoption may remain insufficient to close the existing operationalization chasm.

Table 1: Sustainability Model Card framework proposed by Jouneaux and Cabot (2025)

Section	**Technical Purpose (DSL / YAML Role)**	**Unique Contribution**
Metadata	Encoded as a meta_data YAML mapping block. This represents the link between the newly developed sustainability card to the original model card framework developed by (Mitchell et al., 2019) for combined automated analysis.	This is the first attempt to introduce a typed identity layer into the model card design, and it enables seamless filtering of models by type ahead of energy efficiency comparison
Training	Encoded as a training YAML block. The Training class inherits from the abstract Computation class, which associates it to Water Consumption, Carbon Emissions, Energy Consumption, and Platform objects.	The inclusion of water consumption level set the card apart from earlier model cards including the popular Hugging face extension. Water consumption has been consistently overlooked by earlier model cards.
Inference	Encoded as a YAML inference sequence, this is a list of task blocks, one per supported inference type. The Task class inherits from Computation ensuring structural consistency. Because each task type is a controlled enumeration drawn from the AI Energy Score taxonomy.	The card allows for model selection based on the specific task to be completed. This approach stems from the fact tasks differs from one another based on the energy consumption requirement and reporting a sole score for 1000 request such as the HuggingFace AI Energy Score may not represent the best practice for optimum sustainable decision

Platform	This is categorized as a top-level YAML list apart from the training and inference blocks and it is referenced by name within them and it ensures avoidance of redundant duplication when the same infrastructure is used for both training and multiple inference tasks.	The sustainability model card is inclusive of energy mix metric indicating the ratio of renewable energy versus fossil fuel thereby enabling optimum model deployment location.

Another reason for inability of transparency mechanisms such as model cards to address the existing gap between awareness and action is documentation fatigue. Arnold et al. (2024) introduced this concept in which documentation fatigue relates to the insufficient collaboration and understanding between information providers and their corresponding users, for example, they discovered that only 16% of AI documentation is produced for decision makers as against a considerable 64% documentation for AI developers. This disparity reflects a key weakness whereby model cards are developed by engineers for engineers which explain their focus on technical details which are naturally more complex for a non-technical AI Practitioner to understand instantly. Moreover, Oreamuno et al. (2024, p. 1) argues that tools will be more useful if their usage procedure is unambiguous. Thus, Crisan et al. (2022) concluded that model cards effectiveness would be enhanced by making their metrics more relatable and familiar to the decision maker allowing them to make comparison among decision variables which otherwise would have been impossible.

Furthermore, the limitation on tools usability can be traced to three different reasons. The first reason for tool's ineffectiveness is information overload, for example, the output from framework such as eco2AI proposed by Budennyy et al. (2022) while they were very impressive and rigorous especially as it concerns carbon emission tracking, the framework's output is currently provided in the form of raw metrics which greatly limits their usefulness for decision making. Secondly, tools that present information in static and unrelatable format are incapable of assisting decision makers overcome their satisficing behaviour and improving their system 1 thinking capability, therefore a dynamic tool format should be prioritized. The third reason is the workflow compatibility, tools that require huge initial investment for adoption have generally shown to attract reduced interest from users regardless of their merit (Robertson & Samy, 2019, p. 14).

The idea of reducing simplification of transparency objectives to a series of checklists to be ticked has been frowned upon in literature because it creates a false sense of accountability while the actual user’s familiarity with the topic of discussion decreases (Bolte et al., 2022, p. 4). This often creates a complex situation whereby a process that was introduced to improve decision making by making an otherwise invisible factor such as sustainability metrics visible could translate into a bureaucratic process that decision makers feel compelled to do. Hence, this led to the development of the concept Explicability by Osifo (2023) where the author states that artifacts dedicated to the promotion of transparency must serve a higher purpose of ensuring that users educated and informed not just to facilitate declaration of information only. This is why the information to be provided to the AI Practitioners needs to extend beyond a raw metric of "1287 MWh training energy" which is meaningless except a context or similarity to everyday technologies is made to enable them progress to the stage of ethics of desirability where behavioral changes occurred easily (Bolte et al., 2022, p. 8).

Meanwhile, Zhou et al. (2026) already warned about the danger of transparency becoming a chore if strategic intent is not built in. The authors focus on ESG disclosure and are of the opinion that the adoption of transparency artifacts must be followed by keen understanding by the stakeholders otherwise they will become overwhelming (Zhou et al., 2026, p. 7). This implies that such information are usually ignored, and this aligns with the concept of bounded rationality whereby excessive information may result in the process of abandoning such information entirely during decision making and reliance on already familiar factors by the decision makers which lead us back to the established accuracy first paradigm in the first chapter. Thus, Zhou recommended that an artifact which desire to be effective must focus on being more strategic by guiding the users to what is important rather than being overly comprehensive with excessive details that overwhelm the users.

The identified inadequacies of transparency mechanisms including the model cards point to one important fact, the need to reimagine the models' cards not just as a compliance artifact but also as a decision support instrument. Accordingly, Crisan et al. (2022) created an interactive model card which allows the adjustment of different settings for fairness and the visibility of each setting's impact on fairness in real time thereby making otherwise invisible tradeoffs evident.

However, employing a dynamic model card is just one side of the coin and it's insufficient to close the operationalization chasm. To maximize the effectiveness of model cards, it must be integrated as part of the workflow and not function as a standalone activity to be completed. Moreover, previous literature found that organizational structure which allows cross functional collaboration and executive management buy-in are essential for achieving a successful integrated reporting (Robertson & Samy, 2019, p. 15). Operationalization chasm that exists currently is not due to the absence of transparency tools but rather a misalignment between its design and the cognitive reality of the decision makers. Thus, its design must progress from its focus on excessive information that overwhelms the decision maker such as the AI Practitioner to a tool that moves decision making from system 2 to system 1 where sustainability impact is prominent without much effort to the decision maker.

Table 2: Comparative Analysis of Model Card Frameworks

Name / Author(s) & Year	Key Attributes	Implementation Challenges
Model Cards for Model ReportingMitchell et al. (2019)	i. It's a brief document with nine unique sections prepared for every trained ML model ii. It allows for intersectional group comparison for example age and race	i.The model card does not include environmental impacts information is missing on the card ii.Information overload arising from the checklist nature of the document
eco2AIBudennyy et al. (2022)	i. It's an Open-source package that permits tracking energy consumption ii. It aims to provide the most optimal solution with cheapest computational cost iii. Its motivation lies in attainment of Green AI objectives	i. Output provided in raw metrics form thereby limiting its usefulness for decision making ii. There are no reference points to enable easier comparison of different models iii. Contextualization is missing hence the prevalence of information overload arising from interpretation of raw output

Interactive Model CardsCrisan et al. (2022)	i.Interactive format augmenting static model cards with exploration affordances ii. It allows real time Introduces observability in real time into model cards iii. Fairness level can be adjusted with impact visible in real time iv. It prioritizes human-centered design approach for analysts without formal ML training v. It uses relatable and familiar metrics for non-expert decision makers	i. Absence of environment impact information ii. Ineffective in closing the chasm since environmental information is omitted on the card
GAISSALabel (Energy Label for ML Models) Duran et al. (2024)	i. Adopted simplified labelling using consumer energy labels to indicate energy efficiency ii. Reduce complexity barrier by making information relatable regardless of practitioners' background	i.Comprehensive environmental footprint information is not included, data provided is limited to energy consumption only

EnvCard (Environmental Impact Card) Nagi (2025)	i. It’s a standardized environmental impact reporting system ii. Coverage is inclusive of lifecycle environmental assessment and not limited to carbon iii. It Enhances the fomating of the model card thereby improving visibility. iv. Allows comparisons of models regardless of user’s expertise or experience level	i. Comprehensive lifetime measurement is technically demanding and resource-intensive ii. Adoption requires industry-wide standardization agreement and coordination
Sustainability Model Cards Jouneaux & Cabot (2025)	i. Amended model card framework to include sustainability as a core requirement ii. Ensure coverage of both inference and training stage of AI	i. The framework is nascent which implies that its effectiveness in the industry remains unknown ii. Does not include contextualization of sustainability metrics for non-technical practitioners

	iii. Included metric such as water consumption which is regularly overlooked by other model cards	iii. Compatibility with existing workflow is essential for adoption

2.3 Operationalization Chasm

Section 2.2 shows that the current design of model cards contributes to their inability to influence AI Practitioners' ability to make sustainability conscious decisions. However, this claim represents only one side of the coin, therefore this section goes ahead to further expand the argument to include the behavioral paradox that exists in the Green AI domain whereby the model selection process disregard environmental cost of AI usage despite the availability of such information. Tarka (2017) described this gap as the knowledge action gap and this represents a situation in which managers inaction about an issue does not indicate lack of information but rather a general attributes shown by managers operating under a bounded rationality. Consequently, this section provides empirical proof that AI model selection process places minimal importance on sustainability and the reason for this occurrence.

Liang et al. (2024) provides convincing evidence that AI model cards relegate the importance of sustainability. The authors in their study of 32,111 AI model cards on the Hugging face platform discovered the huge disparity that exist in the number of data provided for different segments of the cards, for example while training data were available in 74.3% of the cases, it is disturbing that environmental impact metrics were only provided in just 2% of the cards. To further test the veracity of their findings, the authors minimize the study object to the top 1k most downloaded model cards, yet the sustainability metrics were only provided in just 3.7% of the cases (Liang et al., 2024, p. 3,4) . This minimal rate of sustainability disclosure across the huge collection of model cards points to the fact that sustainability has been relegated to back position.

Moreover, this neglect of sustainability metrics becomes worrisome because the environmental cost of AI usage is known and documented. Strubell et al. (2019) in their works did not just provide statistics on the negative impacts of AI on the environment, they further emphasized their points by benchmarking these figures against those of other everyday technologies. For example, training just one BERT model emits as much as the emission as that from a trans-America 126k CO2 which is equivalent to the entire carbon footprint of five cars in their lifetime, this cost scale up when it is a transformer whose emissions has been shown to equal (Strubell et al., 2019, p. 1,4). However, the author's discovery has not impacted on the workflow for AI selection and sustainability metrics remain on the sideline.

Perhaps one reason for this is the fact that accuracy metrics of different AI models enjoy prominence today and it is the parameter that continues to dominate the various AI models leaderboard while manual digging is required to obtain sustainability metrics if they are provided at all. Arnold et al. (2024) found that the usefulness of checklist is severely limited because their setup requires stressful collation of information. This implies that AI Practitioner faces additional stress of searching for sustainability information as it is not embedding in their workflow which further confirms the existence of bounded rationality because when information is not readily available to be processed, decision makers often become "satisficer" that is resulting to what is familiar and in this case the accuracy metric.

Another factor contributing to the persistence of the operationalization chasm is the limited number of tools available to measure sustainability metrics across different AI phases. For instance, while the inference phase of AI usage has been documented to be responsible for the bulk of the energy cost yet it energy consumption figure continue to be missing from model card while the same is only provided for the training phase whose energy usage is approximately 10% of the total cost (Desislavov et al., 2023, p. 2,3) . Moreover, providing this figure would be challenging as there is no tool that currently covers comprehensively the energy efficiency of AI models across the two phases of inference and training (Duran et al., 2024, p. 1). Thus, this tool inadequacy results in what researchers has termed the “intentions vs reality gap”, Xie and Iyer, (2025) discovered that the adoption of sustainable options is not directly related impacted by a customer’s having positive disposition towards sustainability. Therefore, the absence of tools to showcase the energy demands for all phases of AI usage impact AI Practitioners Green AI choices due to the inability to benchmark the choices against one another.

Furthermore, the organization structure also adds additional challenges to this issue. Rakova et al. (2021) study discovered that responsible AI work in the organization are currently rooted in individual seniority and personal competency, and a coherence structure is yet to be formalized. Hence this makes the possibility of achieving accountability difficult since there are no unified guidelines in the organization. Similarly, much of the research output in the Green AI field has been limited to academic environment and much of the tools resulting from this research were unavailable for the industry’s adoption (Verdecchia et al., 2023, p. 17). This points to the fact that while organization workflow is at its nascent stage with respect to responsible AI, the academic output needed to fast track its development remains in silo further compounding the awareness to action gap.

2.4 Bounded Rationality (BR) as Cognitive Constraint

In section 2.3, we have established the existence of the operationalization chasm despite abundant evidence from previous research on the negative impacts of AI adoption on the environment. In this section, the theory of bounded rationality is applied towards the understanding of the reasons why awareness alone has proven to be insufficient in bridging the chasm.

2.4.1 The Rational Actor Myth and the Emergence of Satisficing

To begin with, the foundational theory of economics argues that humans are rational beings, and that they possess the ability to fairly consider every relevant factor before arriving at the best decision (Simon, 1955, p. 99). Going by this argument, the assumption is that AI Practitioners would arrive at the best possible decision during AI model selection irrespective of the number of decision-making criteria presented to them since they fall into this category of rational decision maker. However, Simon's (1955) theory of bounded rationality disputed the possibility of the above. According Simon, optimum attention should be paid to the cognitive capacity of decision makers as an important factor which limits human's ability to comprehensively evaluates the multitude of factors essential for making optimal decision therefore in a situation whereby overwhelming amount of information are presented to a decision maker, they resort to simplification of the factors in order to make the decision making process smoother (Simon, 1955, p. 114). This simplification reflects human coping mechanism and should not be viewed as a deliberate effort to ignore the optimal decision.

Simon's answer to this human limitation was his bounded rationality theory. This theory provided an approach to decision making whereby the decision maker's set the baseline criteria ahead of the decision-making process and alternatives are sequentially evaluated until the first option that satisfies the baseline criteria is arrived at (Simon, 1955, p. 114) . This replaces the assumption that rationality exists in human decision making inherently but instead proposes a recognized approach to be followed for decision making. Applying this to the AI Practitioners making AI model decisions implies that AI Practitioners consider the available options serially and settle for the first option which meets the performance and cost benchmark without giving any attention to other choices thereafter. The drawback of this process is clear, criteria which have invisible impact in the short term such as environmental impacts of AI may be easily sidelined using this approach. This choice of the first optimal solution from Simon's work is what is termed as "satisficing" and a followed up study reconfirm the conclusion that found that in the presence excessive information and with limited time for decision making, decision makers resort to the use of incomplete heuristic in deciding among the several options at their disposal (Simon, 1972, p. 163). The challenge now lies in making less visible but highly significant factors such as environmental metrics to feature prominently on such heuristic.

Although Simon study has been conducted several decades ago yet its potency remains undeniable. This claim is based on the findings from recent studies ,for example, a recent research efforts seek to extend Simon's theory into the understanding of how attention is allocated in dynamic environments, the authors, Beil et al. (2025) showed that it is challenging for decision makers to give equal level of mental efforts to complex problems especially if difficult in such problems are evenly distributed in their different phases. Their study considered two different scenarios in a project, one in which cost is fixed and the other where cost variance was introduced in the middle of the project, the outcome differs for both scenario, where cost was fixed, humans performed excellently well where variance was introduced, human performance level declined considerably (Beil et al., 2025, p. 14) . The misjudgment between the two scenarios arose from the difference in visibility of the costs, the fixed costs require a simple heuristic while the variable cost introduced at the midpoint of the project requires a complex heuristic. This further applies to AI Practitioners in their model selection and deployment decision since accuracy is the headline of most benchmarks with immediate visibility of its impact as against the visibility of environmental impacts that are unobvious from the onset.

2.4.2 System 1 Dominance and the Failure of Deliberate Processing

In addition to Simon's bounded rationality theory, Kahneman (2011) dual processing theory provides an additional insight as to the reason why sustainability remains sideline from decision making. According to Kahneman, information processing for decision making falls under two major categories including system 1 and system 2 processing. These two systems differ in terms of time taken and quality of the decisions being made, System 1 information processing is fast, consumes less time and requires minimum cognitive efforts from the decision maker while system 2 consumes significant mental effort and usually involves more time from the decision maker (Kahneman, 2011, p. 20). Moreover, the quality of the decisions made using these systems also differs substantially, the reliance on simplification by system 1 to arrive at a decision implies that it is more susceptible to bias but system 2 decisions are better since time and mental resources are more invested into them, however they are less employed. Therefore, for AI Practitioners whose job environment involves constant shipping of solutions within short deadlines or time pressure and information overload, system 1 thinking is bound to be dominant.

2.4.3 Bounded Awareness and the Invisibility of Carbon Metrics

Even when sustainability information is present and accessible, bounded rationality does not guarantee its integration into decision-making. This assertion result from the research conducted during a live basketball match in which a selected group of participants were given the task of counting the scores in the game but only 21% of the participants noticed a woman who walked past in the court with umbrella despite her being clearly visible hence the concept of bounded awareness was born (Chugh & Bazerman, 2007) . This theory explains the rationale for missing out on obvious information due to the decision maker entire focus on other information considering that they consider to be more important. Also, this concept of bounded awareness is equally important towards the understanding of sustainability transparency on model cards. In its current design pattern, model cards contain numerous pieces of information in which sustainability when provided constitutes only a subcomponent among a plethora of other information ranging from the AI training data, ethical information, use cases among others and this volume of information exceeds the attention span of an average AI Practitioner. In fact, it is this overwhelming information that led to the clamors for decision aid for AI Product Manager in contemporary studies, for example, in one case the authors argued that the AI Product Manager role has hit a threshold whereby human cognitive capability is insufficient to effective processes the amount of information at their disposal therefore tools should be provided them to ease decision making (Oladeji, 2026, p. 3)

According to the author, AI Practitioners experience different forms of cognitive ceiling, and its manifestation is classified into three different forms. First, there is the inherent load which primarily refers to the degree of complexity of the decision making tool, the second form of ceiling is the cognitive load which is external in nature and it addresses the format in which the information is presented and the consolidation across different tools and finally, the germane load which is the optimum one dealing with synthesization of different information across board for decision making (Oladeji, 2026, p. 8). These different forms of cognitive requirements when combine usually outpace the mental capacity of the decision maker, thereby resulting in decision fatigue. This phenomenon is equally responsible for restriction of AI Practitioners' to the most salient criteria which in this thesis is the accuracy of the model.

Meanwhile Bonisoli et al. (2024) brought another angle into the picture by providing clarification for the reason why having a generic awareness about the advantages of environmentally friendly options by a person is inadequate to serve as catalyst for change. According to authors, a beneficial innovation is insufficient to influence adoption on their own until these benefits are visible and difficult to ignore therefore, they concluded that observability is a prerequisite attribute for adoption to occur (Bonisoli et al., 2024, p. 5) . Taking a cue from this finding, the model card must be reimagined not just as a documentation-oriented artifact but rather as a decision enhancing tool that focuses on the use of familiar metrics or simplifies hardcore such as $kgCO_2e$ into a relatable measure for AI Practitioners especially considering their limited time span.

2.4.4 Time Pressure, Complexity, and the Collapse of Analytical Processing

The cognitive limitation identified above is one of the factors responsible for the existence of chasm but not the only culprit, time pressure arising from the organization where AI practitioners represents another factor. Time pressure is a major impediment to effective decision making due to the additional pressure it exerts on decision makers, it is not to be confused with the generic concept of time constraint whereby the concerns is restricted to the knowledge of having insufficient time but time pressure represent higher degree of constraint as it induces stress and mental fatigue on the decision maker, owing to these undesirable effects of time pressure, more errors are made by managers (Phillips-Wren & Adya, 2020, pp. 578, 580). Furthermore, the origin of the declining ability to synthesize diverse information for effective decision making has also been traced indirectly to time pressure. Time pressure causes stress which is responsible for the release of undesirable steroids that causes reduced functionality of the short-term memory and short-term memory efficiency on the other hand is crucial for timely decision making (Phillips-Wren & Adya, 2020, p. 582).

Despite these shortcomings of time pressure in the workplace, effective decision remains crucial to AI practitioners productivity in the workplace. To remain productive in the face of time pressure and information overload, certain adaptability approaches have been developed by managers and have now become a commonplace among managers, some of these adaptable strategies included assigning priority to some information and satisficing (M. Arnold et al., 2023, p. 12) . While these approaches have achieved some level of success in terms of productivity, their failing lies in their inability to project sustainability to the top of the mind for decision makers, in the earlier section we have has shown that sustainability metrics such as carbon emission are regularly omitted from the model cards, therefore not being considered as a factor during AI model selection and decision process. This challenge of the need to process excessive data which usually surpasses the amount of information that an individual manager can reasonably process within the available timeframe has gained attention of researchers and consequently has led to the development of a framework that address the issue, the propose framework involves an AI-human collaboration which each person having an active role to play, the AI role is to analyze the data while the human role is complimenting the AI outputs by providing contextual judgment (Gupta & Gupta, 2025, p. 4) . Even this solution has not gone without being faulted, caution has been issued on the reliance on AI as a decision support tool for managers because of the tendency to result in Perceived Cognitive Assistance, a situation whereby managers become overly confident in their decision-making ability without a corresponding improvement in performance (Gimmelberg & Ludviga, 2025, p. 12) . This may further expand the sustainability implementation gap, especially if AI equally follows in the footsteps of earlier decision makers by excluding sustainability from its recommendation.

2.4.5 Paradoxical Tensions and the Structural Impossibility of Optimization

Although several tenable reasons have been provided for the existence of the operationalization chasm, the role of the clash between organization strategic objectives and sustainability prioritization is yet to be evaluated. Mill et al. (2022) in their work found that marginal improvement in AI models' accuracy is dependent on massive consumption of electricity. This presents a paradox whereby the pursuit of sustainable AI options may be at the cost of sacrificing performance. This explains the current disposition of AI researchers to accuracy as the utmost deciding parameter. The evidence for this claim stems from the minimal numbers of researchers, which are about 1 in 5, that consider it important to provide the energy savings information of their different AI projects (Mill et al., 2022, p. 5). Due to the logarithmic curve relationship that existed between sustainability and accuracy, practitioners often resort to assigning a peripheral importance to sustainable options.

Similarly, the goal to maximize profit or shareholders wealth remains the primary motivation for the publicly owned AI companies. Therefore, companies pursue the achievement of cutting-edge AI model accuracy to be at a vantage position in comparison to their peers even if it comes at an astronomical environmental cost (Gellers, 2026, p. 4). In fact, Gellers opine that organizations deprioritize sustainability initiatives in their quest to honor the profit aspiration promised to their shareholders Gellers (Gellers, 2026, p. 2). This obsession with profit realization trickles down to the AI Practitioners whose performance appraisal would reflect the organization priorities in which environmental metrics are accorded insignificant status. Moreover, studies show sustainability in some organizations is left at the prerogative of the manager since the existing organization structure does not factor sustainability into its framework (Rakova et al., 2021, p. 5). This absence of sustainability from the overall framework further contributes to the occurrence of chasm.

2.4.6 Conclusion: Bounded Rationality as Systemic Constraint

The application of bounded rationality has shown that the existence of the operationalization chasm is not due to nonchalance attitude of AI pratitioners but rather a coping mechanism arising from the cognitive limitation experience by managers and worsen by organisations' major priority which involves increasing the value of their shareholders investment. Moreover, the lack of simplification of the current tool design and its excessive focus on raw environmental impacts further amplify the difficult faced by AI practitioners who by their role are already under stress to meet product deadlines. Therefore, the way forward requires a rethinking of the model cards design not just as a documentation but also as a decision support tool to improve the quality of the decisions being made by managers and enable them to overcome their bounded rationality challenge.

2.5 Diffusion of Innovations (DOI) as Adoption Framework

In the previous section, the application of the boundary rationality theory enable us to diagnose the reason why operationalization chasm exists, however, diagnosing the cause of the chasm is only a side of the coin, it is important that an effective solution is proposed to mend the lapses hence the application of the second theory that is the diffusion of innovation theory to complement bounded rationality. According to Rogers (2003) diffusion of innovation theory, there are five attributes that enhance the adoption of an innovation, three of these attributes are relevant to this study, their adoption to the redesigning effort of the existing model cards will enable the bridging of the chasm. The cognitive tax or the mental effort required to process raw information provided on the Green AI model card relates to the complexity attributes of the diffusion of innovation theory while compatibility as a second attribute relates to the removal of bottlenecks limiting the integration of models' cards into AI practitioners workflows, lastly, observability attributes involves visualization of environmental impacts such that they become impossible to ignore.

2.5.1 Complexity: The Cognitive Tax of Raw Metrics

Rogers (2003) defined Complexity as "the degree to which an innovation is perceived as difficult to understand and use." Using this definition, complexity with regards to the Green AI domain refers to inability of the model card to present environmental impact information in a manner that enables AI practitioners to accurately imagine the magnitude of the negative impacts on the environment. For example, ascertaining the real carbon estimation value based on the available tool represents a great cognitive tax on the user as the process involves numerous adjustments for errors before arriving at the true value. Bouza et al. (2023) identified four primary sources of estimation error that make raw carbon metrics complex for managers to interpret with confidence. First, the lack of standardization among the available tools results in the generation of different power usage effectiveness figures and users' approach to the usage of this figure in their calculation also differs from one another (Bouza et al., 2023, p. 6). Secondly, the grid carbon intensity metric introduces another error prone estimation activity as it sources its values from the mean figure from yesteryears as against the most desirable option of instant capturing of the grid carbon intensity which provides a clear picture of affairs including energy variations (Bouza et al., 2023, p. 7). Thirdly, not all sources that consume significant amounts of energy are revealed to the end users even though they are included in the power usage effectiveness figure, example of such source is the cooling systems (Bouza et al., 2023, p. 4). Finally, carbon emissions emanating from different hardware employed are unknown since such data are not rendered by the original manufacturer (Bouza et al., 2023, p. 8).

The consequence of complexity attribute is that even when environmental metrics are reported, they remain inaccessible to decision-makers. For instance, researchers continue to omit the reporting of crucial environmental impact information as part of their research paper as discovered in a survey of research papers submitted to NeurIPS conference and the few researchers who did only provide energy consumption figure while conveniently leaving out carbon and water related metrics, this indicate the lack of general guidance on reporting in the industry (Nagi, 2025, p. 2). This lack of standardization implies that it is impossible to obtain comprehensive information on an AI model from one source, and this constitutes the herculean task identified by Jouneaux and Cabot (2025) where users including AI Practitioners are required to consult various platforms to obtain information on a model before meaningful comparison can be done (Jouneaux & Cabot, (2025, p. 2). Furthermore, Jouneaux and Cabot (2025) observed that the existing workflow for machine learning operations does not include sustainability which informs their efforts towards the formulation of their sustainability model cards to address the complexity observed in the current solution (Jouneaux & Cabot, 2025, p. 2,3). Their solution ensures that sustainability information for models is available across all stages of development both training and inference stage. Their introduction of standardization represents one of the early efforts to address complexity attribute of the model card.

2.5.2 Compatibility: Workflow Friction as Adoption Barrier

Rogers (2003) defined Compatibility as "the degree to which an innovation is perceived as consistent with the existing values, past experiences, and needs of potential adopters." For this research, we are viewing compatibility from a sole lens of how well the innovation of Green AI model cards fits into the current AI Practitioner workflow. The importance of combability cannot be understated, it has been touted as one of the major reasons why users would be willing to use new technology, it must be able to seamlessly integrate into their routine activities (Salah et al., 2021, p. 4). This discovery has been shown to be relevant also in the broad field of green innovation as well, for example, Siyal et al. (2023) found that seamless adoption of technology is easier depending on the complexity of the new technologies, they obtained p-value of 0.000 and β of 0.287 when they tested the relationship between compatibility and innovation adoption behavior depicting high significance level. This further drive home the point that innovation adoption requires reduction in complexity and combability with the existing system in the organization.

Fortunately, Zada et al. (2025) provided the roadmap to achieve integration of sustainability into existing workflow in their research. The authors proposed a framework that includes a blend of Lean, Agile and Green Sustainable software engineering as an example that sustainability can be infuse into the modern workflow, by doing this, they elevated sustainability to the consciousness of practitioners as it stops being a peripheral requirement but rather a major component of development process (Zada et al., 2025, p. 14) . Also, this framework arose from their study of the prevalent practices in modern organization therefore they are equally applicable to the AI practitioner workflows as well (Zada et al., 2025, pp. 15–16) . Specifically, using this approach by AI Practitioner ensures that sustainability becomes an active nonfunctional requirement to be given consideration during product planning and away from the current practice of an item to be inculcated as part of the final report upon product delivery.

2.5.3 Observability: The Engine of Behavioral Change

Rogers (2003) defined Observability as "the degree to which the results of innovation are visible to others." But its adaptation to the sustainability realm follows a modified definition whereby observability refers to the degree at which results of innovation is visible to the user or consumer themselves, therefore in this study, observability involves making the invisible technical metrics visible to the decision maker.

For Green AI Model Cards, observability requires making abstract environmental metrics concrete and comparable through visual communication systems. One of the ways to achieve this is through adaptation of the energy labels classification to the categorization of different machine learning models depending on their energy efficiency (Duran et al., 2024, p. 5). Duran et al. (2024) showed that by assigning label A to E to depict energy efficiency level it is possible to easily understand esoteric technical information regardless of the machine learning engineer background therefore even managers with limited technical expertise can benefit from this labelling. This labelling practice essentially serves to improve industry adoption of the research findings by simplifying complex energy data into relatable visuals for the decision maker (Duran et al., 2024, p. 3). This is useful for AI Practitioners since this information simplification enables familiarization with energy efficiency data that would otherwise require advance energy estimation knowledge.

One significant limitation from literature is the sole focus on the optimization of energy consumption to achieve green initiatives. Therefore, Nagi (2025) advocated for a system that not only focuses on energy consumption but considers the environmental impacts of models over their entire lifetime hence they created the Envcard to achieve this goal. These EnvCard makes it possible to include environmental considerations during model selection and associated costs for each model is known to the decision maker, so comparison becomes seamless regardless of the user's background whether they are sustainability expert or not. Therefore, observability efforts must transcend just one metric or a phase and must include a comprehensive assessment of environmental footprints over the model lifetime.

2.5.4 Synthesis: DOI as Design Prescription for Green AI Model Cards

The three attributes of DOI discussed in this section serve the overall purpose of bridging the earlier identified chasm. We anticipated decrease in complexity through standardization and providing context to each metrics such that it improves the familiarity with sustainability data and catapults them from the abstract imagination realm where they exist currently to relatable everyday concept to the user. The earlier discussed work of Jouneaux and Cabot (2025) and Nagi (2025) are useful in achieving this objective. Jouneaux and Cabot (2025) introduced the sustainability framework that brought in standardization of the metrics and Nagi (2025) emphasize the need for a comprehensive measurement of environmental impact and then introduced their Envcard for this purpose. Combability attributes reduce the friction that exists in the current sustainability implementation process whereby environmental information is warehouse on different platforms are decision makers are required to consult numerous documents or visit different benchmarking websites to arrive at their decision. Here using the LAGSSE framework propounded by Zada et al. (2025) ensures that green objectives are key component of the work process and specifically the framework ensures that sustainability is planned into the development of the products in the organization. Observability concepts remove the barrier which render environmental metrics as an abstract or unfamiliar metric and transform it into visible metric by providing relatable context such as appropriate labelling using the energy label concept. An example of earlier efforts on this matter include that of Duran's et al. (2024) GAISSALabel and the EnvCard of Nagi's (2025).

These three attributes serve as the catalyst that empowers AI Practitioners to overcome the identified barriers to the process of making environmental conscious decisions during AI model selection. Furthermore, model cards adoption for decision making among AI Practitioners will improve if these DOI principles are adopted since this literature review has established that the challenge to adoption is not a merely technical in nature but the behavioural aspect which deals with the limit on information processing needs to be addressed as well.

2.6 The Dual-Lens Synthesis: Mapping Cognitive Limits to Innovation Attributes and the Research Framework

The preceding sections have established two complementary theoretical lenses for understanding the Green AI adoption challenge. The bounded rationality theory assisted with the reason for the current the situation and it enhances our understanding of the difficulty inherent in the process of consolidating numerous information by humans for decision making. This understanding gained from BR is further improves upon by the application of the diffusion of innovation theory which deals with the “how to fix” component of the challenge, it presents a solution in form of the attributes that enables innovation such as the model cards gained adoption among AI Practitioners. Although there are five DOI attributes, the scope of this study is limited to three most relevant ones including complexity, observability and compatibility. Together, these two theories are fused together to form three integrated themes which are discussed below:

The first integrated theme is the Complexity-Cognition Nexus which emerges from the intersection of information overload and high perceived complexity. Simon (1972) makes it clear that the problem with decision making in the organization does not arise from insufficient information but rather insufficient time to process them, managers' attention span is limited and time as a resource is scarce. Thus, a AI Practitioner making AI product selection also grapples with this problem in their role to deliver functional products to their organization. This is more pressing considering that some layers of AI models are invisible by design and they constitute part of components driving up the energy cost (A. E. I. Brownlee et al., 2021, p. 6). Their hidden nature adds another difficulty for PMs because these costs represent another complexity to their workflow, it involves additional information gathering efforts for AI model selection decision. Meanwhile Dwivedi and Islam (2025) advocated for the notion to consider the development of context-aware AI systems that consumes energy based on the task at hand, but this is only feasible if decision support tools including the model cards encompass the required metrics for environmental sustainability. This process can be fast-tracked by simplifying the heuristics for making sustainable AI decisions to the degree of information that could be processed within 30 seconds by AI Practitioners and making the same available on the model card.

The second theme, the Observability-Awareness Bridge, connects bounded awareness to low observability of environmental attributes. Gershoff and Frels (2015) demonstrated that a product with two different attributes that possess equal green benefits are not accessed to offer the same environmental benefits by the user because their judgement is influenced by the role of each attribute hence attributes that plays a central role are judged to be greener than those playing supporting role. This explains why sustainability is treated as a peripheral metric on the current design of the model card and the need to elevate its position into the system 1 thinking of AI model users. To improve observability of sustainability metrics on the model card, Nagi (2025) emphasized the need for embrace standardization of the cards as well as ensuring completeness of the metrics provided, they believe that these adjustments in addition to the improvement in formatting will improve visibility. This position is supported by(Bonisoli et al. (2024), the researchers found that attitude can be altered positively with increase in the level of observability, applying this to the context of environmental benefits implies that improvement in visibility of sustainability metrics on the model cards would translate into improved adoption by AI Practitioners during model selection. The ultimate aspiration is to reach a level whereby observability of green metrics falls under the attention span of an AI Practitioner.

The third theme, Compatibility-Heuristics Integration, addresses the alignment between heuristic reliance and low compatibility with existing workflows. It's imperative that sustainability is presented as an opportunity for operational advantage to AI Practitioners who are already constrained by the time allotted for product delivery. An example of this is shown by Sworna et al. (2023) where green benefits are presented as an avenue to achieve cost reduction objectives because their proposed models achieved better results with regards resources utilization. Moreover, the ease of integration of new technologies into an existing one in the organization ensures smooth experience for the user therefore compatibility attribute is essential (Siyal et al., 2023, p.14) . Meanwhile, the efficacy of a well-designed tool to influence behaviour positively is visible in the works of Ayoola et al. (2025) work whereby the use of persona models led to the adoption of the desired user stories, by extension it implies that sustainability adoption would improve with user-oriented model design. The evidence for this is provided by Leuthe et al. (2024) where they argue that design pattern is capable of transition sustainability from its relegated position to a core role in the organization workflow. The aspiration here is the infusion of sustainability into the workflow such that making sustainable choices requires no additional mental effort from the users.

These three themes point to the fact that model cards must extend beyond being a documentation artifact but must also serve a complementary purpose as a cognitive assistance tool. In fact, (Oladeji, 2026, p. 4) encouraged AI Product Managers to improve their AI skills so that it can enable them to deal with the current challenges of cognitive overload and prioritization activities. These integrated themes combine to reduce complexity sustainability metrics, improve observability and make the tool compatible with the everyday workflow of the AI Practitioner so that sustainability becomes a routine activity. Consequently, the study research questions emanated from the desire to investigate whether model card in its current form is appropriate for the stated objective and to understand how AI Practitioners are coping with the challenge. The visual representation of the three integrated themes is presented in figure 4

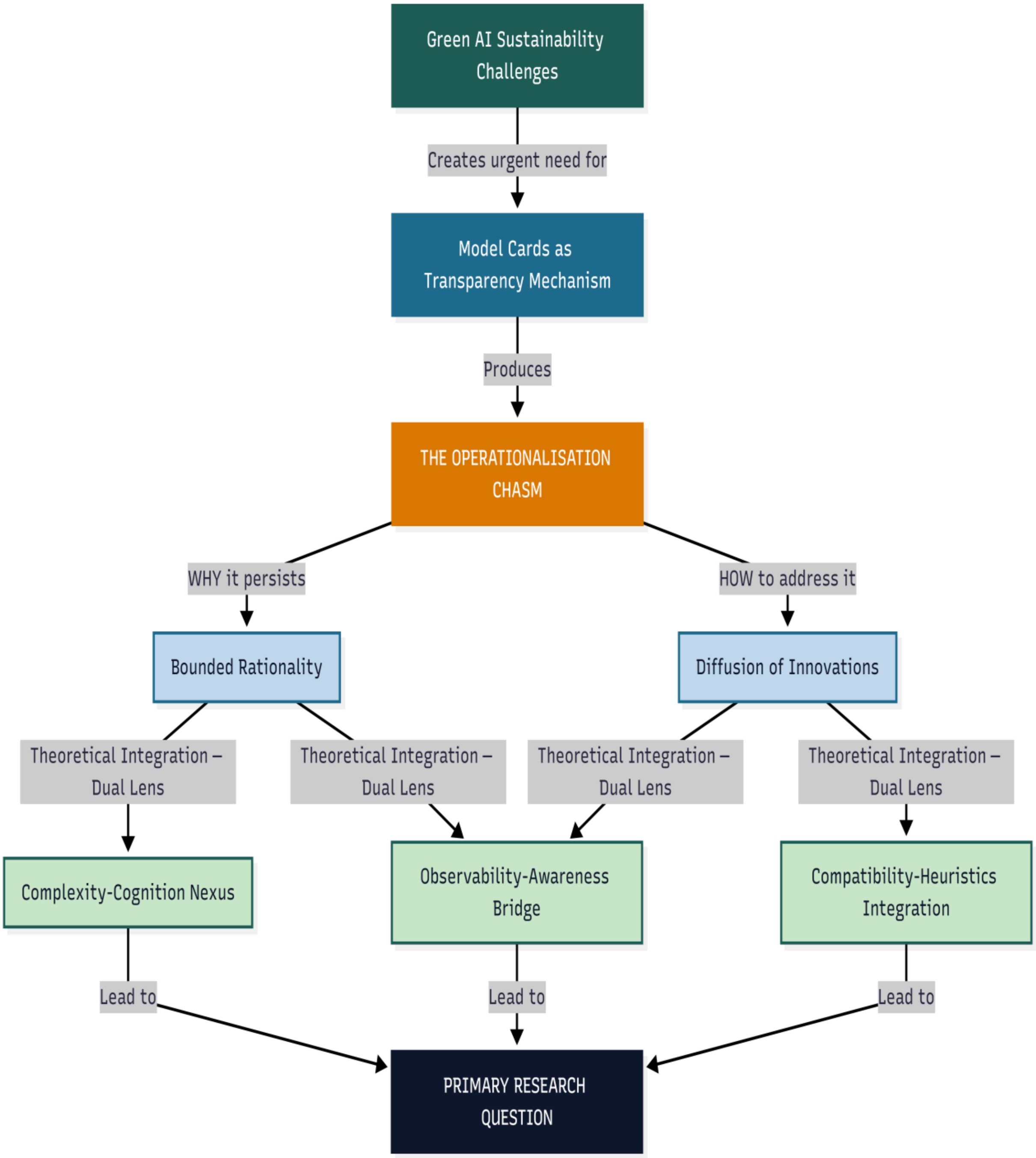

Figure 4: The Visual Representation of the Research Conceptual Framework

3 Methodology

3.1 Research Design and Philosophical Stance

This thesis adopts a qualitative research approach to understand AI practitioner's decision-making process. The research seeks to bring to light the mental burden involved in processing the overwhelming amount of information by product managers in performing their roles and its impact on the prioritization of Green AI, it also seeks to answer the question of whether the usage of model cards can assist in simplifying the decision-making process thereby resulting in the closure of the existing gap between sustainability awareness and action. The researcher plays an important role in deriving meaning from the proposed interview since the study aligns itself with the interpretivist school of thought whose belief is that social interaction is a foundation on which knowledge development originates (Campbell et al., 2021, p. 2012).

Moreover, the difference in each participants' cognitive threshold and their respective organization structure where they work informed the choice of interpretivism approach because these differences point to the fact that participants' decision-making ability and work environment differs from one another hence the importance of the researcher role in understanding these nuances and facilitating the process. Moreover, the risk of the researcher's role constituting bias by employing this approach has been disproven by Campbell et al. (2021) whereby the authors position the reflective thematic analysis inside the interpretive qualitative paradigm and emphasizing the criteria important role of this researcher is bringing interpretation to the conversation. Thus, to adequately answer the proposed research questions requires rich conversation and context which is achievable through the adoption of the semi structured interview as a research instrument.

Furthermore, the thesis adopted exploratory approach as the research endeavor represents one of the earliest efforts to apply the dual synthesis of bounded rationality and diffusion of innovation in the Green AI domain. Previous research efforts have largely focused on technical improvements specifically algorithm optimization and parameters fine tuning with no study paying attention to the significant role of human element especially with regards to AI model selection and deployment. This research effort generated insights which further improves on creation of themes essential to the understanding and closing of the operationalization chasm and the identification of the specific attributes of the DOI that would enhance model card design effectiveness, lastly there are no research hypothesis due to the exploratory nature of the study.

3.2 Sampling Strategy

The research adopted purposive sampling strategy since the required information are only among niche experts and specifically the AI practitioners or experts who have been saddled with the responsibility of selecting and deploying AI models in their organization, Moreover, Byrne (2022) opine that a phenomenon under study is better understood by gathering quality information similar to those which can be accessible from the outcome of a purposive sampling.Futhermore, the choice of AI practitioners as the desired population for this study arose from the responsibities assigned to them in their respective organisation which requires the implementation of AI solutions.

To ensure that participants possess the required knowledge for the study, only AI practitioners and roles with similar responsibilities will be included in the study, the roles must involve selection and deployment of AI solution in the organization, this would add to the richness of the study and would ensure that the tradeoff decisions relating to AI models are perfectly understood by the participants. Finally, research participants are uncategorized, and interviews are conducted under similar conditions using the same research stimulus which is the Green AI dashboard.

The sample size for this thesis is 8 participants which represents the level at which new insights from the participants are no longer probable and in accordance with the recommendations from method oriented study by Byrne (2022), which advice that the choice of sample size should be informed by the attainment of data saturation.

3.3 Data Collection Methods

The data was collected via a semi structured interview conducted on digital platform Zoom with each interview lasting approximately 16-25 minutes. The use of semi structure interview is appropriate as it allows for deep dive into the individual participants experience and presents an opportunity to ask other relevant related questions in addition to the predetermined questions for the semi structured interviews, this allows every participant an opportunity to participate in process of producing the raw data which was useful thereafter for the researcher during theme development for the study (Braun & Clarke, 2006; Ruan, 2022). The interview session was divided into three phases; Phase 1 of the interview is concerned with the as is practices in the respective participants organization. Questions surrounding the current process for AI model decision and whether environmental metrics are given consideration in any form during this process are asked in this phase. The overall aim is to assess the level of awareness of sustainability in AI model decision making process and the barrier to decision making before assessing the effects of the research stimulus.

The second phase used the prototype stimulus, that is the redesigned Green AI model card to evaluate the participants' reaction in real time. This is a key innovation of this study whereby a traffic sign design format of the model card with adjustable feature that shows in real time the environmental cost associated with each level of accuracy and the same is presented to the participants. The Green AI model card provided useful information enabled the comparison of energy savings from AI model selection and decisions to real everyday scenario, for example comparison to energy savings like lifetime emissions of 500 vehicles as against stating the hard-core metrics such as 2GKwh. The aim of this stage is to improve on the visibility of the tradeoff and determine the best way to embed the model card into the existing workflow of the product managers. The redesigned model card was shared via the online platform with the interview participants.

The phase 3 is the conclusion phase where the focus was narrowed down to the organization and questions concerning the different obstacles to Green AI adoption will be investigated and participants suggestion on ways in which sustainability metrics can become part of their daily workflow is captured as the concluding segment of the interview.

The theoretical frameworks adopted in the study informed the choice of interview questions as well as the design of the research stimulus: the dynamic green AI dashboard. For example, the prototype Green AI traffic light design format is employed to simplify the complexity of the raw metrics that currently dominates the AI model cards thereby enabling the participants to overcome their cognitive limitation when making AI model selection decision. In addition to this, carbon emission and other environmental metrics comparison are provided on the dashboard and are also adjustable with the slider button, their inclusion is to cover the observability attribute of DOI by ensuring that information processing transcend from the system 2 efforts system 1. Finally, the everyday life equivalents comparison is also provided in the dashboard to enable familiarity with significance of the anticipated energy savings for respective accuracy levels, this component addresses both observability and complexity attributes of DOI.

All the interviews with the participants are recorded and treated with highest level of confidentiality. Furthermore, Personal Identifiers are removed upon the completion of the recording transcripts and are replaced with tags such as P1 for interview one, P2 for interview two etcetera. Overall, the data was handled ethically and in alignment with GDPR provisions.

3.3.1 Participant Profiles

The participants were selected without restriction to any industry however the key requirement involved the being responsible for making of AI model selection in their current role and experience with implementation or development of AI products or projects in their organization. The flexibility with industry and region was because of the nascent nature of the field and AI practitioners role is still developing and far from attaining maturity.

Table 3: Participant Profiles

Participant	**Role**	**Rating of Cognitive Load (1–7)**	**Sustainability Awareness prior to introduction of Green AI model card**
P1	AI Engineer	1/7	Personal level awareness
P2	Digital Risk Professional	4/7	Zero awareness
P3	Product Manager Startup	5/7	Known but not practicing
P4	AI Trainer	1/7	Zero awareness
P5	AI Strategist	5/7	Unclear recording
P6	Data Analyst	6/7	Full awareness

P7	Banking Business Analyst	5/7	Policy level awareness
P8	Team Lead, EdTech	6/7	Moderate awareness level

3.4 Data Analysis Approach

The broad design for the data analysis followed the popular Braun and Clarke (2006) six phases approach. Thus, the thesis data approach entails a reflective thematic analysis which implies that themes do not arise solely from the data itself but also through the participation of the researcher whose constant reflection leads to the emergence of themes from the interview (Braun & Clarke, 2006, p. 80). Each of these phrases are discussed below:

In the first phase, the researcher reads thoroughly and repeatedly the transcripts from the semi structured interview to ensure familiarization with the data. Careful attention is paid to nuances including shocking moments and important opinions of the interviewee. The second phase is the point where initial coding is carried out. First, codes that align with the theories applied in the thesis including bounded rationality and diffusion of innovation are identified and emerging codes not foreseen are also identified for further processing, the analytical tool used for coding is Nvivo.

Furthermore, a concrete theme development is done in the third phases and in line with dual synthesis of theories of bounded rationality and diffusion of innovation attributes as outline in the research questions. The fourth phase is revalidation of the identified themes against the raw data to ensure the presence of concrete basis for individual team and that they are well supported based on available data. Hence, misrepresentation was avoided in the research. In the fifth stage, proper definition of each theme is done and a clear linkage to the research questions is provided while stage six is the report writing phase where the full narrative of the research is provided. Auditability and transparency are prioritized through the storage of theme development steps and the audiovisual material from the interviews.

3.5 Ethical Considerations

The thesis abides by the relevant ethical principles for conducting research. First, participants' consent was sought for the interview, and they are at liberty at any time to decline their participation in the study. In addition to the consent at the pre-interview stage, continuous consent was obtained throughout the different phases of the interview including before the commencement of recording of the interview session and periodically while the session is ongoing as recommended in the literature (Hosseini & Haukås, 2025, p. 990; Maksutova et al., 2023, p. 3). The consent process clarifies that the researcher's role is to understand participants' experiences, and not to judge their decisions (Maksutova et al., 2023, p. 3). Furthermore, all personal identifiers are removed from the transcripts to ensure confidentiality and participants have the freedom to withdraw from the study without any repercussion.

3.6 Quality Criteria

The Lincoln and Guba's trustworthiness framework was applied in this thesis to ensure that the study is of the best quality. According to this framework, the rigor of a research study can be evaluated based on four distinct criteria including credibility, transferability, dependability and confirmability (Johnson et al., 2020, p. 7). Credibility is built into this study through systematic development of themes from the data and continuous probing of the data for more themes and insights, transferability is ensured through comprehensive description of the research environment and provision of the professional background of each interviewee, dependability is ensure by making all the interview transcript available for auditing purposes and finally confirmability shows through the linkages that exist between the research themes and the raw data.

3.7 Research Process Overview

The research process involves seven stages from research design to theme development and findings. The thesis adopted the qualitative research approach and conducted a semi-structruted interview with eight purposively selected AI practitioners. The interview was categorised into three phases from establishing the as is practise regarding AI selection to the impact of Green AI model card as a research stimulus in overcoming barrier to sustainability inclusion. The data handling followed GDPR best practises and all personal identifiers from the raw data have been successfully anonymized prior to data analysis. The thesis findings and recommendation are presented in the subsequent chapters and the visual depicting this process is presented in figure 6.

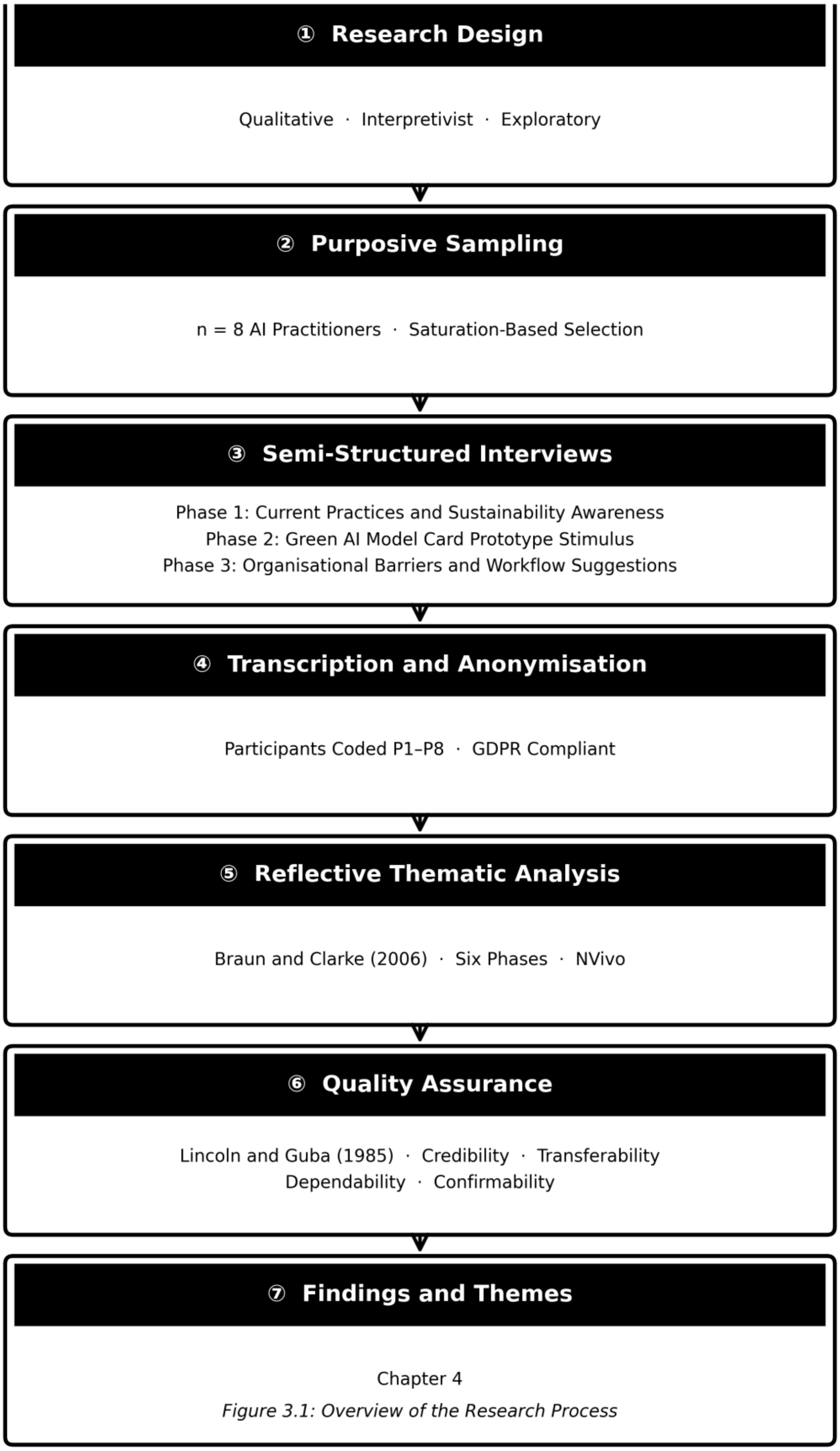

Figure 5: Visual Depicting the thesis research process

4 Findings

4.1 Theme 1: The Complexity-Cognition Barrier

First, the interview data successfully confirmed the existence of information overload among the participants who are practitioners that have implemented AI solutions in their respective organization, but the extent or magnitude of the information overload differs from one participant to another. Two participants, P1 and P4, rated their level of information overload with the least rating of one out of seven however a further engagement with P1 reveals that the amount of information to be processed during AI model selection remains overwhelming even for them but having developed expertise over the 4 years' experience in the field, it has assisted P1 in the normalization of the volume of the task to be done. On the contrary, other participants explicitly rated information overload highly with highest rating visible from P6 and P8 with both ratings' information overload at 6/7. The interesting observation however is that the source of information overload differs for the two participants with the highest ratings, P8's information overload challenge arose from the deadline or time pressure while P6's information overload stems from the number of documents to evaluate, see the excerpts from both participants below

> "It can really be overwhelming, especially when you're working on a project that has timelines and the timelines are tight." (Participant 8)

> "Oh, wow. The model selection phase is a lot. It's so cumbersome and really overwhelming. So I'll give it a six. Although it's something you should and must do as an expert, you can't just select any model randomly." (Participant 6)

Therefore, the data confirms that information overload is real among AI practitioners, but the severity and the source of information overload is heterogeneous. Overall, this finding aligns with bounded rationality theory whereby decision-making ability is affected by the volume of information a decision maker is required to process.

Secondly, the interview outcome confirmed the earlier suspicion of exclusion of sustainability from the AI model selection decision by AI Practitioners. The data revealed the satisficing behaviour of the interview participants and as earlier suspected, sustainability was absent from their decision criteria. For instance, P1 has a list of 5 criteria they consider during AI model selection and this list is exclusive of sustainability,

> "I have a list of criteria… the efficiency of the model… number of parameters… little test I carry out… hallucinating… cost of spending API requests." (Participant 1)

While for P8, their criteria involve four factors with no sustainability, excerpts:

> "Once the model is good enough… reliable to perform the tasks and fit into our budgets… and can easily be deployed, we go ahead with it." (Participant 8)

For P4, all that matters is accuracy and all other criteria play a second fiddle to it,

> "Accuracy is like the umbrella because underneath it we have other things that fall under accuracy—like understanding the right prompt… the memory span… ensuring that the AI does not forget the context." (Participant 4)

In all the cases, sustainability was not included in the initial decision-making criteria to be considered therefore they "satisfice" that is select the first option that meets their predetermine set of criteria without any consideration for sustainability. Furthermore, the assumption from the research theme is that exclusion of sustainability is due to a number of reasons including information overload and the findings partially confirm this assertion however even participants who claimed to have manageable cognitive load also exclude sustainability, for example, P1 rated cognitive load as 1/7 yet do not factor sustainability into decision making criteria.

Another fascinating discovery is that information overload, while it resulted into satisficing without sustainability in 7 out of the 8 cases, it differs significantly for P6. Although P6 also experiences high information overload but they still ensure they conducts a comprehensive evaluation of their AI options with respect to their list criteria which was inclusive of sustainability and it was the only recorded case whereby sustainability was already pre-integrated prior to the introduction of the research artifact-the Green AI model card hence their satisficing occur with inclusion of sustainability. This disparity from the norm is alluded to the nature of their profession, for consultants who are placed on higher pedestal and are required to possess topnotch knowhow hence the reason this participant possess showcase high tolerance for information processing. This shows that even in the absence of sufficient information, consultant still strive to go beyond expectation. Furthermore, the P3 confirms the existence of complexity attributes in situations whereby context is lacking or insufficient as shown in P3 immediate response to the raw metric data including $C0_2$ value,

> “Inference cost, CO2, yeah, I would say I don’t have so much context there.” This implies that making environmental data visible is essential for observability but does not necessarily guarantee optimum interpretation and understanding if context is lacking” (Participant 3)

The final findings in the complexity-cognition theme deals with the evaluation of the potency of the simplified the Green AI model artefact to reduce complexity and by extension the information overload experienced by AI Practitoners when deciding on the model to select. The data showed that the redesigned Green AI model card was effective for some participants in simplifying the information, one of such success stories is P7, whereby the card was effective when making their analysis. Also, the use of the side-by-side comparison of the two models was particularly highly effective for P7 who upon seeing the artifact conducted a full model by model comparison without any support.

> “I’m seeing a form of package for an AI model… GPT Standard is about 1.2% more accurate… latency 120 milliseconds versus 68 milliseconds.

> Inference cost GPT Standard is higher. Then I can see the carbon dioxide: the standard emits more compared to the other one at 280 kilograms. Energy use the standard uses more energy too. So this is speaking to the green environment" (Participant 7)

The observation here is that the Green AI model card is particularly effective for practitioners who already have some background information regarding sustainability and the artifact was able to achieve its aim of ensuring that sustainability is promoted to be among the criteria to be considered for decision making, therefore upon seeing the artifacts, the particpants were able to include sustainability as part of the factors needed to considered before satisficing. However, in one case, sustainability was visible to the interviewee, but the interviewer had to step in with brief explanation before P3 started their comparison of the two propose AI models cards shown on the Green AI model card interface and the energy trade off. P3 states that 'If I was presented with this 98.3 to 97.1 and looking at the differences in the carbon footprint, it's only fair. It only makes a bit of sense to go with the second model." This was the sole case where external support assisted in understanding the prototype Green AI model card.

4.2 Theme 2: The Observability-Awareness Bridge

To resolve the bounded awareness challenge with Green AI adoption, this thesis proposes the redesigning of the Green AI model card to include the traffic sign colored code where Green denotes sustainability and Red for less sustainable AI options to visually enhance the visibility of sustainable AI options and to bridge the operationalization chasm. The study data confirms the suspicion of gap between awareness and practise among AI Practitioners to be valid but with a caveat, the awareness gap exists at varying levels. Two participants, P3 and P4 have never considered sustainability until when presented with the redesigned Green AI model card. See the excerpts from P3 below:

> “That has never crossed my mind actually… since I’ve been using AI, I have never drawn any inference to what impact it has on the environment. Never.” (Participant 3)

Then we have those who have moderate knowledge of sustainability but never assign consideration to it, for example, P7 is slightly aware of sustainability from dealing with policies in their organization but sustainability never plays a significant role in deciding which AI model to select. Next is P1 who is aware of sustainability from their own personal research but no transfer of this prior sustainability knowledge to their role in the workplace when deciding on the AI model to work with.

> “On my personal research, I’ve come across that… at industry level, I mean, we barely give consideration to that. We never really give consideration to that.” (Participant 1)

On the positive end of the spectrum is P6 who had initial awareness of sustainability but have not taken any significant action on it since the information are not readily available on the current model cards. P6 states that “First, I think you have to check the performance… and then I checked the sustainability. I think those four factors were the major factors I considered.” This indicates that awareness occurrence among the participants are heterogeneous and not the same for everyone as predicted earlier on in the literature section and due to this varying degree of sustainability awareness, the artifacts must serve a diverse bridging purpose depending on the difficulty limiting a participant’s awareness of sustainable AI alternatives. Also, the data revealed that sustainability absence transcends just individual unawareness but institutional disregard for sustainability at a larger scale, for example, professional social community where AI is being discussed focused majorly on accuracy and this further shape the individual priorities as well.

> “At (their organization name) … we have a Slack community dedicated to just discussing AI and stuff. And never once have I seen anyone [discuss environmental impact]. What we just discuss is accuracy, how well it does.” (Participant 3)

This therefore implies that sustainability exclusion is partly based on the individual awareness level and also compounded by the level of social awareness in their professional communities, therefore an optimum approach would involve broadening the scope of studies beyond using solely the Green AI model card to the level of designing a socio-technical intervention to solve the challenge on a large scale.

The data equally confirmed the assertion that low adoption of sustainable AI options stem from low observability of environmental impact data in the current AI documentation, this understanding was in tune with the diffusion of innovation theory whereby high observability is a catalyst for adoption of new innovation. For instance, P6, who was sole participant to pre-include sustainability as one of the criteria to be considered ahead of selecting an AI model for their tasks stated convincingly that such information is rarely available and when later shown the Green AI model card, P6 reaction was most positive with huge exclamation therefore the artefact was useful in assisting the operationalization of sustainability for P6.

> "To find it is one thing, and to understand it is another. It's very rare, we hardly come across a model card that includes environmental information" (Participant 6)

Excerpts from when the model card was shown to P6.

> "Oh, wow. This is nice. This is really, really nice."

Their reaction shows a positive disposition to the introduction of a missing information on the model card.

Furthermore, the Green AI model card effectiveness in resolving the observability-awareness challenge serves a dual purpose, the first is enhancing visibility for those with zero awareness (P3&P4) to improve the inclusion of sustainability in their decision making and secondly for those who are already familiar with sustainability, it ensures that their personal motivation for sustainability can be put to practice without delay thereby leading to operationalization. Thus, for those already familiar with sustainability the job is half done, the chasm simply requires tool provisioning for behavioural change to happen.

The proposition for the adoption of the visual contrast in the redesigned Green AI model card to enable the transfer of AI model selection process from the system 2 where it is currently located to the system 1, system 1 deals with automatic processing and requires only manageable mental efforts for decision making, the assumption follows that inclusion of sustainability as part of the decision making will improve with system 1 approach. This assertion was also assessed and was confirmed true from the data gathered from the participants. For some participants, the transition was done based on the response to the colour valence, for P8, the card signifies threat detection mechanism, a dangerous or emergency response attitude, for P2, their response is based on their prior moral understanding of what green signifies, they recognized green as something good for the environment and lastly for P1, reference was not made to the colour difference but rather the contextualization of the metrics whereby the card depicts the 10x difference in carbon emission between model A and model B.

> “The one on my left, which is red, it first gives me the signal—danger… while the other one on my right gives me a safety signal.” (Participant 8)

> “The GPT Lite has low impact and it is green. And for me, based on my understanding, green is something that is good.” (Participant 2)

> “Since model B, the accuracy is almost the same as model A and then the carbon emission is way, way down. I’ll most likely work with model B.”(Participant 1)

Overall, the model card visual effects was successful in reducing the complexity already discussed in the first theme and is able to trigger the system 1 thinking of participants based on its different attributes, some participants identified with the red theme as danger, others identified with the green theme as good and others used the contextual difference in magnitude for making their decision.

4.3 Theme 3: The Compatibility-Heuristics Integration

The compatibility-heuristics theme explains that AI Practitioners rely on simple heuristics due to their cognitive overload when making AI models selection decisions and when this is added to the fact that existing model cards possesses minimal compatibility with the current workflows of these practitioners because these model cards are warehoused on different websites such as Hugging Face and SageMaker, the barrier is further exacerbated. Therefore, the suggested solution is to ensure that the redesigned Green AI model card possess attributes which makes its integration to the AI practitioners workflow seamless and readily accessible whenever AI model selection decision is to be made in the organization. The interviewees agree completely with proposition confirming that adoption is dependent on zero friction with the in-house workflow at their respective organization. For example, P8 gave the lowest rating, that is 1/7 for the possibility of retrieving the Green AI model card or sustainability information if hosted on a separate website, they stated that "Having to leave your work domain to another separate domain, then coming back again—it can be exhausting. So it won't work." P7 followed the same footstep of P8 by declaring unequivocal that such information outside their work environment will not receive attention and this position can only be changed if there is a fine for ignoring such information,

> "Considering my environment—if it's not on my platform, then I think it would be unlikely. If there is no cost implication or penalty for ignoring the environmental part, I might not consider it before making my decision." (Participant 7)

P6, who is the most sustainability conscious participant also rated possibility of usage if hosted elsewhere other than their work domain as 3/7 further confirming that adoption is dependent on workflow compatibility as predicted. Excerpts from P6 "I think it's a bit stressful… I would prefer it to be embedded in the platform I'm using." Finally, the excerpts shows that the claim that compatibility with existing workflow is essential for the uptake in adoption of Green AI model cards is totally supported by the data.

Moreover, this theme equally delivered some interesting insights that were unforeseen and not included as part of the original design. First is the social exclusion of sustainability, the assumption earlier on is that heuristic exclusion is limited to individual AI practitioner when making AI selection decision. This is evident from the earlier excerpts provided of P3 where their professional community and colleagues do not reckon sustainability in deciding on the AI model to employ.

> "At (their current organization)… we have a Slack community dedicated to just discussing AI and stuff. And never once have I seen anyone [discuss environmental impact]. What we just discuss is accuracy, how well it does." (Participant 3)

The implication of this finding is that sustainability exclusion also occur as a collective, where colleagues or practitioners' community continue to influence each other behaviour by reenforcing the relegation of sustainability as seen in the above scenario therefore the possibility of the redesigned AI model cards to bridge the social exclusion through compatibility with the broad workflow of the professional community should be considered hence the compatibility aspiration of the prototype AI model card should extend beyond just fitting the cards into each individual practitioners workflow.

The second interesting finding is the institutional barrier that inhibits sustainability adoption because such barrier resists artefact intervention. This resistance is because the barrier exists at the top level while practitioner adoption exists at the sublevel so even if sustainability information is provided on the model card it is unlikely to be efficient in sustainable AI decision making. For example, for P1, top level management approval is essential for AI model selection decision, but management requirements from the onset is exclusive of sustainability , in similar vein for P7, management is only comfortable with solutions already adopted by competitors in the same industry as this gives comfort in terms of risk management, this implies that if the favored solutions by organizations in the same industry excluded sustainability, this organization is geared to follow suit.

> "The management will be like, okay, what is the accuracy? What is the cost? What is the latency? And then, okay, we can go ahead with this" (Participant 1)

> "Management preferred to receive a whitelisted solution already used by [a bank in the participant's country], for confidence reasons. Microsoft had to go back to the drawing board and provide a whitelisted product already given to an existing client." (Participant 7)

Moreover, part of the reason for the top-level indifference towards sustainability adoption in AI model selection or decisions was equally provided by P7 where he declared that the lack of penalty or fines for ignoring environmental data is responsible for this action. Therefore, adoption of Green AI can also be improved through policy intervention as the incentive for using sustainable option does not exist today. Workflow compatibility remains efficient at the individual AI practitioners level by availing different AI models environmental data seamlessly but limited in influencing top level adoption of sustainability.

Furthermore, in addition to the thesis efforts towards promoting sustainability inclusion through redesigning the Green AI model card to enhance AI Practitioners model selection at the individual level, the participants further provided other notable bridging mechanisms through which sustainability adoption can be achieved at the institutional level. First, the framing of sustainable options as part of the broader corporate social responsibility efforts of the organization is suggested as one of the means to improve institutional adoption according to P3. This is quite surprising because P3 represents the least sustainability aware candidate until the introduction of the Green AI model card during the interview, the artefact rejigs their consciousness to the level that their latent sustainability knowledge was revived upon encountering the environmental information which features prominently on the Green AI model card.

> "Corporate social responsibility… every company wants to have that responsibility to the environment… it's good PR." (Participant 3)

Second, P7 explanation revealed a justification framework whereby the important question underpinning the selection of a particular AI model should be whether the carbon or energy cost is justified for a specific increment in the accuracy level therefore reducing institutional barrier to Green AI adoption may be achieved by refocusing the goal from ensuring environmental inclusion in AI decision making to setting environmental considerations as the baseline and each sacrifice of sustainability levels should be justified by a commendable gain in accuracy. P7 "The difference in accuracy is not enough—it's not justifiable given the energy being consumed."

Thirdly, institutional barriers could be broken through influence accrued from the engagement with consulting services. Organizations who employed or delegated their AI initiatives to consultants and who already have sustainability embedded into their own core processes are able to imbibe sustainable AI selection as a result of their relationship with the third party consulting services, this is evident from P6 response on ways to sell sustainability inclusion in AI model selection to top management

> "I already have a kind of flowchart of the factors I consider. And this carbon data is very important when it comes to sustainability… they trust my judgement."(Participant 6)

This implies that although the primary institution may be unaware of sustainability, they remain compliant through the services benefited from consultancy. Thus, the above discussed strategies are effective ways to ensure that barrier to institutional adoption of Green AI are tackled successfully.

Finally, the data analysis revealed a major finding which differs slightly from the literature on the nature of the barrier to sustainability inclusion in AI model selection. The three research themes-the complexity cognition, the observability-awareness and the compatibility-heuristics were presented as parallel barriers that needed to be resolved before Green AI can gain wide acceptance among AI practitioners however the data revealed a causal relationship or dependency among these barriers. Therefore, the challenge of adoption is best solved sequentially from complexity to observability and finally to compatibility. The data revealed that complexity is the primary challenge therefore environmental impacts information must be provided in a meaningful and simplified manner to ensure that the information is manageable cognitive wise for AI Practitioners thereafter the information becomes unignorable leading to high observability for the decision makers and the finally stage is routine use through integration with the existing workflow allowing AI Practitioners to form sustainability conscious habit when deciding on AI models to employ in their organization. The Green AI model card was particularly efficient without any assistance for participants with solid prior knowledge of sustainability whose satisficing criteria ab initio is inclusive of sustainability consideration therefore compatibility is sufficient in resolving the chasm in this scenario, example of such as is P6 stated "I already have a kind of flowchart of the factors I consider. And this carbon data is very important when it comes to sustainability". While for other participants who are just becoming aware of sustainability through the redesigned green model card such as P3, P4, P7 and P8, compatibility is insufficient to close bridge the gap in this instance and the most effective approach is a sequential resolution of the barriers as posited above. The failure to address any of the barriers along the way will reduce the potency of the prototype model card.

4.4 The Classification of the Tipping Point: A Cross-Case Synthesis

This section presents a cross-case synthesis to further illuminate the understanding of the barriers limiting sustainability adoption by AI Practitioners in their organization. The three research themes forecasted that these barriers are resolvable through unique attributes of the redesigned model cards which serves as the research stimulus and while these assertions have held strongly with insights from the empirical data, some additional forms of the barrier which were originally unforeseen have emerged from the data and it represents a unique contribution of this thesis. These different cognitive barriers type and the accompany triggering mechanism of the Green AI model card for the different participants are captured in Table 4.2

Table 4: Cross-Case Tipping Point Classification

Threshold Type	Participant	Cognitve Load	The first attribute of Green AI model Card that triggers Sustainability Inclusion	Kahneman thinking system Classification
Performance Gated	P1	1/7	Side-by-side comparison of hypothetical model	S2 then follow by S1
Colour Triggered	P2	4/7	Traffic light colour valence	S1
Assisted Crossing	P3	5/7	Interviewer contextualisation required	S2 only
Unintentional Crossing	P4	1/7	Task-scale efficiency heuristic	S2
Framing failure	P5	5/7	audio disruption	Unclassified
Gap filler	P6	6/7	Missing information available on the prototype	S1
Cost Benefit-Green	P7	5/7	Deliberate evaluation of metrics	S2
Danger triggered	P8	6/7	Recognition of danger through red colour	S1

To resolve the invisibility of sustainability metrics by AI practitioners, the model card adopted the use of traffic lights color code and visual contrast as one of the properties of the redesigned Green AI model card to propel sustainability to the top of the mind of AI Practitioners and transform sustainability inclusion from system 2 thinking to system 1 thinking which will render sustainability information readable and interpretable within 30 seconds for the model card user. Consequently, the empirical data revealed that this was effective for two participants, P2 and P8 and this was achievable with two participants out of the sample set, P2 and P8, for P2 the response to the cards was morally based and affective, P2 states that

> "GPT Lite has low impact and it is green. And for me, based on my understanding, green is something that is good."(Participant 2)

And for P8, the traffic lights resonate with danger or safety signal.

> "The one on my left, which is red, it first gives me the signal—danger… the other one on my right gives me a safety signal." (Participant 8)

And lastly for P6, they immediately recognized the Green AI model cards as the missing artefacts that could have ensured seamless sustainability inclusion in their role, their reactive to it was positive and transformative , P6 states that "Oh, wow. This is nice. This is really, really nice." Therefore, for these three participants, the redesigned Green AI model cards successfully activated their system 1 thinking although for P6, it was more of confirmation of what's missing while for P2 and P8 it was discovery of a new artifact and information.

The threshold was equally overcome by P1 and P7 but not at the system 1 thinking level. The Green AI model card enabled these two participants to include sustainability in their decision making while still conducting a comprehensive analysis of the two hypothetical AI models presented to them on the model card. Therefore, their decision making remain at system 2 level but with the inclusion of sustainability, for P1, performance remains the decisive factor but, in a scenario, whereby the accuracy differential between two AI model options is comparable then sustainability becomes the tie breaker. P3 "Since model B, the accuracy is almost the same as model A and then the carbon emission is way, way down. I'll most likely work with model B", for this participant, the threshold was crossed by comparing the magnitude of the difference between the carbon emission data for the two AI model options. For P7, they conducted the most systematic and thorough evaluation among all the interview candidates, they did a comparison of the two hypothetical AI models on the Green AI model cards and then introduce a justification framework by asking the topical question thereby redirecting the burden of proof from proving whether sustainability is justified to asking whether adopting accuracy is worth the investment, the participant is of the opinion that the marginal gain in accuracy of 1.2% is not justified with the magnitude of the carbon emission, P7 states that “The difference in accuracy is not enough—it’s not justifiable given the energy being consumed.’ P7 opinion is understandable since P7 works in an environment where regulatory oversight is paramount.

The remaining three participants do not fit directly into either system 1 or system 2 thinking by design, they otherwise revealed other possibilities beyond the conceptualized framework for the research. For example, P4 approached the interpretation from the nature of the task to be done and the model fitness for purpose and not originally from the sustainability and accuracy viewpoint.

> “So for me personally, I'll go for the GPT Lite because I mean, though compared to the other version, the accuracy is a bit, but there's no more difference, basically. There's no more difference in terms of accuracy, in terms of latency, energy use, right? I'll go for GPT Lite, but When it comes to probably large projects, yes, I'll go for the standard 7B.” (Participant 4)

Therefore, their decision lies in the nature of the products or projects and accuracy requirements. The system 1 or 2 was also not activated from P3 until when the interviewer provided more support with the interpretation of the artefacts before the participants was able to understand the environmental information, this implies that prior knowledge of sustainability is a prerequisite for the efficiency of the model, for P5, the quality of the audio was unreliable hence their exclusion from the analysis.

The data also showed that no single attribute of the Green AI model card is solely sufficient in bridging the gap between awareness of sustainability and implementation of same. While traffic lights and visual contrast were effective for P2 and P8, side by side comparison was the effective mechanism for P1 and P7 and even both attributes were not effective for P4 who viewed the decision strictly on the task accuracy requirement. The implication of this is that the Green AI model card will continue to be efficient by ensuring that each of this mechanism are carefully combines to form the final version of the document, this will ensure that regardless of the location of the participants cognitive barrier, the Green AI model card remains effective in resolving the chasm. The nature of the different cognitive thresholds exhibited by the research participants indicates that there is no uniform bridging point but rather a heterogeneous and diverse threshold exists among practitioners which resolvable through a combination of unique design combinations for the Green AI model card.

4.5 Responding to the Research Objectives

The first research objective examined how information overload from the bounded rationality theory of (Simon, 1972) and high diffusion of innovation complexity (Rogers, 2003) interact to prevent environmental consideration in model selection. The literature synthesis foresaw a universal cognitive limitation experience by AI Practitioners which result in satisficing without the inclusion of sustainability and which could be resolved through the introduction of simplified AI model card that is inclusive of environmental information. While the general assumption about the existence of the cognitive barrier is true the empirical data shows that its nature is heterogeneous and not universal for all practitioners and the existing satisficing schemas is excluded of sustainability, seven out of the eight practitioners "satisfice" without sustainability. P1 has the lowest cognitive load yet forgo sustainability criteria in decision making, P3 needed additional information before comprehending the carbon data and P7 overcame the cognitive barrier upon the introduction of the research artifact, the artifact was effective because P7 has latent sustainability knowledge as against P3.

The second research objective seeks to understand why environmental impact information remains invisible in the current AI model cards through the synthesis of the theory of diffusion of innovation theory and specifically the low observability attribute and secondly, the theory of bounded awareness. The efforts are directed towards evaluating the potential of improved observability attribute element of the existing AI model card to bridge the operationalization chasm that is the gap between awareness and implementation of sustainability. The data obtained from the field revealed the efficacy of the redesigned artifact whereby observability attributes such as visual contrasts and side by side comparison assisted in bridging the gap for some practitioners but observability alone as a criterion was insufficient in bridging the chasm across board. The thesis further confirms that the absence of universal level of awareness about sustainability among the AI product managers, but awareness exists on a spectrum from zero awareness to full awareness prior to the introduction of the design artefact. Overall, the existence of bounded awareness is observed but the bridging requires meeting the participants' at their respective sustainability awareness level, for example, P6 that has full awareness of sustainability only prayer is the provision of the information infrastructure that is inclusive of sustainability information while colour valence assisted P2 and P8 that compare the green and the red colour of the hypothetical model to moral good and safety respectively.

The third objective examined how heuristic reliance and low workflow compatibility prevent sustainability from entering routine decision processes. The suggested solution is the removal of friction and ensure seamless integration of the model card to the existing workflow, this will translate to automatic inclusion of sustainability in decision making like the system 1 thinking whereby sustainability becomes default consideration for AI Practitioners. This assertion was confirmed accurate based on the data as all the participants refused the idea of hosting the model cards on a different website apart from their individual workflow. In addition to this confirmation, the data revealed two additional important findings that environmental exclusion from decision making are socially reinforced through professional community who themselves are unaware of sustainability and secondly institutional barrier which operates at higher order level than the Green AI model card. The implications of these findings are further discussed in the next chapter.

Finally, the thesis provided answer to the primary research question which goes thus, to explore how cognitive constraints interact with model card design features to bridge the operationalization chasm for AI practitioners. Findings from data analysis indicate that this question is best answered at two levels, one for the individual and the other for the organization at large. For the individual, both system 1 and system 2 design features on the model card were useful in rejogging their memory for sustainability inclusion in decision making, the organizational level revealed that the effort at level one is insufficient until institutional barriers such as gatekeeping and whitelisting requirements are resolved. The specific interventions to address both individual and institutional barriers are discussed in chapter 5.

4.6 An Exploratory Visual Framework: The Cascading Threshold Model of Green AI Operationalization

The data analysis shows the cascading nature of the three barriers limiting sustainability adoption among AI practitioners as against the forecasted parallel relationship among the themes. Thus, a cascading threshold model (CTM) arising from the findings was developed and the same is presented below:

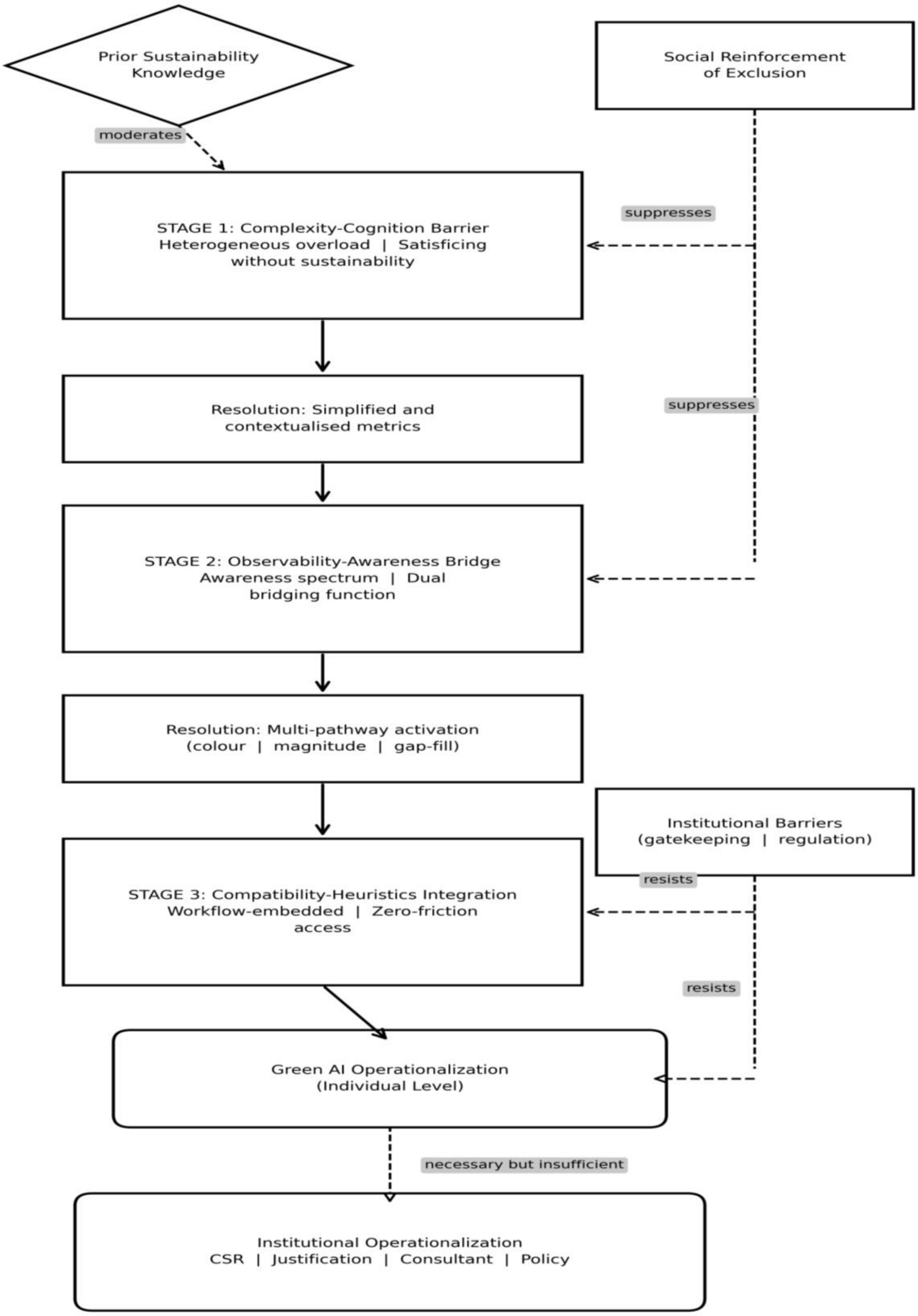

Figure 6: Cascading Threshold Model (CTM) of Green AI Operationalization

First, the findings show that the existence of complexity-cognition barriers is undeniable and its represent the foundational barrier to Green AI adoption, the participants rating of information overload ranges from minimal to maximum load showcasing the heterogeneity of this concept as oppose to the initial expectation of uniform load among the participants however regardless of the level of information overload, sustainability failed to feature in the decision schema of 7/8 participants. The research stimulus was successful in catapulting sustainability into decision makers' consciousness through contextualization and simplification of the model card design, but its impact is moderated by prior sustainability knowledge.

Having successfully resolved the complexity barrier, the next layer is the observability-awareness theme. Here, the findings revealed that awareness exists on a spectrum, at the peak is full awareness but unaccompanied by sustainability-oriented action due to insufficient environmental impact information on the model card and at the bottom is zero awareness. At the zero-awareness level, sustainability is imbibed through the visibility of the information on the model card and at the peak awareness level, the model card serves as a ready-made information infrastructure to be adopted for decision making. Additionally, the Green AI model card features enable the triggering of system 1 thinking from multiple pathways including color coding and contextualization of metrics. The final level is compatibility heuristics which aim to embed the redesigned artefact as part of the existing workflow of the AI product managers. The analysis revealed that this is a non-negotiable requirement for practitioners and compatibility is only efficient provided the penultimate barriers including complexity and observability has been resolved.

Furthermore, two critical barriers exist independent of the sequential individual threshold. The first barrier has its origin in the reinforcement of sustainability exclusion by professional communities where AI model selection conversations continue to center on accuracy and performance and the second barrier is institutional barrier manifesting in organizations' prioritization of competitors certified AI solutions for adoption and the absence of government fine for non-selection of green AI alternatives. These external barriers exert downward pressures on the CTM implying that even when the Green AI model card has successfully bridged individual threshold, the external forces may forestall adoption.

5 DISCUSSION

5.1 Summary of Key Findings

The data analysis confirms the theories that underpin this study. The thesis employs a dual synthesis of bounded rationality theory of Simon and the theory of diffusion of innovation to understand the cognitive load experience by product managers during AI model selection. (Simon, 1955, 1972) propounded that humans satisfice during decision making, this implies that due to time pressure and limit of the human cognitive ability, they often resort to the first optimal solution. Oladeji (2026) classifies the different cognitive load experience by product managers into three unique kinds and each one of these cognitive loads always led to the overwhelming of manager's mental capacity during decision making. Phillips-Wren & Adya, (2020) found that short term memories function is severely dampened due to time pressure faced by professionals and its long-term consequence is reflected in excessive reliance on simple heuristic when making decisions. All these earlier assertions were clearly observable and proven from the research findings, for example, most of the participants satisfice specifically 6/8 arrived at their AI selection model currently without any recourse to sustainability and under time pressure they are unwilling to fetch sustainability information from another external source unless such information are readily included in their workflow and the redesigned Green AI model cards which was employed as a research stimulus achieved substantial result in promoting sustainability to the consciousness of the AI practitioners proving that the artefact possess the ability to influence a participant in overcoming complexity and observability barrier experience when selecting AI models for their projects. These findings are further supported by Siyal's et al., (2023) quantitative evidence which shows that the level of adoption can be ascertain by the degree of compatibility.

The thesis finding equally represents an extension of the diffusion of innovation theory. The study set out with the application of three DOI attributes to understand the ineffectiveness of the existing AI model card in promoting sustainability, but the research outcome indicates that the barrier to sustainability is broader than the three identified barriers. Furthermore, the work also extends the dual processing of Kahneman (2011) whereby it is expected that system 1 thinking remains dominant under limited time availability for managers, but some participants constitute an exception to this theory.

The findings also provided clarity on the nature of the operationalization chasm which refers to the gap between awareness and implementation of sustainability. The awareness level of sustainability among the industry professionals is heterogenous and not uniform, implying that professional awareness exist on a spectrum ranging from default level representing zero awareness to perfect level depicting full awareness and this implies that intervention efforts should be sufficiently comprehensive to bridge the chasm regardless of a professional current level of awareness based on the sustainability spectrum. Chugh and Bazerman (2007) theory of bounded awareness is apt here, when decision maker attention is elsewhere, increasing visibility of a particular information of interest does not guarantee its inclusion in decision making therefore sustainability orientation should precede artefact redesigning for practitioners at the lower rung of the spectrum. Tarka (2017) goes ahead to confirm that access to more information by managers does not lead to improved implementation to close what they describe as the action knowledge gap. Liang et al. (2024) further shows that sustainability information availability is limited currently on the model card and about 97% cards have environmental data excluded. Gutiérrez et al. (2025) found that 27% of papers did not provide energy related data in their studies and Verdecchia et al. (2023) confirmed that Green AI popularity is restricted to the academic environment with no significant industry collaboration yet. As stated earlier, the data obtained from the field equally confirmed the above studies positions, firstly, two participants has never considered any environmental impact factor in choosing the AI model to use in their products and only one participant is fully aware of sustainability and even for this participant, they complained about inability to access sustainability information in most of the cases because they are not available on the model card. Aside from this sustainability conscious candidate, other participants fall under the findings of Chugh and Bazerman, 2007; Tarka 2017, where although the current sustainability information is limited, the practitioners have expressed no initial desire to seek and act on Green AI attainment in their projects. While P6's confirmation of the sustainability information deficit on the current model card confirms the position of earlier studies that documented the sustainability information deficit on current model cards (Gutiérrez et al., 2025; Liang et al., 2024; Verdecchia et al., 2023). Therefore, the probability of achieving sustainable AI adoption would increase significantly with the dual efforts including introduction of artefacts that reduce information complexity for practitioners and ensuring that relevant environmental data are included as a component of this redesigned artefact- the Green AI model card.

5.2 The Dual-Lens BR-DOI Synthesis

The study also shows why the use of either bounded rationality or diffusion of innovation separately without the dual synthesis would have yielded limited research insights. Bounded rationality was useful in understanding the why of the problem, it provided the reason why AI practitioners when faced with time pressure and information overload results to familiar heuristics such as the AI model performance and the diffusion of innovation theory assisted in developing attributes that the intervention research stimulus must possess to resolve the identified challenges from the BR theory. The data indicates that 6/8 of the participants “satisfice” that is they choose AI models that they considered good enough without evaluating the environment implications of their choice and the diffusion of innovation indicates how complexity challenges inherent in the current Green AI model card should be resolved through the contextual information provisioning and reliance on the effectiveness of the color code in promoting visibility.

This study therefore makes a new contribution to the Green AI discourse by depicting the way these two distinct theories combine seamlessly to resolve a major challenge in the sustainable AI field.

This thesis' second theory related contribution deals with the extension of diffusion of innovation theory particularly in the Green AI context by showing that adoption attributes are not linear but rather possesses a causal relationship. The original theory by Rogers treated each innovation attribute as separate factors which require individual optimization to achieve desired result but pertaining to Green AI domain, the data analysis shows that causal relationships exist among the three-innovation attributes under investigation, for example, the front runner barrier to adoption is high complexity and it demands immediate intervention as the data analysis shows that the current habit of providing raw environmental information without context pose a difficulty for the practitioners and has led to minimal adoption and until this barrier is removed, observability cannot create salience for practitioners. It is when observability becomes effective in igniting sustainability consciousness among practitioners that compatibility will become the next pain point to be addressed through integration to practitioner's existing workflow, therefore the current challenges are best resolved sequentially.

5.2.1 The Classification of Different Threshold Tipping Point

In chapter 2, relying on the Kahneman theory, it was assumed that the redesigned artefact would move sustainability information processing entirely from system 2 thinking to system 1 and Bonisoli et al. (2024) provided the context for sustainability in the literature claiming that observability upliftment as a prerequisite for sustainability implementation. The data confirmed the successful bridging of the sustainability exclusion by triggering the system 1 thinking process of some practitioners using the color code for P2 and P8 but system 1 thinking activation using the research stimulus was not universal for all participants. For P1, the thinking started with deliberate and careful analysis which is typical of system 2 before switching to system 1 while P7 rely on system 2 all through their decision making process, the silver lining is that all the participants included sustainability upon presentation of the artefact, therefore system 1 processing is valid but not for everyone even when simplified information is presented to decision makers and Bonisoli's et al. (2024) assertions of observability preceding sustainability adoption is true but the attribute which triggers observability differs from one participant to another.

This thesis findings also extend the Kahneman's dual processing theory, Kahneman classifies thinking into two types, system 1 and 2 whereby system 1 is intuitive and quick but no additional subcategory under system 1 exists under the original theory but empirical data revealed the existence subcategories. Duran et al. (2024) using energy label color coding from A-E promoted observability of sustainability and this aligns with the research findings whereby two participants responded positively to color coding particularly P2 and P8. The color coding triggers system 1 but the individual response differs, P2 showcase colour valence by comparing associating goodness with green while P8 response mirrors danger detection, they claimed that "it first gives me a danger signal", their response indicate an urgency, the need for swift response to avert the impending doom if sustainability is excluded. While this finding is akin to that of Duran et al. (2024), the uniqueness of each participants system 1 thinking response to color coding represents an improvement on previous efforts.

5.2.2 Beyond Bounded Awareness: Infrastructure-Located Chasm

Earlier studies have consistently assumed that individual cognitive barrier and attention deficit are solely responsible for omission of crucial information from decision making (Chugh and Bazerman, 2007; Simon, 1972) hence their conclusion follows that practitioners due to the excessive amount of information that needed to be processed when making decisions often forgo the less visible factor such as sustainability. This assumption further informs the redesigned model card where it was assumed that by applying Rogers (2003) DOI high observability attribute to the current card, it would result in improved sustainability consideration in decision for practitioners. P6 response shows that not all practitioners ignore sustainability and its exclusion may be because of information deficit therefore the universal claim of cognitive limitation as the sole culprit for not considering sustainability is unsubstantiated in all cases especially where sustainability is already integrated into the participants decision criteria because even if the participants were to consider sustainability at the point of selecting a model, the information to guide their decision is not readily available, P6 states that "To find it is one thing, and to understand it is another. It's very rare—we hardly come across a model card that includes environmental information", therefore the limitation is not cognitive alone, but information deficit is also additional challenge that needed to be tackled. Chugh and Bazerman (2007) remedy for bounded awareness rely on making information more visible but visibility in the absence of the real information is unattainable, moreover, Liang et al. (2024) analysis of one of the top websites for hosting AI model cards confirms that environmental information is only available in rare cases about 2%. Gutiérrez et al. (2025) showed that beyond model cards, even in academic AI research energy consumption information, were only provided in only 27% of published articles. Jouneaux and Cabot (2025) redesigned the model card to include sustainability, but their efforts are still at design stage and not industry proven and Verdecchia et al. (2023) concluded that the limited tools arising from academic research are yet to make it into the industry. Therefore, this reinforces the argument that the limitation to sustainability inclusion is not the cognitive barrier experiences by practitioners alone but insufficient environmental information on the existing tool for making AI model decisions in practice.

5.2.3 The Sustainability Paradox

This section takes a step outside of this study to discuss Jevons Paradox, although this concern did not arise from the interview discussions, but the phenomenon is crucial in the broad context of energy efficiency. Originally, Jevons addresses a situation whereby energy gain from technological innovation resulted in more demand thereby offsetting whatever progress that has obtained from the adoption of same technology (Alcott, 2005; Sorrell, 2007). Jevons paradox in the context of this study addresses a situation whereby practitioners continue to deploy AI products on astronomical level such that the aggregate energy use continues to grow since users now assume that AI model selection decisions are energy efficient thereby offsetting the anticipated energy savings from adoption of sustainability. The overall objective of the study is to promote the ability to make greener choices by AI product managers at the micro level using a research stimulus-the Green AI model card and considering the fact that AI ecosystem is still growing and evolving, the optimization at the micro level is set to contribute to the attainment of the Green AI sustainability targets but its actual net environmental contribution at the broader scale remain unaddressed.

5.3 Practical Implications

This thesis' findings are useful for different stakeholders including AI model cards developers who are concerned with the effectiveness of their cards in assisting with AI models' selection decision and organizations who are aspiring to improve their AI governance policy by including sustainability as a key consideration when carrying out AI related projects. The research outcome usefulness is not restricted to these micro level groups only but also useful to the government in their quest to develop contemporary policies to promote sustainable AI would find the recommendations timely and beneficial since this represent one of the earliest efforts to study Green AI from the behavioral lens and the findings are rooted in real life participants experiences.

5.3.1 Practical Implication for Model Card Designers

The data analysis revealed that the cognitive load experience by AI practitioners varies greatly from one participant to another and that no single feature of the redesigned model card is sufficient on their own to resolve this load rather it shows that each respective mechanism of the card was necessary and effective in closing a unique type of the threshold therefore exclusion of a feature pose a danger to the closure of the particular threshold it addresses. Therefore, the model should imbibe the different mechanisms that have been proven successful by this thesis such as the immediate response to color coding by P2 &P8, P2 clearly stated that —"green is something that is good"— and for P8 response depict someone who recognize danger from the onset and attributed the red colour allocated to the less environmental friendly option on the model card to a not suitable option. The reaction of P2 and P8 is consistent with the dual processing theory of Kahneman's (2011) whereby decision makers relying on system 1 thinking can speedily make decisions, they achieve this prompt decision making by relying on the colour coding of the redesigned model card to select a more sustainable AI option. However, for P1 and P7 they adopted a more rigorous evaluation in the form of numerical quantification of the environmental impacts of the two hypothetical AI models option on the redesigned card before arriving at a more environmental friendly option, their approach aligns Kahneman's (2011) system 2 thinking, where decision making process is deliberate and thorough, therefore effective model cards should consist of both the colour coding and contextualization of the sustainability metrics to ensure seamless bridging of the identified chasm, the gap between awareness and practice.

Furthermore, the data analyzed confirmed that indeed relatable metrics are more effective in driving sustainability adoption as against provision of raw metrics. For example, P7 in his response to the best way to secure management buy in for marginal accuracy sacrifice in order to choose a more greener AI alternative carved out a pitch centered on the energy consumption value rather than the use of the carbon weight values even though both parameters are available on the model card stating that “energy consumption of 1,287 compared to 1,029—that’s almost a 1,000-unit difference” , P7 interpretation follows industry specific focus which is banking where operational cost efficiency is a key performance indicator hence the reason this participant settled for a similar value measurement in the form of energy use value which also inform their interpretation of the metric, this further buttresses the point that reframing sustainability to align with familiar key performance indicators in a target industry present an opportunity for real adoption to take place which guarantee more success compare to the use of abstract metrics such as carbon values. This finding mirrors that of Duran et al. (2024), where the use of familiar energy efficiency labels which are also a form of color-coding aided comprehension of sustainability information and equally the work of Bonisoli et al. (2024) where attitude changes towards sustainability became feasible by making information more visible.

Lastly, most of the Green AI studies have focused on the optimization of energy use at the inference stage of the AI however, future studies should expand the scope to include the lifecycle energy efficiency of the model so that the same comprehensive energy consumption information would be provided on the model card as against information limited to just a phase of its lifespan. This would significantly influence the quality of decision making, especially concerning the sustainability of AI, the provision of such lifecycle data covering the development of the model and everything in-between and to retirement of the model would enable holistic comparison of AI models across all stages of their lifespan. The inclusion of complete lifecycle environmental data will further enrich this thesis and other related prior research including Jouneaux and Cabot (2025), who propose the first version of sustainability model card included water consumption in both training and inference stage for the first time as a component of the model card.

5.3.2 Practical Implication for Organisations

The research outcome also exposes the existence of institutional barriers to sustainable AI and the attendant strategies to overcome these institutional bottlenecks that were identified from the interview conducted with AI practitioners.

To begin with, participants suggested numerous ways to advocate sustainability inclusion in organizational AI decision making and to make sustainable AI reception the new normal. For P3, management buy-in for sustainable AI is best attained through reframing of Green AI efforts as a contributor to the overall corporate social responsibility efforts of the organization, they claimed that “every company wants to have that responsibility to the environment… it’s good PR,”, for another participants, P7, selling sustainable AI to top management could be done using a justifiability framework whereby each additional unit of improvement in accuracy is justified by the magnitude of energy consumed, the decision lies in gauging the fairness and commensurateness of accuracy versus energy consumption, they stated that “the difference in accuracy is not enough—it’s not justifiable given the energy being consumed.”, participant 8 favors the projection of sustainable AI as an effort towards achieving responsible A and SDG goals, P4 clamor for approaching the sustainability acceptance from the lens of promoting transparency and P6 relied on professional authority to secure management acceptance. Overall, overcoming institutional barrier to sustainability requires effective collaboration among the stakeholders and top management support and this coincides with the position of Robertson and Samy (2019), where the authors opine that sustainability inclusion should be deemed a core governance activity and that management support is essential towards achieving this objective.

Institutional barriers can also be bridged through the engagement of professional consulting services. P6, who is a consultant on AI projects believes that the principal organization trust in the professional services offered is sufficient to secure their approval for sustainability inclusion in their AI model selection, she stated that —“they trust my judgement. As a consultant, they trust my judgement”. However, relying on a single consultant authority to drive sustainability in the organization poses a key man risk and is not reliable long term, a more sustainable option requires the training of more top IT expert personnel in the organization on the inclusion of sustainability as a key criterion in their AI selection decisions. These findings align with the discovery of Rakova et al. (2021), where the authors stated that responsible AI efforts are driven by motivated experts in the organization due to absence of organization policy. Gellers (2026) further asserted that in the absence of external accountability, firms assign minimal importance to sustainability initiatives which further buttress the argument for top level management efforts to drive sustainability inclusion as against an organic or individual personal motivation.

Third, Participant 3’s observation that sustainability was never discussed in the organisation’s Slack community dedicated to AI—“what we just discuss is accuracy, how well it does”—. This revealed that sustainability exclusion is a norm in the professional circle and performance and accuracy remain the dominant decision criteria among the larger professional community therefore organization should introduce sustainability as part of the focus area on internal channels where knowledge sharing are carried out, this represent easy low hanging fruit towards improving sustainability consciousness among professionals. This is consistent with Bolte et al. (2022), where they found environmental considerations would improve among professionals if such considerations were considered acceptable and valid among their broad social circle. The current culture of performance first clearly omits sustainability resulting in the impossibility of sustainability attaining the so-called social validity among experts.

5.3.3 Practical Implication for Policymakers

These policy improvement suggestions were developed to fill the lacuna that persists after necessary inventions aim at removing individual and organization barriers have been successfully implemented. This thesis is making two policy improvement suggestions that are rooted in participants real life experience and the third improvement deals with the extension of existing theory.

First, the non-prioritization of sustainability in Green AI decision making has been linked to absence of consequences for defaulting organizations by the government. P7 unequivocally states that if there are no repercussions for not selecting a more sustainable option and if such option is not cost efficient then sustainability as a reason is insufficient, P7 stated that “if there is no cost implication or penalty for ignoring the environmental part, I might not consider it”. Therefore, the introduction of a compulsory disclosure policy like the regulatory requirement for organization to announce their financial performance periodically and file same with the regulator, similar pronouncement should be emulated for sustainable AI, this would move the practice of sustainable AI from personal choice or decision to regulatory requirement. Earlier work has shown that self-acceptance of sustainability responsibility is inefficient, Mill et al. (2022) studies revealed that only 20% of researchers voluntarily revealed the energy consumption information of their project and Gellers (2026) confirmed the demotion of sustainability by organizations because of their prioritization of profitability. Thus, an effective way for organization to toe the line of sustainability compliance is through regulation.

The second regulatory intervention is the mandatory requirement to companies primarily developing foundational AI models, companies such as Anthropic, OpenAI, Google, Deepseek and other technological giants for mandatory provision of every model’s environmental information. This information deficit issue was raised by P6 where some models were not accompanied by their environmental impact metric therefore it impossible to determine their greenness. This data omission issue was also raised by other authors most notably Liang et al. (2024) whereby environmental related information is only provided in 2-3% of the cases in their analysis of model cards and Jouneaux and Cabot (2025) provided a structure for the provision of this missing sustainability information but without government support, their template adoption may remain insignificant.

5.4 Limitations

The first limitation of this study lies in the geographical location of the participants. The participants are professional based in Nigeria which is an emerging economy and sustainability maturity of the organizations may not be at par with Western Countries including Europe and North American. This implies that some findings may not be applicable in European context, particularly the CSR initiatives and promotion of Strategic Development Goals.

Furthermore, the research prototype was visualized via the screen sharing option of the online meeting platform and was not deployed in real life active workflow for the participants. This implies that responses capture the intention of the participants and not the real action. Although the entire research participants declared positive intention towards compatibility with workflow, the real-life use of the prototype will provide undeniable proof of real adoption. A longitudinal study of real-life usage of the redesigned Green AI model card will further enrich the findings.

Finally, the study focuses on resolving the individual cognitive barrier to sustainability inclusion in decision making and organization barrier to sustainability inclusion was out of scope. However, the thesis revealed the potential of clashes between individual adoption motivation and organization decision making. For instance, the existence of management approval phase gate before model selection concurrence for P1 whereby requirements from management excluding sustainability pose a dilemma in which individual awareness of sustainability is insufficient to bridge the gap. This limits the potential to generalize whether individual sustainability adoption would translate to broad adoption at the organizational level.

5.5 Conclusion: The Path from Awareness to Action

This study examined how cognitive constraints interact with model card design features to bridge the operationalization chasm for practitioners navigating Green AI trade-offs. The thesis used reflexive thematic analysis to analyze the data gathered from eight participants that currently make AI selection decisions in their role. The analysis of the data resulted in three important conclusions, first, the operationalization chasm is real the lacuna in sustainable AI implementation is real, but its form differs from the theorized as it exists as a spectrum and not uniform for all practitioners. The evidence of the chasm existence is visible since 6/7 of the participants do not bother about sustainability impacts when selecting the AI model to work with, the six participants all "satisfice" by focusing only on their criteria of interest including performance and risk management. Another form of chasm was exemplified by lack of environmental information on the existing model card therefore the card requires an urgent review to include a dedicated session catering for environment impacts of the individual AI model. Therefore, a combination of intervention efforts aims at resolving individual barriers to Green AI and the ecosystem data provision for decision makers should be prioritized. Second, the cognitive limitation experienced by each professional differs from each other and different model cards attributes are effective for different barrier type, for example, color coding was extremely useful for two participants as it assist them in choosing a more environmental friendly AI option, for other participants, the contextualization of the environmental metrics enable them to overcome their cognitive limitation, the cards must therefore be designed such that its effectiveness remains regardless of the practitioners' form of cognitive limitation.

5.6 Final Reflection

As adoption of AI increases globally, the data centers powering them continue to consume electricity at an unprecedented rate, their share of worldwide electricity usage is projected to reach 3% by 2030 representing a 100% increase in only six years. The impact of AI model selection decisions at the micro level by practitioners is not insignificant to this problem, especially when millions of such decisions are made by employees globally and managing these decisions for optimum sustainability presents a crucial opportunity to tame the continuous surge in energy demand by AI. The environmental impact of AI was studied at the practitioners' level by examining individual model selection decisions and whether sustainability receives attention or not. The outcome presents a starting point for intervention efforts towards sustainability inclusion both for the individual and the organization. Intervention efforts for individuals should major in threshold crossing by combining the attributes of diffusion of innovation theory and studies participants identified sustainability framing including CSR and responsible AI efforts as the dominant narrative that could serve as the catalyst for organizational adoption. Overall, this thesis identified the specific barriers limiting individual from sustainability consideration while selecting AI models for their projects and introduced a redesigned artefact that successfully bridge this gap under certain conditions and for some professionals, it shows the potential of what could be achieved should environmental impacts data become available and visible on the model card.

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Appendices

Appendix 1. Interview Question Guide

Phase 1: The Decision Baseline (Complexity-Cognition Nexus)

Current Heuristics & Decision-Making

1. "Talk me through your last model selection process. What information was on your screen, and what technical factors did you look at first to decide if a model was 'good enough' to move forward with?"

2. Information Overload & Cognitive Load

"On a scale of 1 to 7, where 1 is 'Never' and 7 is 'All the time,' how often do you feel overwhelmed by the amount of data and documentation you must process during model selection?

Phase 2: Visibility and Awareness (Observability-Awareness Bridge)

3. Existing Visibility of Impacts

"In the tools you currently use (like HuggingFace or SageMaker), how easy is it to find and understand the model's environmental footprint, such as its energy use or carbon emissions?"

4. The Stimulus Response

"Looking at the comparison of these two models on the prototype screen, walk me through your thought process as you evaluate which one fits your current project needs."

Phase 3: Integration and The Tipping Point (Compatibility-Heuristics Integration)

5. Workflow Friction & Compatibility

"On a scale of 1 to 7, where 1 is 'Not likely at all' and 7 is 'Extremely likely,' how likely would you be to use this carbon data if it was located on a separate website instead of being embedded in your main dashboard?

6. The Organizational Tipping Point (Justification & Friction)

"Imagine you have to present your final model selection to your stakeholders tomorrow. How would having this specific Model Card change the way you justify your decision, if at all?"

Appendix 2. The Redesigned Green AI Model Card