A methodology for consistent scenario construction through novel crowdsourcing and advanced impact analysis techniques

By

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DECLARATION

I, Robyn Cindy Thompson, declare that this thesis is a representation of my own work, both in conception and execution. This work has not been submitted in any form for another degree at any university or institution of higher learning. All information cited from published or unpublished works have been acknowledged.

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DEDICATION

To my beloved family:

To my husband, whose encouragement has been my strength throughout this journey: Your faith in me has been a constant source of motivation, and I am forever grateful for your companionship and support.

To my children, whose love and pride inspire me every day: Thank you for your understanding and the sacrifices you have made along the way, and for your constant encouragement.

To my precious grandchildren, whose laughter and light fill my life with joy: May this work serve as a testament to the love and dreams I hold for each of you.

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This thesis is dedicated to you all, with endless love and gratitude.

PUBLICATIONS FROM THIS RESEARCH

Published journal articles

i. Thompson, R. C., Olugbara, O. O. and Singh, A. 2018. Deriving critical success factors for implementation of enterprise resource planning systems in higher education institution. *African Journal of Information Systems*, 10 (1).

ii. Thompson, R. C., Olugbara, O. O. and Singh, A. 2026. Crowdsourcing knowledge for constructing consistent scenarios. *Algorithms*, 19(10), 41.

Published conference paper

i. Thompson, R. C., Olugbara, O. O. and Singh, A. 2020. *CIMgen method for generating cross-impact matrix in impact factor analysis*. In: Proceedings of 2020 Conference on Information Communications Technology and Society (ICTAS). IEEE, 1-5.

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i. Thompson, R. C., Olugbara, O. O. and Singh, A. 2025. Trends in Scenario studies: A Bibliometric Review.
ii. Thompson, R. C., Olugbara, O. O. and Singh, A. 2025. Scenarios for the adoption of artificial intelligence in higher education: A CIA4Scenario approach.

TABLE OF CONTENTS

LIST OF ABBREVIATIONS

ADVIAN®	Advanced impact analysis
AI	Artificial intelligence
AWS	Amazon Web Service
CIA	Cross-impact analysis
CIB	Cross-impact balance
CIM	Cross-impact matrix
CRI	Criticality
DRE	Driven
DRI	Driving
DSR	Design Science Research
GPT	Generative pretrained transformer
GST	General systems theory
ILM	Intuitive logic method
INT	Integration
LDA	Linear discriminant analysis
LLM	Large language model
LP	La Prospective
MACTOR	Actor strategy mapping
MICMAC	Impact matrix cross-reference multiplication applied to a classification
ML	Machine learning
NLP	Natural language processing
PCA	Principal component analysis
PMT	Probabilistic modified trends
PRE	Precarious
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-analysis
PST	Potential surprise theory
RDAS	Relative direct active sum
RDPS	Relative direct passive sum
RIAS	Relative indirect active sum
RIPS	Relative indirect passive sum
SDG	Sustainable Development Goal
SEM	Structural equation modelling
STA	Stability
TIA	Trend impact analysis

LIST OF FIGURES

LIST OF TABLES

ABSTRACT

The construction of consistent and time-sensitive scenarios plays a crucial role in strategic planning, foresight, and decision making across a wide range of disciplines. By anticipating future trends and uncertainties, scenarios allow organizations and policymakers to better comprehend current situations, prepare for possible futures and mitigate possible risks. However, scenario construction methods are increasingly criticized for time intensive data collection and analysis processes, the influence of cognitive bias, difficulty in handling complex interactions, over-reliance on a limited pool of experts, and inconsistency in assigning judgements, all of which can affect the validity, inclusivity, and utility of the resulting scenarios. In addition to these methodological limitations, traditional scenario construction approaches lack a coherent theoretical foundation. Many methods are grounded in either overly rigid quantitative models or unstructured qualitative exercises, failing to adequately account for the interconnected, dynamic, and interpretive nature of complex socio-technical systems.

This study addresses this gap by developing a methodology explicitly grounded in a complementary theoretical framework comprising general systems theory (GST), complexity theory, potential surprise theory (PST) and constructivism. This framework provides the conceptual basis for ensuring structural rigour, embracing dynamic uncertainty, and incorporating diverse perspectives, thereby enabling the construction of scenarios that are both analytically robust and strategically relevant. This study proposes a novel cross-impact analysis methodology for scenario construction that is based on the crowdsourcing process, advanced impact analysis (ADVIAN®), and cross-impact balance (CIB) analysis. The aim is to overcome the limitations of conventional methods by enabling faster, more diverse, and more theoretically grounded scenario development.

The methodology was implemented and validated over two practical applications. The first was the adoption of renewable energy and the second artificial intelligence (AI) adoption in higher education. In addition to validating the robustness and scalability of the proposed approach, these applications generate practical, context-specific scenario outputs. For renewable energy adoption, the resulting scenarios provide structured insights into potential transition pathways under varying conditions. For AI adoption in higher education, the scenarios highlight alternative trajectories shaped by institutional, technological, and socio-cognitive factors. These outputs offer actionable value for policymakers, institutional leaders, and other stakeholders engaged in strategic planning within these domains.

The primary contribution of this research lies in the development of a novel, theory-driven scenario construction methodology that systematically integrates the crowdsourcing process, ADVIAN®, and CIB analysis within a coherent analytical framework. The study demonstrates how this integration enables faster, more efficient scenario construction, reduces potential bias, and increases the diversity of perspectives. These advancements address the major challenges of traditional scenario planning, such as lengthy data collection and analysis processes and the risk of over-reliance on a narrow pool of expert opinions. This research makes a significant contribution by introducing a novel, scalable methodology, grounded in theory, that blends advanced

analytical techniques with crowdsourcing to enhance scenario construction. By strengthening the theoretical foundation, improving methodological efficiency, and expanding the diversity of perspectives, the study provides a practical and academically rigorous approach to scenario planning. Future research can build on this approach to further refine scenario methods and explore broader applications across sectors facing complexity and uncertainty.

CHAPTER 1: INTRODUCTION

This thesis explores the implementation of the crowdsourcing process with the application of the advanced impact analysis (ADVIAN®) method and cross-impact balance (CIB) analysis in the construction of scenarios. Specifically, it addresses the theoretical and methodological criticisms levelled at existing scenario construction methods, with a focus on data collection strategies, analysis methods and the recruitment of study participants. This chapter offers an overview of the thesis and outlines the key questions that inspired and shaped the research process.

The study is framed within the context of two areas of literature: scenario construction methods and crowdsourcing for participant recruitment and data collection. The chapter begins with a background discussion of scenario construction methods and the benefits they provide, while also highlighting inherent challenges such as time-consuming data collection and analysis processes; cognitive bias; limited sets of study participants; inconsistency within scenarios; and the difficulty of analysing scenarios with complex interactions. Alongside these methodological limitations, the chapter also acknowledges theoretical challenges that have plagued the domain. Taken together, these limitations underscore the need for a more comprehensive and theoretically grounded approach. The problem statement section culminates in the research question, which then leads on to the aim of the research and the objectives that had to be met to achieve this aim. This is followed by a discussion on the relevance and importance of the study along with the contributions that this study makes to the field. The chapter concludes with an overview of the structure of the thesis.

1.1 Background

Scenario construction is a well-established method that is widely used in both the private and public sectors to facilitate strategic planning and decision making. Despite its established benefits, the methodologies for constructing scenarios have garnered significant criticism (Burt and van der Heijden 2008; Hiltunen 2009; Rohrbeck and Schwarz 2013; Kok *et al.* 2017; Rosa *et al.* 2017; Tiberius, Siglow and Sendra-García 2020). Common challenges include time delays, biases, plausibility of scenarios, and a lack of diversity, which collectively impede real-time decision making, reduce the effectiveness of scenarios in dynamic contexts, and limit their diversity and scope (Weimer-Jehle *et al.* 2020; Douglas *et al.* 2021; Cordova-Pozo and Rouwette 2023). These challenges hinder real-time decision making, reduce the effectiveness of scenarios in dynamic contexts and produce scenarios that are limited in diversity and scope (Wiebe *et al.* 2018; Kayser and Shala 2020; Hichert *et al.* 2021). Moreover, these issues occur across multiple scenario construction methods and throughout the different phases of their application.

Time delays are particularly problematic, occurring at multiple stages of the scenario construction process. Empirical, participatory techniques, which are reported as being time consuming, are frequently used for the initial identification of factors, for the reduction of these factors to only those deemed important, and for examining the relationships that exist between them (Amer, Daim and Jetter 2013; Kemp-Benedict, Carlsen and Kartha 2019; Kayser and Shala 2020; Kishita *et al.* 2020). Methods relying on group discussions that require consensus further exacerbate delays and introduce subjectivity and bias (Schweizer and Lazurko 2020). Additionally, cognitive biases arise from the reliance on small, expert groups for data collection and analysis (Kaviani *et al.* 2023). These groups, often dominated by senior decision makers and purposively selected by the scenario team, tend to lack diversity, further constraining the scope and inclusivity of the resulting scenarios (Heinonen, Kuusi and Salminen 2017). Scholars advocate for alternative approaches to mitigate these challenges, including advanced data collection and analysis methods, more inclusive participant selection strategies, and the integration of automated online tools (Wiebe *et al.* 2018; Davis, Jetter and Giabbanelli 2023). Among these alternatives, the crowdsourcing process emerges as a promising solution. By outsourcing tasks to a diverse online crowd, crowdsourcing offers a time-efficient process for participant recruitment and data collection (Bhatti, Gao and Chen 2020). This process offers access to a broader and more varied pool of participants, addressing the issues of time delays, bias, and limited diversity that plague traditional methods (Hichert *et al.* 2021; Skinner *et al.* 2024). With methods relying on subjective data for the construction of scenarios, ensuring the plausibility or internal consistency of these scenarios is highlighted as a challenge (Weimer-Jehle 2006). CIB analysis offers a technique that rather relies on the interrelationships between factors of the system to ensure consistency.

In addition to practical concerns, several theoretical issues underpin the limitations of scenario construction methods. Many traditional approaches lack a robust integration of the theoretical principles necessary to address complex socio-technical systems. Specifically, there is often an underappreciation of general systems theory (GST), leading to analyses that focus on isolated trends rather than systemic interconnections and feedback loops, thereby failing to represent the system as an integrated whole (Von Bertalanffy 1968; Meadows 2008). Furthermore, methods frequently overlook the insights of complexity theory, resulting in an inability to adequately model non-linear dynamics, emergent behaviour, and deep uncertainty, which are defining features of the systems under study (Cilliers 2002; Snowden and Boone 2007). Equally, many approaches lack a strong constructivist grounding, creating ambiguity about how knowledge of the future is generated and validated; this often marginalizes participatory sense-making and fails to acknowledge that scenarios are socially co-constructed interpretations rather than objective predictions (Berger Peter and

Thomas 1966; Voros 2003). A further limitation lies in the insufficient consideration of potential surprise theory (PST), originally proposed by Shackle and later developed for scenario planning by Derbyshire (2017). PST emphasizes the role of *plausibility* over *probability* in exploring futures and foregrounds the importance of preparing for “potential surprises”, i.e., low-probability, high-impact outcomes that conventional, trend-based models tend to ignore. The neglect of PST contributes to overly deterministic or risk-averse scenario designs that do not convey the full breadth of uncertainty and the potential for disruptive change. Integrating PST into scenario methodologies introduces a theoretical mechanism for systematically addressing surprise, expanding the range of plausible futures considered, and strengthening decision making under deep uncertainty. Taken together, these theoretical shortcomings—which include the neglect of systemic structure (GST), dynamic complexity (complexity theory), interpretive legitimacy (constructivism), and potential surprise (PST)—compound methodological challenges and reinforce the need for an integrative framework that explicitly draws on these complementary perspectives to enhance the rigour, inclusivity, and resilience of scenario construction.

This research study contends that the persistent challenges plaguing scenario construction methods can be addressed by integrating advanced analytical techniques within a robust theoretical framework. By applying methods for data reduction (ADVIAN®), crowdsourcing for participant recruitment ("X"), and CIB analysis for consistency, all underpinned by the integrated principles of GST, complexity theory, PST and constructivism, this study offers a pathway to more rigorous, scalable, and defensible scenario development.

1.2 Problem Statement

In an era of economic uncertainty and rapid change, scenario construction has become indispensable for strategic planning across various sectors. Prominent examples, like Royal Dutch Shell’s response to the 1970s oil crisis, highlight its value in managing uncertainty (Schoemaker and van der Heijden 1992; Joseph 2000; Chermack, Lynham and Ruona 2001). As narratives of possible futures, scenarios enable organizations to anticipate challenges, foster innovation, and enhance decision making (Hiltunen 2009; Wiebe *et al.* 2018; Meadows 2020; Kaviani *et al.* 2023). However, the methods for constructing these scenarios present significant practical challenges that limit their effectiveness, reliability, and widespread adoption.

The field is characterized by a trade-off between qualitative and quantitative approaches. Qualitative methods, such as the intuitive logics method (ILM), are praised for their narrative richness but criticized for a lack of systematic rigour, making it difficult to ensure consistency and transparency when dealing with complex systems (Weimer-Jehle *et al.* 2020; Tori, Te Boveldt and Keseru 2023). Conversely, quantitative methods, like la prospective (LP), offer analytical power but are often too complex, resource-intensive, and inaccessible for many organizations, limiting participatory engagement (Weimer-Jehle *et al.* 2020; Tori, Te Boveldt and Keseru 2023). Cross-impact analysis (CIA) methods, particularly the CIB technique, address some of these challenges but still require further development and refinement to address persistent challenges (Nygrén 2019; Weimer-Jehle *et al.* 2020; Prehofer *et al.* 2021; Tori, Te Boveldt and Keseru 2023). This has prompted calls for novel methods that balance flexibility with analytical robustness (Cordova-Pozo and Rouwette 2023). These methodological shortcomings create critical practical barriers. Key among them are the time-consuming nature of traditional techniques, which delays decision making in dynamic environments; the cognitive biases introduced by reliance on small, homogenous expert groups; and the persistent challenge of ensuring that scenarios are both internally consistent and plausible reflections of a complex world (Mietzner and Reger 2005; Heinonen, Kuusi and Salminen 2017; Kaviani *et al.* 2023). Additionally, reliance on small, senior-dominated groups limits diversity and introduces cognitive biases that can skew scenario outcomes (Mietzner and

Reger 2005; Lloyd and Schweizer 2014; Heinonen, Kuusi and Salminen 2017; Douglas *et al.* 2021; Kaviani *et al.* 2023).

A more foundational issue underlying these practical limitations is that methods often lack a coherent foundation in the principles necessary to model real-world complexities. Many rely on either deterministic or linear assumptions that do not align with the uncertainty and complexity inherent in real-world systems (Van Notten *et al.* 2003; Ramirez and Wilkinson 2016). Moreover, these methods often lack epistemological clarity, failing to define how knowledge is generated or validated during the scenario process (Bishop, Hines and Collins 2007). This theoretical ambiguity limits methodological rigour, makes it difficult to evaluate outcomes across studies, and reduces the credibility of scenarios as decision-making tools. The absence of an integrated foundation reduces the credibility and strategic value of scenario outcomes.

This thesis therefore addresses the research question: **"***How can a theoretically grounded methodology combining computational impact analysis and the collective intelligence of human experts overcome the key limitations of rigour, scalability, and consistency in traditional scenario construction?*"

1.3 Research Aim and Objectives

Traditional scenario construction methods are hindered by a fundamental trade-off: qualitative approaches often lack analytical rigour and systemic transparency (Cordova-Pozo and Rouwette 2023), while quantitative methods can be computationally rigid and fail to capture diverse human judgement (Weimer-Jehle *et al.* 2020; Tori, Te Boveldt and Keseru 2023). This results in scenarios that are either not robustly consistent, not developed in a timely manner, or not inclusive of critical perspectives. There is a critical need for a methodology that systematically integrates structural analysis, participatory input, and computational consistency checking to overcome these limitations (Pillkahn

2008; Haegeman *et al.* 2013; Hirsch, Burggraf and Daheim 2013; Kayser and Shala 2020; Pan *et al.* 2020).

The aim of this study is to develop a theoretically grounded methodology for scenario construction, underpinned by GST, complexity theory, constructivism, and PST. The proposed approach operationalizes these foundations with the application of ADVIAN® for factor refinement, the use of crowdsourcing to elicit diverse expert judgements, and CIB analysis to ensure internal consistency, thereby generating robust, credible, and timely scenarios.

To realize the **aim** and answer the **research question**, the study pursues the following objectives:

1.	To critically evaluate the theoretical and methodological limitations of existing scenario construction techniques by means of a literature review, establishing the necessity for an integrated approach;
2.	To identify and critically structure the key factors and their interdependencies from a set of factors derived from of a structured literature review, as a foundational analytical step informing scenario construction;
3.	To develop a theoretically grounded methodology for constructing consistent scenarios and
4.	To validate the methodology through the practical implementation and application to renewable energy adoption and AI adoption in higher education.

1.5 Importance of the Research

This study aims to contribute to the fields of scenario construction and crowdsourcing by addressing enduring methodological challenges such as bias, inefficiency, subjectivity, limited participant diversity, and inconsistency, using a theoretically grounded approach. Drawing on GST, complexity theory, constructivism, and PST, the study seeks to establish an alternative methodology that is structured, time-efficient, and reproducible, enabling organizations to generate diverse and credible scenarios more effectively.

Traditional methods of factor identification and refinement in scenario projects are criticized for their subjectivity and susceptibility to bias. This study mitigates these problems in two key ways: Firstly, by considering only those factors that have been empirically evaluated and validated in the literature. The use of SEM path coefficients to represent the strength of relationships between factors represents a methodological innovation not previously explored in scenario construction. Secondly, the ADVIAN® analysis method is used to assess the strength of factor relationships identified through SEM. By automating this process with a researcher-developed tool, the study eliminates the risk of human error in the complex calculations required. In addition, ADVIAN® provides quantitative classifications and rankings, such as driving, precarious, and criticality, thereby offering a robust alternative for factor reduction. These advancements enhance the objectivity and reliability of the scenario construction process in this study while also enhancing the speed at which scenarios are constructed.

Traditional methods for the collection of judgement data often rely on participatory techniques such as lengthy group discussions and interviews, which are resource-intensive and slow. There is also a limited set of expert participants. Crowdsourcing accelerates participant recruitment and enhances diversity, while employing a researcher-developed online survey tool for data collection and analysis streamlines data collection and analysis, eliminating the need for prolonged participatory engagements. The use of a researcher-developed online tool to gather complex factor state judgements represents a novel contribution to the field as no prior research has combined these elements for scenario construction.

While CIB analysis has successfully been applied to studies for the construction of consistent scenarios without the need to consider probabilities, the analysis technique has not been combined with ADVIAN® and crowdsourcing for scenario construction. By integrating these innovative methods, the research addresses longstanding challenges in the field, offering both practical and theoretical advancements via:

1. **Enhancing efficiency:** The method overcomes time delays associated with traditional methods, enabling quicker and more responsive scenario construction.

2. **Bridging methodological gaps:** It combines the strengths of qualitative and quantitative techniques, fostering a balanced and replicable mixed-methods framework.

3. **Expanding inclusivity:** It demonstrates the potential of crowdsourcing as a scalable and diverse data collection strategy, reaching a global participant pool.

4. **Laying a research foundation:** The method provides a foundation for future studies, advancing the application of cutting-edge data collection and analysis techniques in scenario construction and futures studies.

In summary, this research demonstrates that a methodology combining ADVIAN®'s systematic factor reduction, crowdsourcing's diverse participation, and CIB's consistency analysis produces more robust, efficient, and inclusive scenarios than conventional approaches. This integrated methodology is grounded in a theoretical framework that prioritizes systemic rigour, the navigation of complexity and uncertainty, and collaborative knowledge construction, ensuring the resulting scenarios are both analytically sound and strategically relevant.

1.6 Contribution of the Study

This study makes several contributions to knowledge, theory, methodology, and practice in the field of scenario construction. These contributions arise from the development and application of an integrated, theoretically grounded methodology that addresses key limitations in existing scenario approaches, including subjectivity, inefficiency, limited participation, and inconsistency.

This study contributes to theory by operationalising and integrating four foundational perspectives (GST, complexity theory, constructivism, and PST) into a unified framework for scenario construction. In doing so, it addresses a key limitation in the field, namely the lack of theoretical coherence underpinning many scenario methodologies. The study extends theoretical understanding by demonstrating how system interdependencies, non-linearity, emergence, and socially constructed knowledge can be incorporated into a structured and replicable scenario development process. By moving beyond purely narrative-driven approaches, the research introduces a theoretically grounded and internally consistent logic for scenario construction. Furthermore, the study reinforces the role of foresight as a participatory and interpretive process, while simultaneously embedding it within a systemically rigorous and analytically structured framework.

A central methodological contribution of this study is the development of a six-step, theoretically grounded methodology for constructing internally consistent scenarios. This methodology integrates complementary techniques, including secondary data analysis, ADVIAN®-based factor reduction, crowdsourcing for expert judgement elicitation, and CIB analysis for ensuring internal consistency.

The study introduces several methodological innovations:

- The automation of the ADVIAN® process, improving efficiency, reducing human error, and enhancing reproducibility
- The use of SEM-derived path coefficients to construct factor relationship matrices
- The development of an online tool for collecting expert judgements and generating cross-impact matrices
- The integration of qualitative and quantitative techniques into a balanced and replicable mixed-methods framework

Unlike traditional approaches that rely heavily on workshops and subjective assessments, the proposed methodology provides a structured, scalable, and time-efficient alternative for scenario construction.

From a practical perspective, this study provides a robust and replicable approach for scenario construction that can be applied across a wide range of domains. The use of crowdsourcing via the “X” platform demonstrates a scalable and inclusive method for recruiting expert participants, overcoming geographical and institutional constraints associated with traditional approaches. This enhances diversity in expert input and supports more representative scenario development. The online data collection tool enables asynchronous participation, significantly reducing the logistical and time burdens associated with participatory workshops while improving the consistency and quality of collected judgements. The methodology also enables decision-makers to construct internally consistent scenarios without relying on complex probabilistic modelling, making it particularly suitable for environments characterised by uncertainty and limited data availability.

In addition to its methodological and theoretical contributions, this study provides important empirical contributions through the application of the proposed methodology to two domains: renewable energy adoption and AI adoption in higher education. The application of the methodology across these domains demonstrates its robustness, scalability, and practical relevance. In both cases, the analysis revealed that perceived value, awareness, and perceived support consistently emerged as the most influential drivers of adoption, highlighting the importance of both cognitive and institutional factors in shaping technology uptake. The case studies further demonstrate that scenario outcomes are highly sensitive to the configuration of interdependent factors, confirming the importance of modelling systemic interdependencies and feedback mechanisms in scenario construction. The identification of multiple internally consistent scenarios (including best-case, worst-case, and base-case configurations) illustrates the ability of the methodology to capture both expected and divergent futures across different contexts. Importantly, the empirical applications show that scenario construction can move beyond small, constrained factor sets. In contrast to prior studies that typically rely on fewer than ten variables, this study successfully incorporates larger sets of factors (36 for renewable energy and 27 for AI adoption in higher education), enabling a more comprehensive and nuanced representation of complex systems. These findings provide practical insights for policymakers, institutional leaders, and technology developers by identifying key leverage points for intervention. In particular, improving perceived value, increasing awareness, and strengthening institutional support mechanisms are shown to be critical for enabling successful adoption outcomes.

The research undertaken during this study has been disseminated through a combination of peer-reviewed journal articles and conference publications. These outputs reflect both the findings of the thesis and related methodological and exploratory work conducted during the research process. It is important to note that not all publications listed are direct outputs of the thesis. Some papers were developed during the investigation and evaluation of various methods, tools, and techniques that informed the design and development of the proposed methodology. As such, these publications provide supporting context and demonstrate the broader research trajectory underpinning the study. At least one publication directly presents the methodology developed in this thesis, providing external validation of its novelty and academic contribution. Other publications are more exploratory in nature and reflect earlier or parallel work that contributed to shaping the research direction. The publications serve to evidence scholarly engagement and dissemination, rather than constituting the primary contributions of the PhD.

Published journal articles:

1 Thompson, R. C., Olugbara, O. O. and Singh, A. 2018. Deriving critical success factors for implementation of enterprise resource planning systems in higher education institution. *African Journal of Information Systems*, 10(1).

2 Thompson, R. C., Olugbara, O. O. and Singh, A. 2026. Crowdsourcing knowledge for constructing consistent scenarios. *Algorithms*, 19(10), 41.

Published conference paper:

3 Thompson, R. C., Olugbara, O. O. and Singh, A. 2020. *CIMgen method for generating cross-impact matrix in impact factor analysis*. In: Proceedings of 2020 Conference on Information Communications Technology and Society (ICTAS). IEEE, 1-5.

Journal articles submitted for publication:

4 Olugbara, C. T., Thompson, R. C. and Olugbara, O. O. and Singh, A. 2024. Classifying factors impacting student acceptance of MOOC. *IEEE Access*.

With its combination of empirical rigour, process innovation, and theoretical integration, this study sets a new benchmark for scenario construction. It demonstrates that methodological innovation, when grounded in robust theory, can address longstanding gaps in futures research and offer scalable, reliable, and inclusive tools for decision making under uncertainty.

1.7 Thesis Structure

The thesis is succinctly arranged into seven chapters as discussed below.

Chapter 1 introduces the study by presenting the background to scenarios and the challenges inherent in existing scenario construction methods. It defines the research problem, research question, aim, and four objectives that guide the study. The importance of the research is explained, highlighting its theoretical and practical contributions to both scenario studies and crowdsourcing. The contributions of the study are discussed, including the novel methodology developed and the papers published or submitted based on the research. The chapter concludes by outlining the structure of the thesis.

Chapter 2 reviews the literature on scenario studies, examining both conceptual foundations and practical applications of scenario construction methods. It explores the benefits and contexts in which scenario methods have been applied and critically evaluates four principal methods: ILM, LP, CIA, and CIB, assessing their contributions and limitations. The chapter also discusses theoretical limitations of existing approaches. Recognizing that crowdsourcing offers an alternative avenue for participant engagement and data collection, the chapter explores its benefits, applications, and platform-specific challenges. Particular attention is given to the use of social media, specifically the “X” platform, for expert recruitment and data gathering. This chapter establishes the conceptual basis of the study and achieves the first objective of the research.

Chapter 3 establishes the theoretical foundation of the study. It begins by discussing the founding theories underpinning foresight and scenario studies, namely GST, complexity theory, constructivism, and PST. Each is examined for its relevance to systems behaviour, uncertainty, knowledge construction, and the exploration of alternative futures. The chapter then presents the theoretical rationale for the methodological techniques employed, including the use of secondary data, ADVIAN® analysis, crowdsourcing, and CIB analysis. The integration of these techniques is justified conceptually, demonstrating their coherence with the study's theoretical and epistemological underpinnings.

Chapter 4 details the materials and methods used for data collection and analysis, outlining the tools and platforms applied in the research process, including Microsoft Excel, the "X" platform, ADVIAN®, and ScenarioWizard for CIB analysis. It presents the six-step methodological framework developed to construct internally consistent scenarios. Steps 1 and 2 involve the identification of key factors and their interrelationships using secondary data and reported SEM path coefficients. Step 3 applies ADVIAN® analysis to reduce the set of factors to those most influential within the system. Step 4 collects expert judgements through crowdsourcing, while Step 5 develops the judgement matrix required for the CIB analysis conducted in Step 6. Steps 1, 2, and 3 together achieve Objective 2, relating to the identification and refinement of system factors and relationships. The development and application of the complete six-step methodology contribute directly to Objective 4, representing a key methodological advancement of the study. The detailed visual representation of the theoretically grounded methodology that integrates the conceptual framework and analytical techniques is not presented in this chapter but is rather displayed in Chapter 4 to allow for a discussion on its development. The adopted methodology is also revisited and synthesised in the conclusion chapter, where it is presented as the central contribution of the study.

Chapter 5 tracks the application of the developed methodology to two practical case studies, demonstrating its utility in constructing internally consistent scenarios. The first application focuses on the adoption of renewable energy, illustrating how the methodology identifies key factors, reduces them via ADVIAN®, gathers expert judgements through crowdsourcing, and generates consistent scenarios using CIB analysis. The second application examines the adoption of AI in higher education, applying the same six-step framework to explore factors influencing AI uptake and implementation in academic contexts. Through these applications, the chapter evaluates the methodology's effectiveness in producing plausible and analytically robust scenarios across diverse domains. The results highlight how the approach captures system interdependencies, emergent behaviours, and potential uncertainties, providing evidence of its practical and theoretical contributions to scenario construction.

Chapter 6 provides discusses the findings of the study, synthesizing the findings from the previous chapters and examining how the research objectives have been met. Each objective is evaluated in relation to the results obtained and contextualized within the existing literature on scenario construction and crowdsourcing. The chapter also explores the practical applications of the developed methodology, demonstrating how the findings can inform decision making and strategy in real-world contexts, including renewable energy adoption and AI implementation in higher education. The discussion highlights the alignment of the results with prior research, identifying areas of convergence and divergence, and reflecting on the implications for both theory and practice.

Chapter 7 presents the conclusions of the study, answering the research question and indicating how the research aim and objectives were achieved. It provides a reflective summary of the study's key contributions to both theoretical understanding and practical application in scenario construction and crowdsourcing. The chapter also discusses the limitations of the research, acknowledging methodological constraints and contextual factors that may have influenced the findings. Finally, it outlines potential avenues for future research, highlighting opportunities to extend and apply the developed methodology in other domains or to further refine the integration of systems thinking, crowdsourcing, and scenario construction approaches.

CHAPTER 2: LITERATURE REVIEW

This chapter presents a comprehensive review of the literature relevant to scenario construction. The first section begins with an exploration of scenarios and their applications, providing context on the importance and versatility of scenario construction in diverse fields such as strategic planning and decision making. This is followed by an analysis of the benefits associated with scenario construction, as well as a critical examination of notable methodologies currently in use. In evaluating these methods, particular attention is given to the limitations and challenges highlighted in previous studies as these underscore the need for improved methods to enhance scenario consistency and reliability.

The second section focuses on crowdsourcing, providing definitions and a review of available platforms that facilitate data collection through large-scale participant engagement. This section discusses the advantages of the crowdsourcing process, such as cost-effectiveness, scalability, and data diversity, and provides a rationale for its use in this study. Emphasis is placed on the potential of social media and the 'X' platform as an innovative tool for recruiting participants and gathering diverse, timely data, leveraging its broad reach to enrich scenario-building efforts. Attention is also given to the challenges inherent to crowdsourcing and social media platforms.

The chapter meet study's first objective, *to critically evaluate the theoretical and methodological limitations of existing scenario construction techniques by means of a literature review, establishing the necessity for an integrated approach*.

2.1 Definition of Scenarios

Foresight is described as "the act of thinking of the future to guide decisions today" (Wiebe *et al.* 2018: 546). It is an integral part of daily life. Decisions such as "should I wear a jersey today?" or "which route to work will be fastest?" can be made relatively quickly given the ease of access to weather forecasts and to daily traffic patterns. However, we inhabit a world defined by volatility, ambiguity, complexity, and uncertainty, with constant and unpredictable shifts (Hartman 2023), which makes the future challenging to interpret, analyse, and forecast (Major and Clarke 2022). In addition, the decision-making process increases in complexity as the number of parameters increase (Meadows 2008). Parameters could include longer time periods to make the decision, a larger number of people involved in the decision-making process, and issues involving spatial, social, and temporal dimensions (Meadows 2008). The resultant heightened complexity of the decision-making system therefore warrants the need for a systematic process. Grounded in the conviction that change is always possible, strategic foresight and scenario construction provide a practical mindset and methodology for building actionable insights about the future today. Rather than assuming a single predetermined outcome, this approach recognizes a range of plausible futures that should be considered (Voros 2003; Ramirez and Wilkinson 2016). By imagining extreme yet credible scenarios, organizations, destinations, and businesses can proactively prepare by designing strategies and policies that enhance resilience and "future-proof" them against whatever lies ahead (Wack 1985; Schwartz 1997).

Scenarios are commonly used to anticipate short-term uncertainties and long-term strategic goals (Van der Heijden 2011). They allow the individual or a group of people to explore possible futures, test alternative strategies, and identify potential pathways in uncertain contexts (Schoemaker 1995). Although scenario construction has been used in diverse fields for decades, the methodology still faces numerous challenges and a lack of consensus on its definition (Bradfield *et al.* 2005; Varum and Melo 2010; Chermack 2011; Amer, Daim and Jetter 2013; Spaniol and Rowland 2019). The Oxford Dictionary defines a "scenario" as "a postulated sequence or development of events". In contrast, Kahn and Wiener (1967a: 6-7) define scenarios in a future context as "a set of hypothetical events set in the future, constructed to clarify a possible chain of causal events as well as their decision points”. Subsequent authors have expanded on this foundation, offering definitions that reflect evolving perspectives (Table 1). Despite these variations, most scholars in this field agree that scenarios are narrative tools designed not to predict the future but to constructively explore potential futures, raising awareness and supporting decision making (Kahn and Wiener 1967b; Metz *et al.* 2007; Van der Heijden 2011; Saritas and Nugroho 2012; Schwartz 2012; Kishita *et al.* 2016; Spaniol and Rowland 2019; Kishita *et al.* 2020).

Table 1: Scenario definitions

Reference	Definition
Porter (1985)	A scenario is an internally consistent vision of a possible future.
Godet (1986)	Scenarios provide a view of the various paths that lead to possible futures.
Fontela and Hingel (1993)	Scenarios reflect trends and policies shaping potential outcomes.
Van der Heijden (1996)	Scenarios as structurally distinct, plausible future states.
Jarke, Bui and Carroll (1998)	Scenarios are descriptions of events that may take place.
Scholz, Mieg and Oswald (2000)	Scenarios are vectors that consider the impact that all factors have on each other.
Gordon and Glenn (2018)	Scenarios are rich narratives that illustrate plausible trajectories to the future.

The fundamental purpose of scenarios, which seems to be consistent across literature, is to highlight the possible futures while raising stakeholder and decision makers’ awareness so that decision-making tasks are supported (Tourki, Keisler and Linkov 2013). For this study and in line with definitions of other authors, scenarios are defined as:

> *“The set of plausible pathways to the future that considers the key drivers and uncertainties with the aim of raising awareness and increasing performance”.*

With scenarios seen as the various narratives that are used to explain the possible sequences of events that could lead to futures, scenario construction is then the process used to craft the different scenario narratives (Schoemaker 1995). While this study adopts the phrase “scenario construction”, similar terms such as “scenario development”, “scenario thinking”, and “scenario planning” are also prevalent in literature (Cordova-Pozo and Rouwette 2023). Scenario construction is generally a strategic, long-term planning process aimed at understanding and preparing for the effects of driving forces on potential outcomes, unveiling uncertainties in the external environment to inform planning and awareness (Boyonas and Olavarria 2016; Meadows 2020). It is the construction of these scenarios and the methodology used to gather and analyse data that is the focus of this thesis rather than the implementation of developed scenarios.

2.3 Benefits of Scenarios

This sub-section reflects the transformative role of scenario construction along the themes of planning, decision making, and innovation across diverse contexts.

Scenario construction allows for the questioning of what is to come, and serves as a powerful tool for exploring, planning, and preparing for possible and unexpected futures by examining interactions between key drivers and influencers (Martino 2003; Barber 2009; Hiltunen 2009; Schweizer and Lazurko 2020). It has been proven beneficial for addressing both short-term disruptions, as well as for guiding long-term strategies (Cordova-Pozo and Rouwette 2023). Strauss and Radnor (2004) highlight that scenarios can help policymakers evaluate the potential effects of policy choices, anticipate system failures, and understand the broader implications of discontinuing established systems.

On a global scale, scenario construction enhances decision making, supports contingency planning, integrates varied data models, and refines scientific inquiry (Kok *et al.* 2017; Rosa *et al.* 2017; Kaviani *et al.* 2023). According to Rohrbeck *et al.* (2018), companies that use systematic scenario construction tend to achieve greater stability and profitability than their competitors. While scenarios may spark controversy, their role in guiding strategic planning and shaping preferred futures has proven influential and invaluable (Kaviani *et al.* 2023). The process of creating scenarios challenges existing mindsets and fosters decision making through lateral thinking and debate, encouraging the exploration of innovative, nontraditional alternatives (Grunwald 2011). Schoemaker (1991), de Brabandere and Iny (2010) and Chermack (2011) emphasize that scenario construction not only pushes organizations beyond their operational comfort zones but also generates fresh insights and novel strategies through open, imaginative thinking. This willingness to explore unconventional perspectives helps organizations identify unique opportunities and better prepare for a range of potential futures.

The above discussion highlights the benefits of scenarios in future planning across various sectors, underscoring the importance of enhancing and refining scenario construction methods.

2.2 Scenario Applications

Scenario construction methods have been widely adopted across diverse fields, including military strategy, food security, healthcare, environmental management, renewable energy, AI, global finance and commerce (Kishita *et al.* 2020; Cordova-Pozo and Rouwette 2023). Governments, organizations, and institutions leverage these techniques to navigate complex decision-making processes and to anticipate potential future challenges (Santoyo-Castelazo and Azapagic 2014; Wiebe *et al.* 2018; Leung *et al.* 2020; Zhang *et al.* 2020; Satpute and Kumar 2021).

Early applications of scenario construction date back to the late 1950s, when America’s RAND Corporation employed these methods for military strategy and weapons system development (Kahn and Wiener 1967b; Coates 2000; Van der Heijden 2011). Scenario-based war games also became invaluable for assessing non-mathematical issues involving human decision making (Wiebe *et* *al.* 2018). In environmental studies, scenario construction plays a central role in impact assessment, forecasting, and policy development (Tourki, Keisler and Linkov 2013; Cordova-Pozo and Rouwette 2023; Benitez *et al.* 2024). Notable examples include the 1970s Limits to Growth report, which warned of environmental risks posed by unchecked growth (Meadows, Randers and Meadows 2013) and more recent studies that demonstrate how extending credit card life and increasing renewable energy use can significantly reduce environmental impacts (Lindgreen *et al.* 2018). In energy planning, researchers like Satpute and Kumar (2021) illustrate potential carbon emission reductions in India through wind energy adoption. Scenarios also play a vital role in humanitarian fields, such as food security, where future supply and demand uncertainties have been investigated (Reilly and Willenbockel 2010; van Meijl *et al.* 2020). Kraus *et al.* (2020) also predicted an increase in interest in scenario studies following the outbreak of COVID-19. It was during the pandemic that scenario construction helped explore potential effects on food systems (Udmale *et al.* 2020; Laborde, Martin and Vos 2021), as well as health outcomes, including predicted reductions in life expectancy among COVID-19 patients (Pires *et al.* 2022) and the effectiveness of vaccination centres (Hanly *et al.* 2022). Health policy makers have long used scenario techniques for strategic planning, particularly to forecast the need for health technologies like telemedicine and bio-nanotechnology (Bradfield and El-Sayed 2009; Swierstra, Stemerding and Boenink 2009; Boenink, Swierstra and Stemerding 2010; Kiran 2012). In recent years scenarios assisted in the future planning of community pharmacist requirements in Portugal (Gregório, Cavaco and Velez Lapão 2014) and for the future planning of health service costs in the Netherlands (Wouterse *et al.* 2015). Additionally, Douglas *et al.* (2021) unveiled key drivers for rare disease health policy and uncovered a plausible set of future scenarios concerning treatments for rare diseases.

With the prominence of AI and machine learning in academia, scenario construction has also expanded into these domains. Studies have used machine learning to optimize scenario analysis tools and forecast climate impacts on energy performance (Nápoles *et al.* 2018; Fathi *et al.* 2020). Additional applications include modelling deforestation trends (Mayfield *et al.* 2020) and predicting soil erosion (Gianinetto *et al.* 2020), which have all relied on machine learning approaches. Business management also rely on scenario studies for making strategic choices, for creating norms, and for making sense of futures. Burt and van der Heijden (2008) find benefits for business management such as being prepared for future economic disruptions, encouraging conversation, implementing alternate perspectives, improving understanding, and enabling stakeholders to better plan the future (Hiltunen 2009; Rohrbeck and Schwarz 2013). The discourse indicates a steady rise in interest in scenario-based business research after 2009, particularly in response to increasing market volatility (Tiberius, Siglow and Sendra-García 2020). Furthermore, Schweizer and Lazurko (2020) indicate that scenario tools help organizations understand their roles in an evolving landscape. Both private and public entities rely on scenarios for critical decision making, testing strategies, and managing transformative challenges, such as market disruptions and policy gaps (Varum and Melo 2010; Schweizer and Lazurko 2020).

This overview portrays the practical application of scenario construction in the dimensions of the global economy, social wellbeing, and environmental sustainability, citing it as a contemporary methodology (Bennett 2012; Tourki, Keisler and Linkov 2013; Kraus *et al.* 2020). Moreover, given the disruptive effects of technological advances, climate change, and COVID-19 on numerous sectors, students, academics, and practitioners alike still strive to understand and navigate the current transformed landscape.

2.4 Scenario Theory

Despite its popularity, the field has faced criticism for inconsistent methods and theoretical ambiguity (Chermack 2005; Amer, Daim and Jetter 2013; Spaniol and Rowland 2018). Chermack (2002) observes that “the status of theory development in the area of scenario planning is dismal” (Chermack 2002: 25), while Derbyshire (2017), Spaniol and Rowland (2018), and Meadows (2020) note that much research emphasizes scenario description over theoretical justification. Miller (2006) further asserts that compared to other academic disciplines, scenario construction lacks a widely accepted theoretical foundation. This historical weakness is traced to early scenario development, where Kahn, Brown and Martel (1976) argued that “human societies are complicated beyond scientific generalization” (Kahn, Brown and Martel 1976: 146), leading early methods to evolve around practical application rather than theoretical grounding. Consequently, scenario construction has remained a practice-driven discipline, often focusing on “who did what” rather than “why it works” (Spaniol and Rowland 2018).

One notable contribution to scenario construction theory comes from Derbyshire (2017), who applied Shackle’s potential surprise theory (PST) to foresight. PST emphasizes plausibility over probability and prioritizes the exploration of surprising yet coherent futures (Derbyshire and Wright 2014). By framing scenarios as cognitive tools rather than predictive models, PST supports learning, dialogue, and the reframing of assumptions, aligning with the dialogic paradigm of foresight (Van der Heijden 2011). While PST introduces interpretive richness, it has limitations: operational guidance is limited, it relies heavily on subjective interpretation, and it does not fully address systemic interdependencies or dynamic behaviours (Derbyshire 2017). Integrating PST with frameworks such as GST and complexity theory helps address these gaps, adding structural, dynamic, and systemic coherence to scenario construction.

Scheomaker (1993) also contributed to theoretical development, examining the cognitive processes underpinning strategic scenario planning and highlighting biases such as overconfidence and the conjunction fallacy. This work helped legitimize scenario planning within academic contexts as it had previously suffered from a lack of empirical support. Although scholars have attempted to provide theoretical grounding, criticisms persist regarding rigour. Chermack (2002) cautions against conflating method with theory, while Martelli (2001) considers Schwartz's seminal work to be theoretically "flimsy." Bradfield (2008) and Bradfield, Derbyshire and Wright (2016) support the view that scenario studies often exhibit a-theoretical tendencies. Lang and Lang (2012) and Moriarty (2012) argue that a stronger theoretical foundation is necessary to address methodological inconsistencies. Most existing theories either offer limited practical guidance, lack empirical validation, or focus narrowly on specific aspects of scenario construction. These limitations and the alignment of the methodology proposed in this study with the existing theoretical foundations, are discussed further in Chapter 3.

With scenario construction still in a state of flux and numerous methodologies available (Douglas *et al.* 2021), researchers have developed typologies to clarify the aims and applications of different approaches, reinforcing the importance of integrating theory, practice, and methodological rigour. A foundational classification by Marien (2002) suggests scenarios should be distinguished by their focus on probable, possible, or preferable outcomes. In a more detailed typology, Börjeson *et al.* (2006) classify scenarios into three main types: predictive, explorative, and normative, each aligned with specific questions about the future (Figure 1).

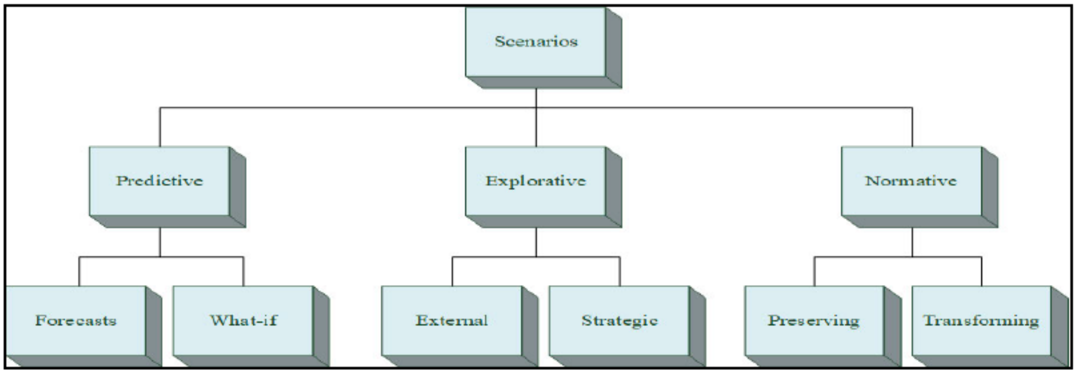


Figure 1: Comprehensive Scenario Typology (Source: Börjeson et al. (2006))

Predictive scenarios address the question, "What will happen?" and allows for adaptive planning based on trends, existing structures, and projected events. In this category, *forecast scenarios* predict likely outcomes if current trends persist, while *what-if scenarios* explore outcomes of specific, potentially disruptive events (Boissonneault *et al.* 2020). Normative scenarios, focus on "How can a specific target be achieved?" and chart pathways to desired outcomes (Kosow and Gaßner 2008; Martelli 2014). They are further divided into *preserving scenarios*, which work within current systems to reach goals, and *transformative scenarios*, which propose structural changes when existing frameworks cannot achieve the objective (Börjeson *et al.* 2006). This type of scenario is crucial for goal-driven planning where both internal and external factors are considered to reveal critical steps for reaching long-term objectives.

Explorative scenarios which rather answer the question "What could happen?", are valuable during times of volatility and rapid change. They assess various potential futures using multiple drivers and perspectives, often with a focus on external factors (Bijak and Czaika 2024). This type of scenario aids strategic planning by anticipating external influences and preparing for change (Van der Heijden 2011). In this type, *external scenarios* analyse outside forces that influence policies and strategies, while *strategic scenarios* incorporate internal and external elements to evaluate policy impacts and strategic decisions (Börjeson *et al.* 2006).

This makes explorative approaches especially appropriate for systems where causal relationships are not fully understood and where outcomes cannot be reliably predicted. Importantly, the explorative stance adopted in this study is theoretically grounded in the principles of complexity theory and potential surprise theory. These perspectives emphasise that complex systems exhibit non-linearity, emergent behaviour, and sensitivity to initial conditions, making precise prediction impractical (Cilliers 2002; Meadows 2008; Derbyshire 2017). Consequently, the objective shifts from predicting a single future to exploring a range of plausible futures, thereby enhancing preparedness and strategic flexibility. Within this context, explorative scenarios provide the most appropriate framework for examining the interactions between system factors and for capturing uncertainty in a structured manner.

In this study, the practical implementations of the proposed novel methodology, which is demonstrated in Chapter 5, align with the explorative approaches as they address the question, "What could happen given the system of factors being evaluated?" This alignment is consistent with the study's objective of modelling complex, uncertain systems rather than prescribing a single desired outcome. While explorative scenarios are used as the primary application context, the intention of this study is not to be constrained by a single typology. As noted by Cordova-Pozo and Rouwette (2023), the scenario construction process needs not adhere strictly to one typology. Rather, the methods employed in each phase should be adapted across different typologies. In line with this perspective, the proposed methodology is designed to be flexible and transferable, enabling its application across explorative, predictive, and normative scenario contexts. This flexibility reflects the study's broader aim of developing a comprehensive and theoretically grounded methodology that provides systematic guidance for scenario construction while remaining adaptable to different typological requirements.

2.5 Scenario Methods Evaluation

Although no single, universal method exists for scenario construction, the qualitative *intuitive logic method (ILM)* and the *la prospective (LP)*, and the more quantitative *probabilistic modified trends (PMT)*, which includes cross-impact methods (Amer, Daim and Jetter 2013; Cordova-Pozo and Rouwette 2023) have emerged as prominent in literature. This sub-section provides a discussion and evaluation of these methods.

2.5.1 Intuitive logic

The intuitive logic method (ILM) is one of the most widely applied scenario planning techniques, valued for its adaptability and ability to generate context-specific insights (Bradfield *et al.* 2005; Bishop, Hines and Collins 2007; Phadnis *et al.* 2014). Originally developed in the context of war gaming and business strategy (Millett 2009), ILM was popularized by Royal Dutch Shell's pioneering work and Peter Schwartz's *The Art of the Long View* (Schwartz 2012) which remains a seminal text in the field. While ILM is most commonly used in corporate strategy, its applications have extended into policy, education, and sustainability contexts (Bradfield *et al.* 2005; Bishop, Hines and Collins 2007; Phadnis *et al.* 2014). Methodologically, ILM emphasizes the co-construction of narrative scenarios through dialogue, structured discussion, and "disciplined intuition" (Schwartz 2012). The process typically involves stakeholder workshops or expert interviews where participants identify critical uncertainties and key drivers of change. These are then combined into axes of uncertainty, forming the basis for the development of a set of plausible, exploratory futures (Lloyd and Schweizer 2014; Cordova-Pozo and Rouwette 2023). Its strength lies in its ability to engage participants in reflective, long-term thinking, challenge entrenched assumptions, and stimulate strategic conversations (Van der Heijden 2011).

From a theoretical standpoint, ILM connects with the perspectives outlined in Chapter 3. Most notably, it aligns with constructivism, as it is built on the premise that futures are not discovered but socially constructed through interaction and dialogue (Schwandt 1994). This gives ILM legitimacy as a participatory and meaning-making process but also exposes it to risks of relativism and fragmentation (Guba and Lincoln 1994). In relation to GST, ILM contributes little to systematic structural mapping or prioritization of interdependencies, often overlooking the holistic dynamics of complex systems (Von Bertalanffy 1968). Likewise, although complexity theory highlights non-linearity, emergence, and adaptive cycles, ILM only engages with these indirectly, without formal tools for operationalizing such dynamics (Bradfield *et al.* 2005). Thus, while the method resonates with the theoretical foundation discussed in Chapter 3, it uses these perspectives unevenly, privileging inclusivity and narrative richness over analytic rigour and systemic mapping. While not an explicit foundation of ILM, PST provides a robust theoretical explanation for its core strength: the construction of scenarios that are valuable precisely because they represent plausible and disruptive surprises that challenge prevailing mental models (Derbyshire 2017). The method's success in anticipating the 1973 oil crisis exemplifies the practical application of exploring 'potential surprise,' even if the terminology was not used (Wack 1985). Therefore, PST offers a valuable theoretical justification for the most impactful output of the intuitive process, even if it does not inform its methodological steps.

Despite its widespread use, ILM faces several methodological challenges arising from both its theoretical foundations and practical implementation. Table 2 below consolidates the key criticisms of ILM as identified in the literature.

Table 2: Limitations of ILM. Source: author's own creation.

	Limitation	Reference
1	Lack of structured, transparent processes; ambiguity in scenario development and factor selection	Wright, Bradfield and Cairns (2013); Douglas *et al.* (2021); Kishita *et al.* (2020); Phadnis *et al.* (2014)
2	Dependence on expert intuition, which introduces cognitive and group bias.	Lloyd and Schweizer (2014); Wright and Goodwin (2009)
3	Limited reproducibility due to subjectivity and contextual dependence.	Bradfield *et al.* (2005); van't Klooster and van Asselt (2006)
4	Primarily business-oriented; less suited for policymaking without significant adaptation.	Schwartz (2012); Wright, Stahl and Hatzakis (2020)
5	Heavy reliance on group consensus can slow down processes and dilute divergent perspective.	Phadnis *et al.* (2014); Kishita *et al.* (2020); Kayser and Shala (2020)
6	Lack of systematic guidance for placing drivers on the uncertainty-impact matrix.	Bradfield and El-Sayed (2009); Douglas *et al.* (2021)
7	Scenario logic axis selection is subjective and may omit high-impact drivers.	van't Klooster and van Asselt (2006); Douglas *et al.* (2021); Phadnis *et al.* (2014)
8	Weak integration with quantitative methods; difficulty validating or comparing scenarios.	Kosow and Gaßner (2008); Börjeson *et al.* (2006)

In response to these limitations, scholars have proposed a number of refinements to improve ILM's robustness and applicability. For example, Phadnis *et al.* (2014) introduced a more structured framework for scenario development, while Douglas *et al.* (2021) suggested frequency-based factor selection to reduce subjectivity. Wright, Stahl and Hatzakis (2020) adapted ILM for policy contexts by embedding policymakers directly into project teams, thereby enhancing both legitimacy and contextual validity. These refinements illustrate a broader trend toward hybrid approaches, where ILM is complemented by more structured techniques such as CIB analysis. Such integrations enhance transparency, analytical depth, and scalability while preserving ILM's core strengths in participatory engagement and narrative richness.

2.5.2 La Prospective

The la prospective (LP) method, developed by Michel Godet and inspired by the early foresight work of Gaston Berger, is a structured and analytical approach to scenario construction that stands in sharp contrast to the intuitive, narrative-driven style of ILM (Godet 2000). LP combines qualitative insights with quantitative modelling, employing a systems-based and actor-centred methodology that has been widely applied in policy, strategic planning, and organizational foresight (Bradfield *et al.* 2005; Cordova-Pozo and Rouwette 2023). The process integrates a variety of tools, including MICMAC (impact matrix cross-reference multiplication applied to classification) for mapping systemic interdependencies and MACTOR (actor strategy mapping) for analysing stakeholder strategies and influence (Godet and Durance 2011). These tools enable LP to provide a comprehensive structural map of systems, support long-term decision making, and enhance the intentional shaping of futures.

The theoretical foundations of LP are firmly rooted in GST, complexity theory, and constructivism (discussed in Chapter 3 Section 3.3), each of which informs its distinctive orientation. GST underpins LP's structural analysis, where variables are mapped as interdependent parts of a broader system. This systemic orientation provides transparency and reproducibility by making causal relationships explicit, though it also contributes to LP's reputation for methodological complexity, requiring advanced expertise and technical resources (Mietzner and Reger 2005; Rohrbeck *et al.* 2018). Complexity theory informs LP's attention to non-linearity and emergence, most clearly reflected in MACTOR, which models adaptive interactions between actors in evolving environments (Amer, Daim and Jetter 2013). While this strengthens LP's capacity to capture dynamic stakeholder behaviour, it also heightens dependence on software tools and external expertise, limiting accessibility and reproducibility (Bradfield *et al.* 2005). Constructivism shapes LP's integration of stakeholder perspectives, embedding qualitative insights from interviews, workshops, and panels into its modelling framework (Cordova-Pozo and Rouwette 2023). This participatory element grounds the process socially but introduces opacity, as qualitative judgements are translated into quantitative structures in ways that are not always transparent or easily validated. Moreover, LP's normative orientation, which emphasizes desirable or preferred futures, can favour strategic aspirations over openness to disruptive or low-probability scenarios (Van Vught 1987).

Applications of LP have ranged across urban planning, regional development, environmental management, and education policy (Amer, Daim and Jetter 2013). Its strength lies in its ability to operationalize GST, providing rigorous structural insights into complex systems, thereby addressing the subjectivity and opaqueness often attributed to ILM (Bradfield *et al.* 2005; Amer, Daim and Jetter 2013). Yet, its heavy reliance on structured modelling also introduces important limitations (Amer, Daim and Jetter 2013; Cordova-Pozo and Rouwette 2023). The method can appear mechanistic, underemphasizing the inclusive, sense-making aspects of constructivism, while its deterministic tendencies risk overlooking the unpredictable, emergent behaviours central to complexity theory (Amer, Daim and Jetter 2013). These limitations, as summarized in Table 3, underscore the tensions between LP's theoretical grounding and its practical application.

Table 3: Limitations of LP

	Limitation	References
1	Difficult to apply in small or under-resourced organizations due to required systems expertise.	Mietzner and Reger (2005); Bishop, Hines and Collins (2007); Rohrbeck *et al.* (2018); Chen and Huang (2019); del Villar and Melgarejo (2020)
2	High dependency on external experts for facilitating software-based structural and stakeholder modelling.	Bradfield *et al.* (2005); Godet (2006)
3	Resource-intensive evaluation of large numbers of variables and actor strategies.	Amer, Daim and Jetter (2013)
4	Lack of methodological transparency due to integration of qualitative assumptions into quantitative tools.	Cordova-Pozo and Rouwette (2023); Bradfield *et al.* (2005)
5	Scenarios may reflect normative biases and suppress low-probability, high-impact possibilities.	Van Vught (1987); Cordova-Pozo and Rouwette (2023)
6	Use of multiple modelling tools increases complexity and may reduce process replicability.	Godet (2006); Amer, Daim and Jetter (2013)
5	Weak standardization and reduced reproducibility across contexts.	Amer, Daim and Jetter (2013); Bradfield *et al.* (2005)

The LP method is a powerful tool for long-term strategic planning, integrating rigorous systems analysis, complexity modelling, and normative scenario construction (Godet 2006). It offers a structured alternative to intuitive methods and is well-suited to high-stakes policy environments (Amer, Daim and Jetter 2013). However, its theoretical sophistication contributes to practical challenges, including high resource demands, reliance on expert facilitation, and methodological opacity (Bradfield *et al.* 2005; Cordova-Pozo and Rouwette 2023). To mitigate these challenges, recent efforts in the field have explored hybridization with participatory methods, simplification of modelling tools, and clearer protocols for stakeholder input. These adaptations seek to maintain the depth of LP while enhancing its usability across diverse contexts.

2.5.3 Probabilistic modified trends

The *probabilistic modified trends (PMT)* school uses a quantitative method that expands traditional forecasting techniques by incorporating the potential impact of future events, rather than relying solely on historical trends (Cordova-Pozo and Rouwette 2023). The PMT school and its derivatives offer quantitative techniques that address many of the inherent challenges of the qualitative ILM and LP (Schweizer and Lazurko 2020). Advantages of the PMT methods over ILM and LP include enhanced traceability and reproducibility of scenarios, improved consistency, and the ability to generate a larger number of potential scenarios (Schweizer and Lazurko 2020; Weimer-Jehle *et al.* 2020). Within the PMT school, two different methodologies exist: CIA and trend-impact analysis (TIA). While the TIA method identifies potential events and evaluates their effects on possible futures, the CIA method focuses on the interrelationships between events, determining the probability of one event occurring given the occurrence or non-occurrence of another event (Gordon 1994). Given that this study is more concerned with the interactions between factors rather than the effects of past trends, the CIA method is the primary focus within the PMT framework.

2.5.4 Cross-Impact Analysis

CIA is one of the most analytically rigorous methods of scenario construction and long-term strategic planning, particularly suited for systems with multiple interdependent variables (Schlange and Jüttner 1997; Vecchiato and Roveda 2010; Bañuls and Turoff 2011; Guertler and Spinler 2015; Cordova-Pozo and Rouwette 2023). CIA techniques aim to quantify how the occurrence of one event affects the likelihood of others, enabling internally consistent and probabilistically informed scenario construction (Gordon 1994; Bañuls and Turoff 2011). Unlike ILM, which is primarily qualitative, or LP, which emphasizes systems mapping through structural tools, CIA focuses on quantifying how the occurrence of one event alters the likelihood of others, thereby constructing scenarios that are internally consistent and probabilistically informed (Guertler and Spinler 2015). Its growing appeal lies in its capacity to identify critical drivers, reveal hidden interdependencies, and trace cascading effects across complex systems (Bañuls and Turoff 2011). At the same time, critics point out that its reliance on expert-derived probabilities and limited capacity for narrative integration constrain its accessibility and communicative power, its richness and the human factors that are essential in many foresight applications (Schirrmeister, Göhring and Warnke 2020; Cordova-Pozo and Rouwette 2023).

CIA emerged from the need for a method capable of providing insight into possible futures while accounting for the interrelationships among factors so that factors are not considered in isolation (Gordon 1994; Stankov *et al.* 2021a). Furthermore, as the complexity of systems increased, a mathematical approach became necessary to understand the extensive interdependencies that were beyond the intuitive grasp of earlier methods (Weimer-Jehle 2009). By analysing the effects of identified factors on one another and evaluating their probability of occurrence, CIA methods are able to pinpoint the strongest, most critical drivers within a system, thus validating scenario drivers (Amer, Daim and Jetter 2013). In addition, adjusting the probability of occurrence of a specific event allows for the determination of how future events could affect other events and, ultimately, the entire system (Gordon 1994). The primary advantage of CIA over other methods lies in its ability to assess the influential strength of relationships between drivers without relying on qualitative data from participants (Weimer-Jehle 2006). The flexibility of the CIA method and its independence from predefined matrices allows for the generation of a much larger number of scenarios (Lloyd and Schweizer 2014).

CIA is strongly informed by GST, as it assumes that the variables in a system are interconnected and that changes to one can propagate across the whole. The cross-impact matrix reflects this systems-based logic, providing a structured mechanism for identifying leverage points, dependencies, and systemic vulnerabilities (Meadows 2008). However, unlike more dynamic systems approaches, CIA does not fully account for adaptive feedback or evolving interdependencies, limiting its capacity to model non-linear system behaviour. From the perspective of complexity theory, CIA offers a powerful way to engage with interdependent drivers and trace how change in one part of the system can cascade to others. This makes the method well-suited for handling intricate, multi-variable systems (Weimer-Jehle 2006; Bañuls and Turoff 2011). Yet its modelling remains relatively static and deterministic, underrepresenting emergent, unpredictable dynamics that are central to complex adaptive systems (Weimer-Jehle 2006; Amer, Daim and Jetter 2013). Finally, CIA shows limitations when examined through a constructivist lens. While it incorporates expert judgements to populate cross-impact matrices, the process is highly technical and tends to prioritize quantitative coherence over participatory sense-making. This often reduces opportunities for stakeholder dialogue, reflexivity, and the co-construction of meaning. As a result, scenarios produced through CIA may appear rigorous but risk being detached from contextual narratives or lacking resonance with decision makers (Schweizer 2019).

Developed in the late 1960s by Theodore Gordon and Olaf Helmer at the RAND Corporation, Gordon's derivative of the CIA method was initially conceptualized as a card game before evolving into a structured method based on cross-impact matrices (Gordon 1994; Bradfield *et al.* 2005). In its original form, the method calculates how the assumed occurrence of one event alters the probability of another, thereby producing a coherent and internally consistent model of potential futures. Gordon's version of CIA was innovative because it moved foresight beyond treating events in isolation, enabling a more realistic modelling of systemic interdependencies (Gordon and Hayward 1968; Gordon 1994).

CIA was developed to address the limitations of earlier foresight techniques that treated future events as isolated occurrences (Gordon 1994). Instead, CIA provides a more realistic and systemic perspective by incorporating the interdependencies between events. This allows for more accurate and internally consistent probability estimates (Choi, Kim and Park 2007). The method employs a cross-impact matrix to represent the relationships between events or drivers. Data for these matrices are typically gathered from expert participants, and the analysis focuses on identifying causal links and evaluating the influence that one event may exert on another (Gordon 1994; Weimer-Jehle 2006). Through this process, CIA helps reduce uncertainty by mapping how interactions between events can shape future outcomes (Gordon 1994). One of CIA's main strengths lies in its ability to analyse complex systems with multiple interactions (Guertler and Spinler 2015). It is particularly useful in contexts where qualitative approaches may be insufficient to capture the intricate dynamics at play (Gordon and Hayward 1968; Weimer-Jehle 2006; Medina, de Arce and Mahía 2015). Moreover, the method's flexibility enables it to be used in combination with other techniques, such as the Delphi technique (Enzer 1971) and fuzzy logic (Asan, Bozdağ and Polat 2004), facilitating group-based scenario generation and enhancing its versatility. Its core strength is its capacity to identify event chains and assess how changes to one event can cascade through a system, altering the likelihood of other events and influencing the overall scenario trajectory (Gordon and Hayward 1968; Enzer 1971).

Gordon's original CIA emphasizes the use of expert judgements to create probabilistically coherent future pathways. It aims to enhance strategic foresight by modelling the complex interplay of future developments. However, the method's reliance on expert-derived probabilities introduces subjectivity and potential bias, and the mathematical burden of managing large cross-impact matrices becomes increasingly problematic as the number of variables grows (Choi, Kim and Park 2007). Additionally, CIA's analytical focus limits its narrative and communicative capacity, which can reduce its effectiveness in stakeholder engagement and policy dialogue (Amer, Daim and Jetter 2013). Over time, a number of variants were developed to refine Gordon's original CIA. These include SMIC (cross-impact system and matrices) by Duperrin and Godet (1973), INTERMAX (interactive cross-impact simulation) by Enzer (1971), and IFS (interactive future simulations) developed by the Battelle Memorial Institute in the 1970s (Bradfield *et al.* 2005). These adaptations expanded the method's applicability and analytical scope but retained its dependence on expert-derived inputs and its limited integration of narrative and participatory dimensions.

The limitations of CIA flow directly from its theoretical orientation. While its systemic foundation (GST) allows it to reveal hidden interdependencies, it struggles to capture dynamic feedbacks and emergent outcomes central to complexity (Von Bertalanffy 1968; Prigogine and Stengers 2018). Its constructivist weakness lies in the limited involvement of stakeholders in sense-making as probabilities are typically elicited from technical exercises rather than through participatory dialogue. These critiques are consolidated in Table 4.

Table 4: Limitations of CIA

	Limitation	Reference
1	Subjectivity in expert-derived probability estimates introduces inconsistency and bias.	Choi, Kim and Park (2007); Gordon and Glenn (2018)
2	Low-probability, high-impact events may be excluded due to data scarcity or expert scepticism.	Schweizer (2019)
3	Number of conditional probabilities grows geometrically with more variables, limiting scalability.	Choi, Kim and Park (2007); Weimer-Jehle (2009)
4	Expert participants may unknowingly embed cross-impacts in probability estimates.	Gordon and Glenn (2018)
5	Method lacks narrative or qualitative integration, limiting contextual insight.	Amer, Daim and Jetter (2013)
6	Difficult to validate or replicate outcomes due to reliance on intuition in quantitative judgements.	Gordon (1994); Weimer-Jehle (2006); Bradfield *et al.* (2005)
7	Does not capture non-linear feedbacks or emergent behaviours common in complex systems.	Weimer-Jehle (2006); Medina, de Arce and Mahía (2015)
8	Requires significant time and resources to gather input through interviews, workshops, or surveys.	Phadnis *et al.* (2014); Kishita *et al.* (2020); Kayser and Shala (2020)

2.5.5 Cross-impact Balance

These challenges of CIA have led to the development of CIB, a derivative of CIA that avoids complex probability calculations by relying instead on consistency logic to examine how strongly and in what direction variables are related (Weimer-Jehle 2009). CIB retains CIA's systemic and complexity-aware strengths while offering greater accessibility and improved alignment with constructivist approaches, making it more suitable for participatory foresight processes. The CIB technique, introduced by Weimer-Jehle in 2001, is a systematic method for constructing qualitative and semi-quantitative scenarios based on the internal consistency of interdependent system factors (Weimer-Jehle 2023b). Developed as a response to the subjectivity of intuitive methods like ILM and the complexity of probabilistic CIA approaches, CIB is often applied as a more structured, logic-based alternative to ILM (Kosow 2016). While ILM relies heavily on expert intuition and consensus, CIB operationalizes scenario building by evaluating qualitative impact judgements between factor states. Through this process, it identifies consistent combinations of developments that can co-occur. This shift from narrative speculation to structured logic enhances transparency and reproducibility (Weimer-Jehle 2006; Weimer-Jehle *et al.* 2020).

Researchers are of the view that unlike the analyses performed in other methods, the analysis performed in the CIB technique is more objective in nature, reducing the subjectivity of the scenarios produced (Lloyd and Schweizer 2014; Carlsen, Klein and Wikman-Svahn 2017). In addition, while contemporary CIA methods focus on probabilistic relationships, CIB analysis rather uses qualitative judgements to investigate the influence that factors have on each other.

CIB has been applied widely across diverse domains, including urban mobility (Tori, Te Boveldt and Keseru 2023), public health (Lambe *et al.* 2018; Stankov *et al.* 2021a), energy (Norouzi, Fani and Ziarani 2020; Poganietz and Weimer-Jehle 2020; Kurniawan *et al.* 2022), sustainability (Kosow, Wassermann and D León 2022), urban planning (Fadel and Abu-Eisheh 2024) and climate change (Lazurko, Schweizer and Armitage 2023). In particular Schweizer and Lazurko (2020) show that applying CIB to climate change enhanced both the credibility and legitimacy of scenarios by documenting the logic behind them. One of the method's key strengths lies in its ability to ensure that all factors and their interrelations are aligned, thereby producing internally consistent scenarios under conditions of deep uncertainty (Weimer-Jehle 2001; Lloyd and Schweizer 2014). Furthermore, the CIB analysis develops holistic scenarios by investigating which combinations of factor states are strongest when evaluating the strength of their combined relationships (Weimer-Jehle 2023b).

The CIB technique provides a higher level of transparency, reproducibility, and traceability compared to other methods (Lloyd and Schweizer 2014), and reduces cognitive biases that can affect researchers' judgements (Schweizer and Lazurko 2020). The technique acknowledges the existence of the multiple uncertainties that other qualitative methods ignore and actively addresses them. An example is the selection of factors to include in the scope of the task while another relates to the traceability of direct relationships and the complex indirect relationships that are not otherwise apparent (Schweizer and Lazurko 2020).

The analysis method used in CIB allows for the logic surrounding the scenarios of deeply uncertain qualitative systems to be documented and explained. It emphasizes the creation of consistent scenarios so that all factors and their interactions are aligned (Lloyd and Schweizer 2014). CIB analysis also successfully addresses internal consistency problems that exist in other methods while providing a measure of consistency (Weimer-Jehle 2006). Inconsistent scenarios are those that include factors that are highly unlikely to occur together (Tosoni 2021). CIB analysis eliminates inconsistent scenarios by assessing the interdependence of the factors in the system through cross-impact analysis (Asan and Asan 2007; Schweizer and Lazurko 2020). By ensuring that consistency is obtained through the method, the pressure for experts to assess consistency is removed (Schweizer and Kriegler 2012; Lloyd and Schweizer 2014; Ruth *et al.* 2015).

While some opine that CIB analysis suffers from practical limitations regarding the number of factors that can be considered, studies have demonstrated that CIB analysis can successfully accommodate up to 43 factors, which is well beyond the threshold of other qualitative methods (Weimer-Jehle, Deuschle and Rehaag 2012). Moreover, due to the mathematical algorithm used, the analysis method has the ability to evaluate numerous, unexpected scenarios that may be overlooked or eliminated by other methods (Lloyd and Schweizer 2014). A further strength lies in the ability for the states of the various factors to be of different types, with some factors having states that are numeric while others may be linguistic or binary (Weimer-Jehle 2006).

The theoretical foundation of CIB rests on GST, complexity theory, and constructivism, each shaping both its strengths and its limitations. From a systems perspective, CIB reflects GST by framing the world as an interconnected set of variables whose interdependencies can be mapped (Von Bertalanffy 1968; Weimer-Jehle 2006). The method operationalizes this through the cross-impact matrix, which captures structural relationships and ensures that scenarios remain internally consistent across the system (Weimer-Jehle 2006; Meadows 2008). Yet, as GST assumes largely static interrelationships, it struggles to account for the dynamic feedbacks, path dependencies, and evolving behaviours that characterize many real-world systems (Kopfmüller *et al.* 2021). Complexity theory complements this by recognizing that systems are nonlinear, adaptive, and emergent. CIB mirrors these insights by considering how consistent outcomes emerge from multiple interacting drivers, making it particularly useful for exploring conditions of deep uncertainty (Lloyd and Schweizer 2014). However, the approach necessarily simplifies reality into pairwise judgements, and the exponential growth of possible state combinations poses practical challenges as the number of factors increases (Weimer-Jehle 2006; Stankov *et al.* 2021b). Moreover, while complexity theory highlights disruptive and emergent dynamics, CIB's focus on stable, internally consistent combinations risks, overlooking transformative shifts (Holland 1995; Weimer-Jehle 2006). Constructivism adds a further epistemological dimension by recognizing that knowledge of the future is not discovered but socially constructed (Schwandt 1994). In CIB, this is evident in the way experts identify factors and assess their interdependencies, embedding contextual relevance and legitimacy into the scenarios (Musch and von Streit 2017). At the same time, reliance on expert judgements introduces subjectivity and the potential influence of dominant narratives, meaning that outcomes may reflect partial perspectives rather than holistic system understanding (Kosow 2016; Schweizer and Lazurko 2020). Taken together, these theoretical traditions provide CIB with its strengths of systemic structure, transparency, and contextual legitimacy, but also explain its limitations in terms of static modelling, subjectivity, and practical manageability. While the CIB algorithm is grounded in GST and complexity theory, its application is critically informed by potential surprise theory, which shapes the framing of expert judgements and the strategic interpretation of the resulting scenarios to ensure they capture disruptive, not just consistent, possibilities.

Despite these limitations, the strengths of CIB, in particular its transparency, traceability, and ability to generate internally consistent scenarios, make it a valuable tool for foresight in domains such as energy, climate, public health, and urban planning (Lambe *et al.* 2018; Poganietz and Weimer-Jehle 2020; Fadel and Abu-Eisheh 2024). While the technique addresses several weaknesses associated with ILM and CIA, notably those related to subjectivity, probabilistic complexity, and the opacity of scenario logic, it is not without its own challenges. These limitations stem directly from the theoretical traditions underpinning the method, which simultaneously provide its strengths but also constrain its application. Table 5 below consolidates the most frequently cited limitations of CIB in the literature, illustrating how these challenges emerge from the same theoretical orientations that make the method distinctive.

Table 5: Limitations of CIB

	Limitation	References
1	Time-consuming data gathering workshops.	Kemp-Benedict, Carlsen and Kartha (2019); Lloyd and Schweizer (2014)
2	Factor selection is subjective and shaped by group consensus or dominant narratives.	Musch and von Streit (2017); Kosow (2016)
3	Lack of structured, rigorous process for identifying relevant system factors.	Kemp-Benedict, Carlsen and Kartha (2019); Kosow (2016);
4	Pairwise judgements can be inaccurate due to poor understanding of complex relationships.	Lloyd and Schweizer (2014)
5	Static structure: CIB does not capture evolving system behaviour or feedback over time.	Kopfmüller *et al.* (2021)
6	Qualitative judgements only: method does not quantify the strength of influence.	Weimer-Jehle (2023b)
7	Combinatorial complexity arises as the number of factors increases.	Stankov *et al.* (2021b); Weimer-Jehle (2006)
8	May overlook discontinuities or emergent transformations due to focus on internally consistent outcomes.	Lazurko, Schweizer and Armitage (2023); Lloyd and Schweizer (2014)
9	Subjective judgements may reduce reproducibility across contexts.	(Lloyd and Schweizer 2014); Schweizer and Lazurko (2020)

As shown in Table 5, CIB is limited by its reliance on subjective judgements, static system representation, and scalability challenges due to combinatorial complexity. While its theoretical grounding in systems thinking, complexity theory, and constructivism supports transparency and structural consistency, it constrains the method's ability to capture dynamic change, emergent disruptions, and broader inclusivity.

2.6 Method Shortcomings

Each scenario construction method offers distinct strengths but also introduces limitations affecting rigour, scalability, and practical application. Key challenges include time and resource intensity, bias, analytical constraints, methodological rigour, and scalability. Sub-sections below address these challenges with suggestions on how these can be mitigated. The limitations and mitigating strategies are summarised in Table 6.

2.6.1 Time delays

It is well-established that participatory methods for data collection and factor reduction are often time-intensive, both for participants and analysts. These methods commonly rely on resource-heavy tools such as workshops, interviews, and, focus groups (Phadnis *et al.* 2014; Kishita *et al.* 2020). ILP, LP, CIA and the CIB method have all faced criticism due to their reliance on these time-consuming data-gathering methods, which can significantly slow down the overall scenario construction process (Kemp-Benedict, Carlsen and Kartha 2019). Reports indicate that additional time delays may arise when participants struggle to fully grasp the scope of the subject matter (Kayser and Shala 2020). Further, time can be lost when consensus must be reached among participants, adding layers of complexity and extending the overall timeline (Skinner *et al.* 2015). These delays significantly affect the timeliness of scenario construction, ultimately hindering decision-making processes that require prompt action (Heinonen, Kuusi and Salminen 2017).

To address these inefficiencies, a more time-efficient data gathering method is crucial. Davis, Jetter and Giabbanelli (2023) emphasize the need for researchers to explore automated tools to streamline the time-consuming aspects of scenario development. In previous studies, online tools have been effectively employed to gather data from participants in a timelier manner, eliminating the need for interviews or group discussions (Cooper *et al.* 2006; Thompson, Olugbara and Singh 2020).

2.6.2 Participant diversity

Creating coherent and realistic future scenarios is inherently challenging as the real world is driven by complex, often unrelated factors with intricate feedback mechanisms (Hichert *et al.* 2021). However, incorporating a broad range of perspectives from diverse participants can unveil multiple potential futures, enriching decision-making processes and enhancing the relevance of scenario planning for science and policy (Heinonen, Kuusi and Salminen 2017; Hichert *et al.* 2021). Kaviani *et al.* (2023) argue that when scenarios affect everyday people and their communities, these same stakeholders should be actively involved in the scenario construction process. They contend that the existing techniques used in scenario construction methods, frequently rely on organizational knowledge and assumptions, potentially overlooking the perspectives of those directly affected. Kaviani *et al.* (2023) advocate for a more inclusive participant base to address this, one that reflects diverse social, cultural, and economic realities to improve the accuracy and utility of scenario outcomes. Grunwald (2011) reinforces this view, emphasizing that the quality of scenarios is directly linked to the diversity of input in the planning process.

Relying solely on expert focus groups or discussions may inadvertently introduce cognitive biases, limiting the scope and inclusivity of the scenarios produced (Lloyd and Schweizer 2014; Heinonen, Kuusi and Salminen 2017). To counter these limitations, researchers suggest adopting processes like crowdsourcing and alternate platforms such online tools and social media to expand data collection beyond a small group of experts (O'Reilly 2009; Raford 2015; Kayser and Shala 2020). Despite its potential, the use of crowdsourcing in scenario construction remains an under-explored area, meriting further exploration (Kayser and Shala 2020).

2.6.3 Data analysis

Many data analysis methods adopted for scenario construction, including CIA and CIB, share similar methodological limitations. One of the initial stages in scenario construction involves identifying key factors, typically by means of focus groups or brainstorming sessions with experts. These methods are time-consuming, may limit the scope, and are vulnerable to the biases of those involved (Meadows 2020). After identifying an initial list of factors, the set is reduced so that only factors deemed most relevant to the study and methodology are retained. This factor reduction task is most often performed by experts, introducing cognitive biases and potentially excluding factors that are not well understood or that do not align with the experts' perspectives (Lloyd and Schweizer 2014; Douglas *et al.* 2021). Kemp-Benedict, Carlsen and Kartha (2019) note that methods (including CIB) could be strengthened by integrating alternative, less subjective methods for factor identification.

Ensuring the logical coherence or consistency of scenarios is a challenge for many scenario methods. Purely qualitative methods such as ILS perform no formal consistency checking and coherence is dependent on the expertise of the participants (Alcamo 2008), while CIA relies on subjective judgements that could be biased and lead to scenarios that are inconsistent and contain contradictions (Schirrmeister, Göhring and Warnke 2020). Despite calls for methodological innovations that integrate both qualitative and quantitative methods in scenario construction, such techniques remain underexplored (Haegeman *et al.* 2013; Wiebe *et al.* 2018). It is the aim of this study to respond to these calls by providing a methodology that addresses the shortcomings discussed.

Table 6: Thematic summary of the limitations of ILM, LP, CIA and CIB

Theme	Description	Method	Mitigating Strategy	Reference
Time and Resource Intensity	Time-intensive data collection and stakeholder workshops	ILM, CIA, CIB	Use of online tools and automated data collection methods	Kemp-Benedict, Carlsen and Kartha (2019); Lloyd and Schweizer (2014)
	Evaluation of numerous factors requires extensive expert engagement	LP, CIB	Crowdsourcing to distribute input and reduce expert burden	Amer, Daim and Jetter (2013); Weimer-Jehle (2006)
	Reliance on external facilitation and software for application.	LP	Adoption of scalable and user-friendly digital platforms	Amer, Daim and Jetter (2013); Godet (2006)
Bias and Subjectivity	High subjectivity in scenario development and participant bias.	ILM, CIA, CIB	Increase participant diversity through crowdsourcing	Musch and von Streit (2017); Wright, Bradfield and Cairns (2013)
	Over-reliance on expert intuition.	ILM, CIA	Crowdsourcing to broaden input base and advanced analysis for factor reduction.	Musch and von Streit (2017)
	Inconsistent or biased pairwise judgements between factors.	CIB	Aggregation of multiple inputs through advanced impact analysis.	Lloyd and Schweizer (2014)
	Experts may conflate cross-impacts when estimating probabilities	CIA	Addressed through structured elicitation of impacts.	Gordon and Glenn (2018)
Analytical Limitations	Lack of ability to model evolving, dynamic systems.	LP, CIB	Not directly addressed, outside the scope of the study.	Kopfmüller *et al.* (2021); Godet (2000)
	Difficulty managing large interdependent systems as number of factors grows.	LP, CIA, CIB	Use of computational tools and impact analysis methods	Bradfield *et al.* (2005); Choi, Kim and Park (2007); Weimer-Jehle (2006)
	Focus on consistency may omit disruptive or outlier scenarios.	CIB	Inclusion of diverse perspectives via crowdsourcing	Lazurko, Schweizer and Armitage (2023); Lloyd and Schweizer (2014)
	Lack of narrative richness and human interpretability.	CIA	Not directly addressed, outside the scope of the study.	Lloyd and Schweizer (2014); Schweizer (2019)
	Use of static relationships fails to capture time-sensitive developments.	LP, CIB	Not directly addressed, outside the scope of the study.	Kosow (2016); Weimer-Jehle (2023b)
Methodological Rigour and Clarity	Lack of methodological transparency and reproducibility.	ILM, LP	Structured, documented methodology integrating crowdsourcing, ADVIAN® and CIB.	Wright, Bradfield and Cairns (2013); Douglas *et al.* (2021); Kishita *et al.* (2020); Phadnis *et al.* (2014); Amer, Daim and Jetter (2013)
	Poor guidance for axis and driver selection.	ILM, LP	Use of systematic factor identification and selection techniques	Bradfield and El-Sayed (2009); Douglas *et al.* (2021); van't Klooster and van Asselt (2006)
	Heavy reliance on expert-derived probabilities for input.	CIA	Use of crowdsourcing and alternative data collection approaches.	Brehm, Heinzl and Markus (2001); van't Klooster and van Asselt (2006); Choi, Kim and Park (2007); Schweizer (2019)
	Factor selection and inclusion criteria may lack consistency or structure.	ILM, CIB	Application of structured factor reduction methods	Kemp-Benedict, Carlsen and Kartha (2019); Musch and von Streit (2017)
Scalability and Scope	Unsuitable for smaller organizations due to expertise and resource requirements.	LP	Use of crowdsourcing for diversity.	Lloyd and Schweizer (2014)
	Increased number of relationships overwhelms matrix complexity.	CIA, CIB	Use of systematic factor reduction techniques	Stankov *et al.* (2021a); Weimer-Jehle (2006)
	The method does not account for dynamic changes over time. It is therefore not ideal for analysing evolving systems.	CIB	Not directly addressed, outside the scope of the study.	Kopfmüller *et al.* (2021)
	Inability to integrate seamlessly with other structured, quantitative methods.	ILM, CIB	Development of an integrated hybrid methodology	Kosow (2016); Wright, Stahl and Hatzakis (2020)

This discussion provides a useful foundation for justifying the design of a novel scenario construction methodology that addresses the limitations of traditional approaches. By integrating multiple methodological components, the proposed methodology seeks to overcome challenges such as subjectivity, methodological opacity, and limited scalability. The critical review has also underscored the potential of ADVIAN® and crowdsourcing to address these challenges. While ADVIAN® is discussed further in Chapter 3 where the theoretical foundation is presented, the section that follows explores crowdsourcing and its role in scenario studies.

2.7 The Crowdsourcing Process

Crowdsourcing has the potential to address several of the persistent limitations related to participant bias, limited expertise, and resource constraints, as highlighted in Section 2.6. By engaging a broader and more diverse pool of participants, crowdsourcing reduces dependence on small, homogeneous expert panels and mitigates the influence of dominant voices or organizational power dynamics (Howe 2006; O'Reilly 2009). It also enhances the scalability and inclusiveness of the process, enabling richer data collection within shorter timeframes and at lower cost (Bhatti, Gao and Chen 2020). Moreover, when combined with structured tools (e.g., surveys or judgement elicitation platforms), crowdsourcing can improve transparency, traceability, and the validity of expert inputs, contributing to more balanced and representative scenario outcomes (Kayser and Shala 2020).

2.7.1 Definition of crowdsourcing

Crowdsourcing was initially defined as “the act of a company or institution taking a function once performed by employees and outsourcing it to an undefined (and generally large) network of people in the form of an open call” (Howe 2006b: 1). Since then, it has evolved significantly. In today's interconnected society, crowdsourcing relies on web-based platforms to obtain media, solve problems, conduct research, and perform tasks by outsourcing to an online crowd (Howe 2006a). More recently, Bhatti, Gao and Chen (2020:4) have described it as “an online distributed problem-solving paradigm” that offers individuals and companies access to intelligence, knowledge, and expertise. These evolving definitions highlight the scalability, accessibility, and problem-solving capacity of crowdsourcing, making it an increasingly valuable approach for foresight research.

The crowdsourcing process encompasses a broad range of tools, concepts, and methods for gathering data by engaging a large, often external, and diverse participant base. The approach has gained prominence in research on scenarios, decision support systems (DSS), and information systems (IS) (Thuan, Antunes and Johnstone 2018) as well as in participatory design (Dortheimer *et al.* 2024). Crowdsourcing has also proven highly effective in industries such as manufacturing, agriculture, tourism, healthcare, education, disaster management, and social services (Chatterjee *et al.* 2024), and is particularly valuable for tasks that require human interpretation, such as gathering opinions, language translation, or image tagging (Chittilappilly, Chen and Amer-Yahia 2016; Li *et al.* 2016; Bhatti, Gao and Chen 2020). In corporate settings, crowdsourcing can take on tasks traditionally managed internally, extending them to a broad, diverse audience for faster, more diverse results (Howe 2008).

2.7.2 Benefits of crowdsourcing

Crowdsourcing systems aim to maximize productivity while minimizing time and financial investments, a goal particularly relevant to research activities (Chittilappilly, Chen and Amer-Yahia 2016; Lee, Arida and Donovan 2017). One of the primary benefits of crowdsourcing is its speed: data can be gathered and results produced within as little as 24 hours (Alonso 2011). This efficiency is due to crowdsourcing’s parallel processing model, where participants (or workers) contribute data concurrently using their own devices (Chiu, Liang and Turban

2014). Another advantage of crowdsourcing is its capacity to attract and recruit a large, diverse pool of participants, improving the quality of collected data (Alonso 2011). Diversity in participants is particularly valuable for scenario planning, as a varied and creative range of inputs leads to more comprehensive, nuanced scenarios (Hichert *et al.* 2021). This offers decision makers creative, robust, well-rounded scenarios based on which future decisions can be made (Heinonen, Kuusi and Salminen 2017). Collecting data and recruiting study participants using crowdsourcing to draw from a diverse and extensive participant pool would thus fulfil the aim of securing diverse perspectives (Raford 2015). It also has the potential to address the concerns about the bias that is present when gathering data from a small group of experts, and offers a larger number of responses, resulting in enhanced statistical reliability (Mietzner and Reger 2005; Raford 2015; Heinonen, Kuusi and Salminen 2017).

Crowdsourcing also promotes openness in communication, with participants free to express their opinions while remaining anonymous (Dortheimer *et al.* 2024). This anonymity encourages honest input, enriching data quality. Several studies have validated the reliability of crowdsourcing, showing strong correlations between crowd-sourced and expert-generated data. For example, a study by Chiang *et al.* (2024) demonstrated positive correlations between evaluations from experts and crowd users using an online application. Additionally, Skinner *et al.* (2024) reported comparable accuracy scores for medical image annotations from both crowdsourced data and experts, and Duggan *et al.* (2024) found that crowdsourced labels for lung ultrasound clips achieved expert-level accuracy.

2.7.3 Crowdsourcing applications

Crowdsourcing applications have proven successful across numerous domains for both qualitative and quantitative studies (Cobanoglu, Cavusoglu and Turktarhan 2021). For example, Wikipedia relies on distributed contributors to create and maintain shared content, and internet users contribute to digitizing scanned materials by identifying words in images (Von Ahn *et al.* 2008). Crowdsourcing has enabled advances in scientific research, such as enhancing a computationally designed enzyme through game-driven activities (Eiben *et al.* 2012), and has been used for data management tasks like data cleaning, integration, and knowledge construction. In the I-REACT project, crowdsourcing was combined with early warning services to improve decision support in wildfire emergency management (Bielski *et al.* 2017).

While crowdsourcing has been widely applied in fields such as image classification, language processing, sentiment analysis, idea generation, problem solving, and opinion collection, relatively few studies have explored its use for scenario construction (Krizhevsky, Sutskever and Hinton 2012; Kucherbaev *et al.* 2015; Rowe, Poblet and Thomson 2015; Inel, Caselli and Aroyo 2016; Seeber *et al.* 2017). Moreover, the researcher was unable to find any study that recruited participants for scenario construction studies through crowdsourcing. Bañuls and Turoff (2011) highlight the benefits crowdsourcing can bring to scenario construction, emphasizing that crowds can help address key challenges in the process. For example, Raford (2015) found that data gathering via crowdsourcing was 15–20 times faster than through traditional methods, while Skinner *et al.* (2024) estimate that it saved over 900 hours of expert annotation time for medical data. Researchers like Meadows (2020) have also advocated for the use of novel data collection methods such as social media and the crowdsourcing process in scenario projects to reduce the need for time-intensive face-to-face workshops and brainstorming sessions.

The following sub-section discusses online platforms available for crowdsourced data collection.

2.7.4 Crowdsourcing platforms evaluation

A number of online platforms and tools are available for collecting crowdsourced data (Surveymonkey.com, Amazon's Mechanical Turk, Crowd4U). They offer the potential of engaging a large number of diverse participants for low costs in terms of finances and time (Alonso 2011).

Crowdsourcing platforms consist of four interconnected objects, namely the platform, the task, the crowd, and the requester (Hosseini *et al.* 2014). The requester assigns tasks, the crowd performs these tasks, and the platform connects requesters with the crowd, enabling the efficient publication and completion of tasks. Platforms such as Amazon Mechanical Turk (MTurk), Qualtrics, ClickWorker, Crowd4U, and InnoCentive offer unique functionalities to cater to general or specialized crowdsourcing needs (Kucherbaev *et al.* 2015; Chittilappilly, Chen and Amer-Yahia 2016; Li *et al.* 2016; Bhatti, Gao and Chen 2020). MTurk, one of the most popular crowdsourcing platforms, allows requesters to post microtasks, known as human intelligence tasks (HITs), which crowd workers complete for financial incentives. Similarly, CrowdFlower (now Appen) distributes tasks globally, adding quality controls through gold standard questions. Volunteer-based platforms like Crowd4U, on the other hand, attract workers who participate without financial compensation, typically to contribute to social or research initiatives (Morishima *et al.* 2012; Borromeo and Toyama 2016).

Several limitations make these platforms suboptimal for complex data-gathering projects, particularly those that require the recruitment of experts in the domain. One major challenge is the difficulty of accurately assigning tasks to the right participants, as misallocated tasks can lead to wasted resources and unreliable data (Chen *et al.* 2018). The paid nature of platforms like MTurk also poses challenges. Workers may misrepresent their qualifications to maximize earnings, thereby compromising data quality (Cobanoglu, Cavusoglu and Turktarhan 2021). Additionally, most paid platforms are better suited for tasks with clear, verifiable answers, such as image labelling, rather than open-ended opinion-based research (Kittur, Chi and Suh 2008). Qualtrics offers higher-quality control through screening of the recruited participants but is too costly for many researchers, with participants receiving approximately $5 per survey, an amount that increases for more time-intensive tasks (Ford 2017; Garrow *et al.* 2020). In contrast, unpaid platforms such as Crowd4U require technical skills for task setup and management, limiting their accessibility and ease of use (Borromeo and Toyama 2016). Moreover, proprietary platforms may lack the functionality to screen participants based on specific inclusion criteria crucial for studies needing verified expert input. This limitation is especially relevant for scenario construction studies, which require qualified participants whose opinions reflect a high degree of expertise and relevance (Cummings and Sibona 2017). Given these limitations, an alternative data-gathering and participant recruitment platform that provides a diverse, expert-driven participant pool without financial incentives is necessary.

2.7.5 Social media for crowdsourcing

Social media platforms, with their broad user base and powerful engagement capabilities, offer a viable solution for sourcing diverse and expert participants on a large scale. The global reach and demographic diversity of social media platforms like LinkedIn, “X”, and Facebook provide an expansive pool of potential contributors across various fields and geographic locations (Belfiglio *et al.* 2024). These digital platforms, which include social media sites, web applications, and smartphone applications, also provide opportunities for efficient and effective engagement with various communities for the purpose of research (Raju 2014).

The past two decades have seen a significant rise in the use of social media for data collection in research, revolutionizing how information is accessed and disseminated. Social media platforms have also seen an increasing level of adoption by the public for the purpose of communication (Collins, Shiffman and

Rock 2016) and have been adopted in health research studies for participant recruitment (Johnson *et al.* 2019; Darko, Kleib and Olson 2022; Ejem *et al.* 2023; Lang *et al.* 2023). Moreover, social media provides a powerful and efficient crowdsourcing platform that can be leveraged for decision making through real-time collection of opinions and knowledge from the crowd (Chatterjee *et al.* 2024). Not only are these platforms useful for brainstorming and idea generation, but they also serve as valuable tools for distributing crowdsourced surveys (Chatterjee *et al.* 2024). While platforms like Facebook, Instagram, LinkedIn, YouTube, Pinterest, and TikTok each have their unique characteristics, this study focuses specifically on the “X” platform due to its reported advantages in the context of research data collection.

With over 347 200 tweets shared every minute (Dumo 2022), “X” generates a vast and dynamic stream of public data that is ripe for analysis across various domains. This immense volume of real-time data presents numerous opportunities, such as providing solutions to unresolved problems, enabling businesses to identify new ventures, uncovering new service offerings, enhancing understanding of customer needs, and boosting productivity (Dong and Lian 2021; Niu *et al.* 2021). This large, global data source has attracted significant attention from researchers seeking to address a diverse range of questions. Systematic and scoping reviews of studies that used data from “X” have categorized research into several key domains, including content analysis, sentiment analysis, topic modelling, surveillance, event detection, engagement, forecasting, disease detection, marketing, geographic identification, recruitment, intervention, politics, medical education, and network analysis (Sinnenberg *et al.* 2017; Edo-Osagie *et al.* 2020; Karami *et al.* 2020).

Unlike platforms such as Instagram, Pinterest, and Snapchat, which are primarily visually oriented, “X” is heavily communication-centred, making it an ideal platform for engaging with professionals and researchers. With over 550 million active users, “X” provides the opportunity to connect with diverse groups and stakeholders globally (Kayser and Shala 2020). Additionally, as 90% of user accounts on “X” are public (MacDermott *et al.* 2020), the platform offers researchers access to a substantial and accessible audience. Research also indicates that “X” attracts the highest proportion of participants for research studies compared to other social media platforms (MacDermott *et al.* 2020; Rana *et al.* 2023). To further enhance reach, Robertson *et al.* (2021) note that the strategic use of hashtags in posts accelerates the dissemination of new ideas, increasing visibility and fostering broader engagement. Hashtags also enable targeted interaction with specialists and experts, allowing users to tag relevant individuals and creating opportunities for direct engagement, such as commenting on posts or responding to surveys.

From the above it is evident that the “X” platform has become a popular tool for researchers collecting data (Edo-Osagie *et al.* 2020; Kumar and Jaiswal 2020). This increased popularity can be attributed to “X”’s vast pool of diverse, unstructured data, which can be collected and analysed in real time from heterogeneous sources (Gandomi and Haider 2015; Udanor, Aneke and Ogbuokiri 2016).

2.7.6 “X” in scenario studies

Big data from “X” has also shown significant value in scenario studies, offering a robust platform for mining diverse insights and facilitating communication among participants. Kayser and Shala (2020) and O'Brien, Meadows and Griffiths (2017) used web mining, more specifically data from “X” users, to summarize and describe the scenario field that was being investigated. Kayser and Shala (2020) consolidated data from “X” and other web sources to capture a range of opinions and perspectives, thereby enriching scenario-building inputs. Additionally, Gokhberg *et al.* (2020) used text mining on “X” data to complement desk research and enhance the depth of data available for expert-driven scenario construction. Calleo and Di Zio (2021) extracted influencing factors from “X”, finding that the platform offered a rich set of variables in a short timeframe, supporting rapid scenario analysis.

Numerous studies have highlighted “X”'s role in enhancing communication and engagement in scenario research. O'Brien, Meadows and Griffiths (2017) used “X” as a discussion platform, enabling participants in a scenario project to communicate between workshops, thereby maintaining momentum and fostering continuous dialogue. Similarly, Zeng, Koller and Jahn (2019) found that discussions on “X” served as a valuable source for identifying participant groups and gathering public opinions, which aligned closely with those of experts involved in their scenario study. Meadows and O'Brien (2015) used the platform for ongoing communication with participants, providing event commentary, encouraging engagement through prompts, and sharing study materials. Social media, including “X”, was also used to publish updates and announcements related to scenario planning projects (Raford 2015). Feblowitz *et al.* (2021) directly engaged “X” users by asking for input on factors to consider in their scenario study, gathering valuable public perspectives to guide their research. The “X” platform has proven to be an invaluable crowdsourcing platform for research studies, particularly due to its ability to aggregate "the wisdom of the crowd" (Davis 2022: 45). But, most studies have only scratched the surface of the platform’s potential, using it primarily as a data source rather than an active recruitment platform, highlighting a gap in research focused on participant recruitment.

The rapid growth and widespread adoption of social media make platforms like “X” invaluable for participant recruitment, offering fast, cost-effective alternatives to traditional methods (Whitaker, Stevelink and Fear 2017; Brøgger-Mikkelsen *et al.* 2020; Baker, Mitchell and Thomas 2022; Ellington *et al.* 2022). “X”’s large user base with a 55.1% market share provides extensive reach, making it a powerful tool for engaging diverse audiences beyond conventional academic channels (Guerra *et al.* 2022; Hassan and Kapila 2022). Researchers have leveraged “X” to streamline recruitment processes, particularly during the COVID-19 pandemic, with studies demonstrating its ability to overcome common challenges such as prolonged ethics approval processes and gatekeeper delays (Coyne, Grafton and Reid 2016; Ali *et al.* 2020b). The platforms effectiveness has been highlighted across various disciplines, with systematic reviews identifying its pivotal role in attracting participants, especially through unpaid posts and surveys (Karami *et al.* 2020; Ellington *et al.* 2022). Numerous studies illustrate “X”’s advantages over traditional recruitment methods, including enhanced efficiency, broader reach, and cost savings. For example, Leighton *et al.* (2021) used “X” to gather insights on students’ experiences with online learning, reporting continuous engagement and improved recruitment efficiency compared to multiple physical sites. Belfiglio *et al.* (2024) and Wasilewski *et al.* (2019) expanded their recruitment reach by leveraging personal “X” accounts. In healthcare, Ali *et al.* (2020b) and MacDermott *et al.* (2020) demonstrated the platform’s suitability for recruiting large participant pools and addressing sensitive topics, with unpaid “X” posts often outperforming paid Facebook ads in cost-effectiveness.

These findings highlight the growing significance of “X” as a versatile and efficient platform for participant recruitment within contemporary research methodologies. While several disciplines have successfully leveraged “X” to recruit research participants, the researcher found no published studies that have employed “X” specifically for participant recruitment in the scenario studies domain.

2.7.7 Shortcomings of “X”

While “X”’s global reach and diverse user base provide unique recruitment advantages and opportunities, literature also points to challenges, including ethical considerations and representativeness. These should be carefully managed to maximize the platforms potential as a recruitment platform. Other challenges include sampling bias, high dropout rates, data integrity concerns, relevance of participants, noisy data, and ethical and data privacy concerns.

The “X” platform's user demographics, which skews towards a younger, highly educated, and predominantly urban or suburban population, can introduce sampling bias, limiting the generalizability of findings to a broader population (Wojcik and Hughes 2019). However, in cases where a study targets highly educated participants or experts (like the current study), “X”'s demographic composition may align well with the research requirements, turning this limitation into an advantage.

It is also reported that there may be high dropout rates when using crowdsourcing for participant recruitment. Reports indicate that the dropout rates can range from 2% to 75% (McConnell, Finetto and Heise 2024; Esch, Mylonopoulos and Theoharakis 2025). This range is dependent on the platform being used and the compensation being offered to participants (Ritchey, Jimenez-Gomez and Podlesnik 2023). While compensating participants through incentives may combat dropout rates and improve participant engagement, it poses risks to the integrity of the data collected. Kramer *et al.* (2014) and Teitcher *et al.* (2015) argue that avoiding incentives altogether can help reduce risks associated with compromised data quality.

Attracting the appropriate pool of participants is another common challenge, as not all crowdsourcing efforts succeed in building the required audience (Dahlander and Piezunka 2014). Strategies like timing “X” posts to high-engagement periods (early morning or evening) and increasing follower numbers can be effective in recruiting participants (Hendricks, Düking and Mellalieu 2016). Additional techniques such as tweeting about the study, pinning study announcements, using specific hashtags, and tagging relevant experts or influencers also enhance visibility and participant engagement (Wasilewski *et al.*

2019; MacDermott *et al.* 2020). To mitigate noisy data that contain fraudulent and low-quality responses, Arigo *et al.* (2018) recommends keeping eligibility criteria private and screening participants before data collection.

Ethics and data privacy have also been cited as a concern since social media platforms offer less control over data compared to traditional methods. Users are often hesitant to participate in social media-based surveys due to privacy concerns and the potential misuse of their information by third parties (Barth and De Jong 2017; Oudat and Bakas 2023).

The current study carefully considers each of these limitations in Chapter 4, Section 4.3.

2.8 Chapter Summary

This chapter provided a critical review of the literature on scenario studies, examining both theoretical foundations and practical applications. Four principal scenario construction methods, ILS, LP, CIA, and CIB, were evaluated, highlighting their contributions as well as their theoretical and methodological limitations. This review established the need for an integrated approach to scenario construction, thereby achieving the study's first objective: *to critically evaluate the theoretical and methodological limitations of existing scenario construction techniques by means of a literature review, establishing the necessity for an integrated approach.* It is evident that despite their strengths, scenario construction methods show notable limitations in reliability and adaptability. The critical review highlights central challenges in scenario construction methods, underscoring the need for a method that can address these challenges. By identifying these gaps, this chapter establishes a foundation for a new methodology designed to overcome existing shortcomings.

The chapter also examined the role of crowdsourcing as a participant recruitment and data collection platform, emphasizing its value for engaging distributed expertise. The use of “X” was highlighted as an effective tool for reaching diverse, global participants, facilitating direct interaction with experts and accelerating data collection for scenario studies. Both the benefits and limitations of crowdsourcing were discussed, demonstrating its relevance and potential to enhance scenario research through efficient, scalable, and inclusive participation.

The chapter that follows provides a robust discussion of the theories that underpin the scenario construction domain and the alignment of potential techniques to scenario theories.

CHAPTER 3: THEORETICAL FOUNDATION

The construction of scenarios occupies a central place in the field of foresight, providing a systematic means of grappling with the uncertainty, complexity, and ambiguity inherent in long-term planning. As articulated in Chapter 2 Section 2.5, existing scenario methods are diverse, and while this diversity enriches the field, it has also given rise to what Bradfield *et al.* (2005) refer to as “methodological chaos.” This lack of coherence can be traced to insufficiently specified theories, which in turn affects methodological consistency and rigour. This chapter responds to this challenge by laying out the theories that underpin foresight and scenario construction and in turn inform the new scenario construction methodology proposed in Chapter 4. Building on the literature, this study contends that no single theoretical lens is sufficient to address the multifaceted challenges of scenario construction. A pluralistic framework is required, one that integrates the complementary strengths of GST, complexity theory, constructivism, and PST. Together, these perspectives offer a comprehensive foundation: GST provides the structural and relational lens, complexity theory emphasizes dynamic non-linearity and emergence, constructivism grounds the process in social sense-making and co-creation, and PST introduces the crucial cognitive and imaginative dimension focused on exploring plausible surprises and disruptive possibilities.

This chapter establishes the theoretical foundation for the study in three parts. First, it introduces foresight as the overarching paradigm. Second, it constructs and justifies the study's integrated theoretical framework, built on the complementary pillars of GST, complexity theory, constructivism, and PST. Finally, it details the specific methodological techniques selected for the study, explaining how each is informed and how the techniques are justified by this framework. This structured progression from paradigm to theory to methodology provides a coherent logic for the integrated methodology operationalized in Chapter 4.

3.1 The Foresight Paradigm

Foresight is a distinct paradigm of futures research, differentiating itself from prediction or deterministic forecasting by emphasizing multiple possible futures, social construction, and action-oriented knowledge. It is concerned not with anticipating a single inevitable outcome but with exploring plausible, probable, and preferable futures (Voros 2003). Its purpose is to strengthen decision making in conditions of deep uncertainty and complexity by generating robust insights that expand strategic options. As Slaughter (1995) notes, foresight is the capacity to “create and maintain a high-quality, coherent, and functional forward view,” enabling decision makers to act in ways that shape emerging trajectories (Slaughter 1995: 5).

The foresight paradigm rests on three interrelated principles:

1. **Plurality of futures:** Foresight recognizes that the future is open and indeterminate. The exploration of multiple scenarios accounts for the uncertainty inherent in complex socio-technical systems (Voros 2003).
2. **Participatory sense-making:** Foresight emphasizes inclusive processes of deliberation, where stakeholders construct images of the future and reflect on the assumptions shaping current worldview (Schultz 2006).
3. **Action orientation:** The ultimate value of foresight lies in its capacity to inform present-day strategies and interventions, enabling actors to navigate uncertainty and influence outcomes (Slaughter 1995).

According to this paradigm, scenario construction has emerged as one of the most widely used approaches. Its flexibility allows it to be adapted to different contexts, from corporate strategy to national policy. Yet, its theoretical underpinnings have been underexplored or are inconsistently applied, necessitating a deeper investigation of the perspectives that shape foresight practice.

3.2 Theoretical Perspectives in Foresight

Several theoretical perspectives have influenced the development and practice of foresight and scenario construction. These perspectives provide not only ontological and epistemological grounding but also practical guidance on how to engage with uncertainty, complexity, and the human interpretation of the future.

Van der Heijden (2011) describes two main ways of thinking about the future. The first is the **predictive** approach, which is based on the idea that by studying past trends and using data models, we can predict what will happen next. This way of thinking assumes that the future follows patterns from the past. The second is the **dialogic** approach, which sees thinking about the future as a learning and discussion process. Instead of trying to predict exactly what will happen, it focuses on exploring different possible futures so that people can reflect, share perspectives, and learn together. This study followed this second approach because it values participation, interpretation, and collective learning when building scenarios. PST adds a further epistemological dimension to this dialogic view. Shackle (2012) argues that the future cannot be assigned probabilities because it is shaped by genuinely novel and imaginative acts that cannot be anticipated through statistical extrapolation. Instead, individuals and organizations construct expectations by considering the range of *potential surprises*. These potential surprises could be events or outcomes that are conceivable yet fundamentally uncertain. This view aligns with the logic of scenario construction, which seeks not to forecast but to explore and give form to plausible futures that emerge from creative reasoning rather than deterministic prediction (Ramirez and Wilkinson 2016). By embracing potential surprise as an essential feature of human decision making, foresight becomes an exercise in disciplined imagination that acknowledges both cognitive limits and creative potential.

Critical realism, as described by Ramirez and Wilkinson (2016), adds another useful layer to this way of thinking. It explains that there are three levels to understanding reality: the real, which includes the hidden forces or structures that shape what happens; the actual, which is what really occurs; and the empirical, which is what we can directly observe or experience. By using this perspective, scenarios are not treated as wild guesses about the future, but rather as thoughtful explorations of how different hidden forces might interact to create various possible outcomes. This helps bridge the gap between scientific prediction and human interpretation. Finally, Tsoukas and Shepherd (2009) argue that organizations are always changing due to the interactions and conversations of the people within them. Organizations are not fixed structures but living systems that constantly evolve. Scenarios, in this view, are stories about possible futures that help organizations "try out" changes in advance, allowing them to learn, adapt, and become more flexible when real changes occur.

Complementing these theoretical perspectives, the study is underpinned by a pragmatic research philosophy. Pragmatism prioritizes the usefulness of ideas and methods for addressing real-world problems and accepts that no single epistemological stance can capture the full complexity of social and systemic futures (Saunders, Lewis and Thornhill 2009). Instead, it supports the deliberate integration of multiple theoretical lenses into a coherent framework that is responsive to the research problem. In foresight research, this orientation legitimizes methodological pluralism, enabling the combination of qualitative and quantitative approaches, expert and secondary data, and computational and interpretive techniques. In this way, pragmatism provides the philosophical foundation for the framework that guides this study.

The following section develops this framework in detail, showing how GST, complexity theory, constructivism, and PST are integrated into a coherent structure that underpins the methodological choices and techniques applied in this research.

3.3 A Theoretical Framework

Several theoretical perspectives have influenced the development and practice of foresight and scenario construction. These perspectives provide both ontological and epistemological grounding, offering guidance on how to engage with uncertainty, complexity, and human interpretation of the future. Foresight studies are inherently interdisciplinary, drawing from systems thinking, complexity science, the social construction of knowledge, and decision theory to explore alternative futures in a structured yet adaptive way. This section outlines the principal theories that informed the present study: GST, complexity theory, constructivism, and PST, and explains how these are integrated into a pragmatic philosophical orientation to underpin the methodological choices of the research.

GST, pioneered by Von Bertalanffy (1968), views systems as wholes whose properties emerge from the interaction of their parts. Its core emphasis is systemic interdependence, structural relationships, and relational mapping, enabling analysts to trace how interconnected variables generate dynamic outcomes. This systemic lens aligns closely with the logic of foresight, where futures cannot be understood by examining isolated trends but must instead be approached through interdependencies. In practice, GST has inspired tools such as CIA (Gordon and Hayward 1968) and system dynamics modelling (Sterman 2002), both of which formalize feedback loops and system interactions to inform scenario development. Yet, GST has its limitations, it is strong on holism, offering a broad conceptual map of systems, but often weak on prioritization and empirical validation. Scholars have noted that GST struggles to reduce complexity into actionable insights and lacks mechanisms to determine which variables or interactions matter most (Midgley 2003; Skyttner 2005).

Where GST maps interdependence structurally, **complexity theory** emphasizes dynamics, adaptation, and unpredictability. Emerging from the work of Prigogine and Stengers (2018) on dissipative structures and Holland’s (1995) work on complex adaptive systems, complexity theory highlights the roles of emergence, non-linearity, feedback loops, and adaptation in shaping systemic behaviour. From this view, futures unfold not as linear projections but as the outcomes of interactions across multiple scales, often producing unexpected tipping points or emergent phenomena. This perspective has influenced foresight practice, legitimizing the move away from deterministic forecasting to multiple plausible futures. Methods such as agent-based modelling (Epstein and Axtell 1996), horizon scanning (Hiltunen 2008), and the three horizons framework (Curry 2008) reflect complexity theory's concern with uncertainty and transformation. Nonetheless, complexity theory faces a key challenge. While it sensitizes researchers to uncertainty, non-linearity, and adaptability, it often struggles with operationalization. Its concepts can remain at the level of metaphor or descriptive narrative, making it difficult to apply systematically in empirical scenario construction.

The third theoretical pillar, **constructivism**, provides the epistemological grounding of foresight. Drawing on radical constructivism (Von Glasersfeld 2013) and social constructivism (Berger and Luckmann 2016), it challenges positivist assumptions that the future exists as an objective reality waiting to be discovered. Instead, it posits that futures knowledge is co-created through human interpretation, interaction, and negotiation. This orientation underlies participatory scenario practices where stakeholders provide their assumptions, values, and worldviews to create visions of the future. Methods such as the Delphi method (Linstone and Turoff 1975), scenario workshops (Börjeson *et al.* 2006), and causal layered analysis (Inayatullah 2004) illustrate how constructivism legitimizes inclusivity and diversity in futures thinking. The strength of constructivism lies in its capacity for inclusivity, plurality, and reflexivity, but it also has limitations. Its openness to multiple interpretations risks relativism and fragmentation, and the absence of common ground may undermine synthesis or decision relevance (Guba and Lincoln 1994; Schwandt 1994).

PST, developed by George LS Shackle (Shackle 2012), introduces a distinct epistemological approach to uncertainty and imagination in futures thinking. Shackle challenged the traditional probabilistic view of the future, arguing that the future is inherently open and cannot be meaningfully represented as a set of measurable probabilities. Instead, PST focuses on the *plausibility* of events that might occur and the *surprise* they could generate. In this view, foresight becomes an imaginative exploration of the bounds of possibility rather than an exercise in prediction. PST provides a philosophical grounding for scenario construction by framing uncertainty as a creative and cognitive challenge. It acknowledges that human agents construct possible futures based on subjective perception, contextual understanding, and imaginative reasoning. The theory thus resonates with constructivist epistemology and complements dialogic approaches to scenario planning, where the objective is not to forecast a single outcome but to explore a range of conceivable and meaningful alternatives (Ramirez and Wilkinson 2016; Derbyshire 2017). However, while PST enriches foresight by valuing creativity and cognitive openness, it has limitations in addressing the structural and systemic interconnections that influence future developments. To overcome these limitations, PST is complemented in this study by GST, which situates potential surprises within broader systemic relationships, and by complexity theory, which accounts for emergent and adaptive behaviours in dynamic systems. Together, these theories enable a more holistic and analytically grounded exploration of uncertainty, integrating the imaginative flexibility of PST with the systemic rigour of systems and complexity perspectives.

The integration of GST, complexity theory, constructivism, and PST establishes a multidimensional and comprehensive theoretical foundation for scenario construction. Each contributes distinct strengths while addressing the limitations of the others. GST provides a holistic and structural foundation, emphasizing interconnections, feedback loops, and systemic coherence. However, it is often limited in capturing the non-linear dynamics of change and the subjective or cognitive dimensions of how futures are imagined. Complexity theory complements this by introducing a dynamic and adaptive lens that acknowledges non-linearity, emergence, and uncertainty, highlighting that small changes can trigger significant systemic transformations. Yet, complexity theory can remain largely descriptive and challenging to apply to practical scenario work. Constructivism adds an essential interpretive dimension, recognizing that knowledge of the future is socially constructed through dialogue, participation, and meaning making. It counters the structural rigidity of GST and the abstract tendencies of complexity theory by grounding foresight in human sense-making and social interaction. However, constructivism can overemphasize subjective interpretation at the expense of structural coherence and analytical precision. Finally, PST introduces a cognitive and imaginative dimension to the framework. It frames foresight as an exploration of *plausible surprise*, emphasizing the imaginative, subjective, and non-probabilistic nature of uncertainty. PST encourages scenario planners to move beyond rational extrapolation and to creatively consider discontinuities and novel possibilities. However, while it enhances cognitive openness, it requires grounding in systemic and dynamic analysis to ensure plausibility and coherence.

Together, these four perspectives form an integrated framework in which GST provided structure, complexity theory introduced adaptive dynamics, constructivism embedded social interpretation, and PST activated creative cognition and surprise. This synthesis ensured that scenario construction would be both theoretically grounded and practically actionable, balancing analytical rigour, systemic coherence, interpretive depth, and imaginative reach. Table 7 summarizes the unique contributions of each theory and the deficiencies they address in the others, demonstrating the necessity of a complementary approach.

Table 7: Theories, contributions, and compensations

Theory	What it provides	What it compensates for in other theories
General systems theory (GST) (Von Bertalanffy 1968; Skyttner 2005)	• Structural holism: systems as interconnected wholes. • Mapping of interdependencies and feedback loops. • Basis for formal systemic methods (e.g., cross-impact analysis, system dynamics).	• Adds structural rigour to constructivism, which risks fragmentation. • Provides systemic mapping absent in complexity theory's descriptive focus.
Complexity theory (Holland 1995; Prigogine and Stengers 2018)	• Emphasis on emergence, non-linearity, adaptation. • Justifies multiple plausible futures vs. deterministic forecasts. • Sensitizes foresight to weak signals, tipping points, and uncertainty.	• Introduces dynamism and adaptation missing from GST's structural rigidity. • Adds systemic unpredictability not captured by constructivism's focus on meaning.
Constructivism (Von Glasersfeld 2013; Berger and Luckmann 2016)	• Epistemological grounding: futures knowledge is socially constructed. • Legitimizes participatory and co-creative foresight. • Enables multiple perspectives and stakeholder engagement.	• Brings inclusivity and reflexivity absent from GST's structural abstraction. • Counterbalances complexity theory's descriptive abstraction with meaning-making.
Potential surprise theory (Shackle 2012)	• Cognitive-imaginative foundation for foresight. • Focuses on plausibility rather than probability. • Encourages creative exploration of discontinuities and novel events. • Frames uncertainty as a domain of imaginative reasoning.	• Compensates for GST's mechanistic bias by reintroducing cognitive and imaginative flexibility. • Expands complexity theory's descriptive scope by valuing creative emergence. • Grounds constructivism's social sense-making in individual cognition and imagination.
Combined contribution	• Provides a systemic, dynamic, interpretive, and imaginative foundation for foresight and scenario construction. • Ensures that analysis captures structure (GST), adaptive dynamics (complexity), shared meaning (constructivism), and creative plausibility (PST).	• Balances the rigidity of GST, the operational vagueness of complexity theory, the relativism of constructivism, and the subjectivity of PST through a coherent, multi-lens integration.

This integrated four-theory framework ensures that scenario construction engages the full spectrum of foresight logic: systemic structure (GST), dynamic emergence (complexity theory), social interpretation (constructivism), and imaginative surprise (PST). Each theory complements and stabilizes the others, resulting in a balanced approach that is analytically rigorous, participatory, and open to novelty. The integration of these perspectives provides the conceptual backbone for the methodological framework applied in this study. Figure 2 presents the theoretical framework, illustrating how the four core theories directly inform the study's methodology (elaborated on in Chapter 4). GST provides the structural foundation for mapping system elements and interrelationships. Complexity theory guides the identification and prioritization of critical and uncertain factors, emphasizing non-linearity, emergence, and adaptive dynamics. Constructivism supports the integration of diverse, subjective judgements collected through crowdsourcing, ensuring that scenarios reflect multiple stakeholder perspectives. PST complements these approaches by focusing attention on plausible yet unexpected outcomes, helping to capture extreme or high-impact scenarios that may be overlooked by conventional methods. The final stage, CIB analysis, applies these combined theoretical inputs, generating internally consistent scenarios that synthesize structural, dynamic, interpretive, and plausibility-based considerations.

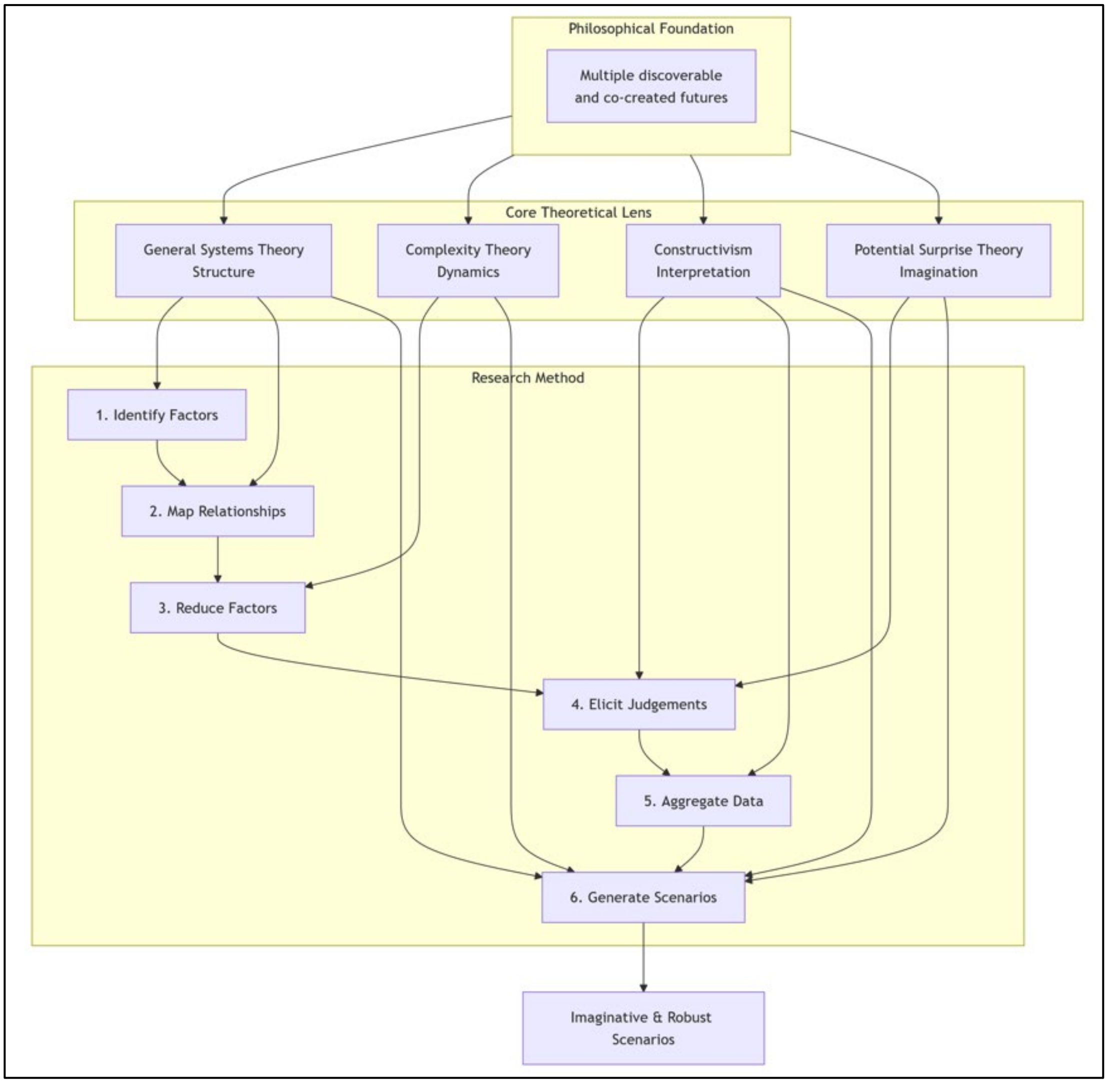


Figure 2: Theoretical framework

This theoretical framework directly informed the selection of specific techniques adopted in this study. These are detailed in the following section. In applying this framework, the study adopted an abductive logic of inquiry. Unlike deduction, which applies general laws to particular cases, or induction, which generalizes from observations, abduction proceeds through iterative movement between data, theory, and interpretation. It is particularly suited to futures research, where uncertainty precludes deterministic explanation, and plausible scenarios emerge from the synthesis of structural evidence, expert judgements, and interpretive reasoning.

3.3 Study Techniques

This section discusses the techniques adopted in the new methodology for the construction of consistent scenarios and aligns them with the theories discussed above.

3.3.1 Theoretical justification for using secondary data

A recurring limitation across many scenario construction methods (as discussed through Chapter 2) is the subjectivity and inconsistency in initial factor identification and relationship mapping. Human-centred participatory methods such as brainstorming, interviews, or facilitated workshops often depend on participant availability, expertise, and perspectives, which can introduce bias, reduce replicability, and limit the scope of analysis (Van der Heijden 2011). As Meadows (2020) observes, the COVID-19 pandemic demonstrated that there should be less emphasis and reliance on participatory, face-to-face workshops, interviews and brainstorming sessions where people need to be brought together in a room, as these will not always be possible (Hall, Gaved and Sargent 2021). Additionally, these methods can be time-consuming and difficult to scale, particularly when attempting to address large, complex systems or multi-sectoral issues. The challenge is compounded when there is limited access to diverse expert input, forcing researchers to rely on a small number of participants to define the key drivers of change.

To address these limitations, **secondary data**, which is data collected for a purpose other than the current research, can be used as a rigorous foundation for initial system mapping. Academic literature and publicly available reports can provide a rich, contextually grounded, and cost-effective basis for identifying a broad set of factors and relationships, especially in data-constrained environments (Johnston, 2017; Bishop, Hines & Collins, 2007). This approach enhances the transparency and replicability of the factor identification process by allowing assumptions to be traced back to credible sources, thereby improving the overall validity of the scenarios (Kishita *et al.* 2020). Using secondary data for initial system structuring provided a scalable, transparent, and theoretically robust method to overcome the critical limitations of traditional, workshop-heavy approaches.

The use of secondary data formed a crucial foundation for the factor identification stage of this study. When used for initial system structuring, it provides a scalable, transparent, and theoretically robust method to overcome the critical limitations of traditional, workshop-heavy approaches. This approach of using secondary data was not merely pragmatic but is deeply grounded in an integrated theoretical framework, with the theories below providing a distinct rationale for its necessity.

GST emphasizes that a system's behaviour can only be understood from the interactions of its components (Von Bertalanffy 1968). In foresight and scenario construction, this translates into identifying and mapping the drivers, trends, and relationships that structure a domain. The use of secondary data enables researchers to synthesize findings across disciplines, capturing not just isolated variables but also the interconnections that underpin plausible futures. As Boulding (1956) argued, knowledge builds cumulatively across fields, and foresight relies on this cumulative mapping to ensure a holistic view of the system under study. Thus, the reliance on literature reflects a systems-theoretic imperative where scenario construction requires a comprehensive systemic foundation from which consistent futures can be developed. Complexity theory provides the sensitizing lens. It recognizes that futures emerge from non-linear interactions, adaptation, and inherent uncertainty (Holland 1995; Cilliers 2002). No single perspective can grasp the entirety of a complex system. Therefore, the use of diverse secondary sources was not just beneficial but necessary to capture the plurality of drivers, potential tipping points, and critical uncertainties where emergent behaviour is most likely. The literature review became a method to assemble a "cognitive network" of knowledge that mirrors the complexity of the system itself, ensuring the analysis was dynamically sensitive from the outset. Constructivism provided the epistemological guide**.** It posits that knowledge is socially constructed and interpretive (Schwandt 1994). A constructivist stance demands a critical approach to secondary data; the literature is not treated as objective truth but as a repository of prior sense-making and co-constructed meaning from various scholarly communities. By beginning here, the study explicitly acknowledged and incorporated these existing worldviews, ensuring the initial factor set was pluralistic and the subsequent participatory stages built on a rich, multi-perspectival foundation.

This integrated theoretical rationale is reflected in established foresight practices such as environmental scanning and horizon scanning (Coates 1985; Amanatidou *et al.* 2012), which prioritize systematic grounding in existing knowledge. By anchoring the process in secondary data, this study ensured that the resulting methodology is both transparent and replicable (Popper 2008), integrating structured evidence with participatory interpretation in a theoretically coherent manner. In summary, the use of secondary data was justified as a multi-theoretical imperative: it was structurally necessitated by GST, dynamically informed by complexity theory, and epistemologically guided by constructivism. This ensured that the scenario construction process would be rigorous, complexity aware, and meaningfully situated within ongoing scholarly and practical discourse.

3.3.2 Theoretical justification for the use of ADVIAN® in factor reduction

A common limitation of scenario construction methods, as highlighted in Chapter 2, Section 2.6, is the lack of a systematic and transparent approach to selecting and prioritizing critical drivers. Traditional techniques, such as brainstorming or facilitated expert workshops, often rely heavily on subjective judgements, which can introduce cognitive bias, reduce reproducibility, and limit the methodological rigour of the scenario design process (Lloyd and Schweizer 2014; Douglas *et al.* 2021; Kaviani *et al.* 2023). These methods also struggle to manage large numbers of variables, making them inefficient or inconsistent when applied in data-rich or complex systems (Amer, Daim and Jetter 2013). Factor reduction methods and ADVIAN® offer alternatives to the human-centred approaches.

Factor reduction is a pivotal step in scenario construction, preventing factor relationship analysis from becoming unmanageably complex. Factor reduction refers to the process of systematically identifying the most influential and most relevant variables from a larger set to ensure that only those that are most critical are retained for further analysis (Feng and Ryan 2013). The selection of an appropriate reduction technique is crucial, as it must align with both the data characteristics of the study and its overarching theoretical foundations. A number of methods for factor reduction were available to the current study. Linear discriminant analysis (LDA) and principal component analysis (PCA) are two prominent techniques used for dimensionality reduction or feature reduction (Reddy *et al.* 2020). LDA is a supervised method that transforms high dimensional data into lower dimensional data and has been applied in areas such as facial recognition (Yu and Yang 2001), text recognition (Park and Park 2008), early disease detection (Xiong *et al.* 2017) and detection of hand movement (Krasoulis, Nazarpour and Vijayakumar 2017). PCA is an unsupervised linear mapping technique that is based on eigen vectors and is applicable to Gaussian data (Ayesha, Hanif and Talib 2020). The aim of PCA is to identify the principal components from a set of data with uncorrelated features (Ayesha, Hanif and Talib 2020). The technique is mostly applied to datasets related to speech and image processing, visualization, sensor data for robots, and exploratory data analysis (Jolliffe and Cadima 2016).

Neither of these data reduction techniques perform well on data that are non-Gaussian and when a small data size is present (Ayesha, Hanif and Talib 2020). Moreover, the number of observations should be at least double the number of factors for accurate processing and analysis to occur (Ayesha, Hanif and Talib 2020). Since the expected number of factors for the current study was less than one hundred, making it a small dataset, the data were anticipated to not be normally distributed, and it was not certain whether the number of observations would be at least double the number of factors, neither the PCA nor the LDA methods for factor reduction were applicable to this study. Additionally, these methods reduce factors based on statistical variance or class separation, but they do not measure factors based on their **driving power** and **uncertainty**, which are the critical characteristics required for effective scenario construction.

Impact analysis methods such as CIA, MICMAC, and ADVIAN® are popular in scenario studies for their ability to leverage inter-factor relationships, unveil hidden systemic connections, and identify the most influential factors in a system (Linss and Fried 2009; Weimer-Jehle 2009). The ADVIAN® method was selected for the factor reduction in this study as it provides a structured, computationally rigorous framework for evaluating the influence and dependency relationships between variables in complex systems (Linss and Fried 2009).

The ADVIAN® technique has been applied in a number of contexts, which include the relationship mapping of resources in performance management (Fried 2010; Guertler and Spinler 2015); critical success factors for business process management (Meara 2021) and enterprise resource planning studies (Thompson, Olugbara and Singh 2018; Epizitone and Olugbara 2019); and scenario planning specific to the gas industry (Servati, Ghodsypour and Soleimani 2016). Since the aim of the current study was to build consistent scenarios and from a small set of driving and uncertain factors (Weimer-Jehle 2006), it was imperative that the method adopted for the reduction of the set of factors would identify only those factors that are categorized as highly driving and highly uncertain. In the ADVIAN® framework, the factors categorized as being highly driving based on their score in the *driving* category, are those factors that are highly influential and can influence the system of factors without the worry of feedback loops (Linss and Fried 2010; Guertler and Spinler 2015). Those factors that rank highly in the *precarious* category are those that are both critical and influence the system to a high degree (Linss and Fried 2010). According to Linss and Fried (2009), *precarious* factors have the highest degree of uncertainty attached to them and were therefore ideal candidates to use in this study for further analysis. In contrast, highly *driven* factors are reactive and are influenced by the system. They were therefore not candidates for further analysis in scenario construction methods (Linss and Fried 2009; Guertler and Spinler 2015).

The ADVIAN® analysis method was applied to an impact matrix, M_{nn}, where the matrix had dimensions nxn, and n represented the number of factors. Before further analysis was performed, the matrix was normalized by dividing all entries in the matrix by the maximum of all impacts. Normalizing the matrix ensured that high impact values could be accommodated without the concern of numeric overflow occurring during matrix calculations. The ADVIAN® technique relies on orders or powers of the matrix being calculated. The first order is equivalent to the initial matrix, M_{nn}, while the subsequent orders, k, are constructed by repeatedly multiplying the original matrix, M_{nn}, by itself, k, number of times. While the original matrix is represented by M_{nn}, the higher order matrices are represented by Ω_{nn}^{k}, with orders being calculated up the $n-1$. These orders allow for the calculation of the indirect active and passive sums. The formulae for the measures and calculations are presented below (Table 8).

Table 8: ADVIAN® formulae

Measure	Description	Formula	Ref
Direct active sum (dAS)	The strength by which a factor directly affects other factors. The direct active sum for factor i is the sum of all impact sums in a row of the matrix with n factors.	$dAS(i) = \sum_{a=1}^{n}(F_{ia})$	(3.1)
Direct passive sum (dPS)	The strength by which a factor is directly affected on by other factors. The direct active sum for factor i is the sum of all impact sums in a column of the matrix with n factors.	$dPS(i) = \sum_{a=1}^{n}(F_{ai})$	(3.2)
Indirect active sum (iAS)	The strength of the indirect effects that a factor has on other factors. The indirect active sum for factor i is the sum of all direct active sums from the 1st order to order k.	$iAS(i) = \sum_{k=1}^{n-1}(dAS_k(i))$	(3.3)
Indirect passive sum (iPS)	The strength of the indirect effects that other factors have on the factor. The indirect passive sum for factor i is the sum of all direct passive sums from the 1st order to order k.	$iPS(i) = \sum_{k=1}^{n-1}(dPS_k(i))$	(3.4)
Relative direct active sum ($rdAS$)	The direct active sum of factor i is converted to a relative value out of 100.	$rdAS(i) = \frac{dAS(i)}{max_{i=1}^{n}\{dAS(i); dPS(i)\}} * 100$	(3.5)
Relative direct passive sum ($rdPS$)	The direct passive sum of factor i is converted to a relative value out of 100.	$rdPS(i) = \frac{dPS(i)}{max_{i=1}^{n}\{dAS(i); dPS(i)\}} * 100$	(3.6)
Relative indirect active sum ($riAS$)	The indirect active sum of factor i is converted to a relative value out of 100.	$riAS(i) = \frac{iAS(i)}{max_{i=1}^{n}\{iAS(i); iPS(i)\}} * 100$	(3.7)
Relative indirect passive sum ($riPS$)	The indirect passive sum of factor i is converted to a relative value out of 100.	$riPS(i) = \frac{iPS(i)}{max_{i=1}^{n}\{iAS(i); iPS(i)\}} * 100$	(3.8)
Criticality (CRI)	The strength of the effect that a factor i has on other factors and the strength of effect that other factors have on factor i. Calculated as the geometric mean of the relative indirect active sum and relative indirect passive sum.	$CRI(i) = \sqrt{riAS(i) * riPS(i)}$	(3.9)
Integration (INT)	A measure of the strength of interrelations that factor i has with other factors. Calculated as the arithmetic mean of the relative indirect active sum and relative indirect passive sum.	$INT(i) = \frac{riAS(i) + riPS(i)}{2}$	(3.10)
Stability (STA)	A measure of the degree to which factor i stabilizes the system of factors. Calculated by subtracting the harmonic mean of the relative indirect active sum and relative indirect passive sum from 100.	$STA(i) = 100 - \frac{2}{(\frac{1}{riAS(i)} + \frac{1}{riPS(i)})}$	(3.11)
Precarious (PRE)	A measure of the degree to which factor i influences the system of factors. Calculated as the harmonic mean of criticality and the relative indirect active sum.	$PRE(i) = \sqrt{CRI(i) * riAS(i)}$	(3.12)
Driving (DRI)	A measure of the degree to which factor i can influence other factors without the presence of feedback loops. Calculated as the harmonic mean of 100 minus criticality and the relative indirect active sum.	$DRI(i) = \sqrt{(100 - CRI(i)) * riAS(i)}$	(3.13)
Driven (DRE)	A measure of the degree to which factor i is influenced by the system of factors. Calculated as the harmonic mean of 100 minus criticality and the relative indirect passive sum.	$DRE(i) = \sqrt{(100 - CRI(i)) * riPS(i)}$	(3.14)

The theoretical justification for using ADVIAN® for factor reduction is also deeply rooted in the study's integrated theoretical framework, with each theory informing a distinct aspect of its application and interpretation.

ADVIAN® is fundamentally an operationalization of GST. GST posits that system behaviour emerges from the interactions between components, not from the components in isolation (Von Bertalanffy 1968). ADVIAN® directly applies this principle by using a *nxn* cross-impact matrix as its input, requiring the explicit mapping of all pairwise factor relationships. The method's core calculations, deriving driving power and dependence from relative active and passive sums, reveal the emergent structural properties of the system (Linss and Fried 2010). ADVIAN® measures and classifications are obtained from calculations performed on the cross-impact matrix and can be used for future planning (Linss and Fried 2009; Thompson, Olugbara and Singh 2018). The resulting classification of factors provided the structural skeleton of the system, ensuring that subsequent analysis is grounded in a holistic, systemic model rather than a collection of isolated trends. The strategic purpose of using ADVIAN® was guided by complexity theory. While GST provides the structural map, complexity theory identifies where to focus on that map by emphasizing nonlinearity, uncertainty, and emergent dynamics (Holland 1995; Cilliers 2002). ADVIAN®'s inclusion of an uncertainty dimension and its calculation of iterated impacts that trace influence ripples through the system, made it uniquely suited for this task (Linss and Fried 2010). It filters the systemic structure to isolate the critical uncertainties, the factors where emergent change is most probable and which are therefore most consequential for exploring divergent futures. This addresses the core foresight challenge of engaging with deep uncertainty in complex systems. PST adds a crucial cognitive and imaginative dimension to the interpretation of ADVIAN®'s output. Pioneered by Shackle (2012), PST was developed as an alternative to probabilistic forecasting, framing uncertainty not in terms of likelihood but as the potential for surprising, discontinuous, and novel futures. A PST lens ensures that when evaluating factors, classified by ADVIAN® as highly uncertain, particular attention is paid to those that could lead to outcomes that would fundamentally challenge prevailing mental models and assumptions. This shifted the focus from mere probabilistic uncertainty to the exploration of plausibly surprising possibilities, ensuring the scenario process captured not just likely uncertainties, but transformative ones. The legitimacy and transparency of the factor reduction process are ensured by constructivism. A constructivist perspective holds that knowledge is co-created and that the selection of "critical" factors must be justifiable and transparent to stakeholders (Guba and Lincoln 1994). ADVIAN® supports this by providing a formalized, reproducible process that mitigates individual researcher bias. It functions not only as a computational tool but also as a communication device, making the systemic rationale for factor prioritization visible and debatable (Linss and Fried 2009). In this study, this balanced analytical rigour with the social construction of meaning, ensuring the process was credible and inclusive. In summary, the ADVIAN® method served not merely as a technical procedure but a theoretically robust step. It was applied using GST, strategically directed by complexity theory, catalytically refined by potential surprise theory, and validated through a constructivist lens. This integrated theoretical foundation effectively addresses longstanding points of criticism about the lack of rigour and transparency in scenario factor reduction, ensuring the process is systematically sound, focused on critical uncertainties, and open to imaginative, transformative possibilities.

3.3.3 Theoretical justification for crowdsourcing of primary data

The elicitation of expert judgements represents a critical stage in foresight and scenario construction, as the selection and interpretation of factors cannot rely solely on algorithmic outputs. Traditional foresight approaches have often been criticized for their dependence on a narrow circle of experts, which risks producing biased, homogeneous, and less robust insights (Bishop, Hines and

Collins 2007; Van der Heijden 2011). Moreover, foresight and scenario methods have also relied on time consuming methods for data gathering and for the identification of expert participants, which affects the speed at which scenarios are constructed (Heinonen, Kuusi and Salminen 2017; Kishita *et al.* 2020). It has also been reported that the task of recruiting participants for a study can be daunting and often leads to delays in the study (Campbell MK 2007; Darmawan *et al.* 2020). Along with these challenges, literature also reports that diversity is essential for scenario planning. Collecting data through alternate approaches such as crowdsourcing, which attracts a wide and diverse participant base, would meet this goal of diversity (Raford 2015). Innes and Booher (2004) and Healy (2020) argue that extending the participant base beyond those suggested by a client would increase the likelihood of attracting diverse viewpoints, resulting in a more creative, robust set of drivers while also reducing individual and group bias, which is a limitation of participatory methods. Crowdsourcing also expands the epistemic base by systematically drawing on a distributed network of knowledgeable individuals. The author further opines that crowdsourcing can improve results and the acceptance of these results.

The persistent challenges that have plagued data collection methods in scenario studies and the need for a more diverse participant base have led to calls for researchers to explore crowdsourcing through social media as an alternate data collection strategy (Raford 2015; Kayser and Shala 2020). This is supported by Zeng, Koller and Jahn (2019), who argue that the opinions expressed by social media participants regarding foresight and futures closely align with traditionally sourced expert groups. Moreover, Raford (2015) report that for scenario studies, the only way to understand the world is through varied perspectives, which can be achieved through social media. For research projects requiring nuanced, expert-driven input, social media platforms offer an effective and accessible approach for data collection.

The global reach and demographic diversity of social media platforms like LinkedIn, “X”, and Facebook provide an expansive pool of potential contributors across various fields and geographic locations (Belfiglio *et al.* 2024). Social media also enables targeted recruitment, allowing researchers to connect with professionals and experts directly, many of whom willingly participate without expecting remuneration (Paniagua and Korzynski 2020). Paniagua and Korzynski (2020) note that social media inherently facilitates crowdsourcing by allowing knowledge and insights to be shared and gathered from a widely dispersed online community. During the recent COVID-19 pandemic, organizations were not able to carry out in person meetings given the uncertainty surrounding future waves of the disease and other pandemics. Increased reliance on online communication revealed the speed at which data can be gathered through social media platforms, causing social media to emerge as providing the ideal platform for attracting participants for data gathering. To date it appears that few studies have investigated the use of crowdsourcing through social media for participant recruitment in a scenario planning project. Leveraging social media platforms will attract a diverse set of expert participants or actors that represents a wide variety of stakeholders with diverse views.

The use of crowdsourcing for expert judgement elicitation is both a methodologically and theoretically grounded choice, directly informed by the study's integrated theoretical framework. The theories provide a distinct and compelling rationale for its application, moving beyond mere convenience to establish it as an essential component of rigorous foresight. Constructivism provides the primary imperative. Constructivism posits that knowledge, particularly of the future, is not discovered but socially constructed through dialogue and the sharing of diverse perspectives (Guba and Lincoln 1994). Crowdsourcing is the practical enactment of this principle, transforming scenario construction from an isolated analytical exercise into a large-scale, participatory process of co-constructing meaning. It ensures that the resulting scenarios are built on a foundation of collective intelligence, thereby enhancing their legitimacy, relevance, and resilience against individual cognitive biases (Surowiecki 2005).

Complexity theory provides the rationale for scale and diversity. Complex adaptive systems are characterized by distributed intelligence, where no single agent can comprehend the whole (Cilliers 2002). To model such a system, the knowledge-gathering process must mirror its structure. Crowdsourcing addresses this epistemological challenge by assembling a "cognitive network" of experts from diverse domains. This diversity is crucial for surfacing weak signals, critical uncertainties, and emergent dynamics that might be invisible to a homogenous group, ensuring the analysis is sensitive to the true nature of complex systems (Page, 2007).

PST emphasizes the importance of exploring plausible surprises and discontinuities over probable trends (Shackle 2012). A diverse crowd, by virtue of its varied experiences and mental models, is a powerful generator of such surprising possibilities. Crowdsourcing, through a PST lens, becomes a mechanism to elicit judgements that challenge conventional wisdom and identify factors with the potential for transformative rather than incremental impact. It ensures the process captures not just uncertainties, but imaginatively rich, disruptive possibilities. While the other theories justify the crowd itself, GST provides the structural framework that ensures the crowd's input is analytically coherent. The predefined set of factors and relationships, i.e., the systemic model derived from the literature, acts as a scaffold that focuses the crowd's collective intelligence. Participants are not asked for open-ended speculation but to evaluate a specific, structured system, ensuring their judgements can be synthesized into a consistent model for subsequent CIB analysis (Von Bertalanffy 1968).

In summary, crowdsourcing is theoretically justified as a multi-faceted tool: it is legitimized by constructivism, necessitated by complexity theory, enriched by potential surprise theory, and structured by general systems theory. This integrated justification establishes it as a robust method for generating the diverse, insightful, and structurally grounded judgements required for building credible and challenging scenarios.

3.3.4 Theoretical justification for cross-impact balance analysis

CIB analysis is a consistency-based scenario technique that bridges qualitative and quantitative approaches. As discussed in Chapter 2, Section 2.5.5, CIB has become a well-established and widely applied method of analysis for scenario construction (Mehrolhassani, Mozhdehifard and Rahimisadegh 2024). It evaluates the mutual influences between potential future states of system variables to generate internally consistent scenarios (Weimer-Jehle 2006). By explicitly testing the logical compatibility of factor combinations, CIB addresses a long-standing criticism of scenario methods: the lack of methodological rigour and internal consistency in traditional, intuition-driven approaches (Bradfield *et al.* 2005; Amer, Daim and Jetter 2013).

The CIB analysis method is performed on a judgement matrix that consists of the effects, in terms of strength and direction, that factors have on each other in all their possible states (Stankov *et al.* 2021b). When considering the matrix in Figure 3, the factors: *“Government”, “Foreign policy”, “Economy”, “Distribution of wealth”, “Social cohesion”,* and *“Social values”,* are all variables or descriptors in the study. “*Patriots party”, “Prosperity party”,* and *“Social party”* all represent states of the “*Government*” factor while “*Cooperation”, “Rivalry”,* and *“Conflict”* are states of the “*Foreign policy*” factor. The states chosen often differ between factors and between different applications and is dependent on the focus of the study (e.g., [‘low’, ‘medium’, ‘high’] or [‘<10%’, ‘≥10%]) (Stankov *et al.* 2021b). CIB studies by Stankov *et al.* (2021b) and Stankov *et al.* (2021a) used two possible states for each factor: ‘*low’* and *‘high’*, while Tori, Te Boveldt and Keseru (2023) also relied on just two states for each factor.

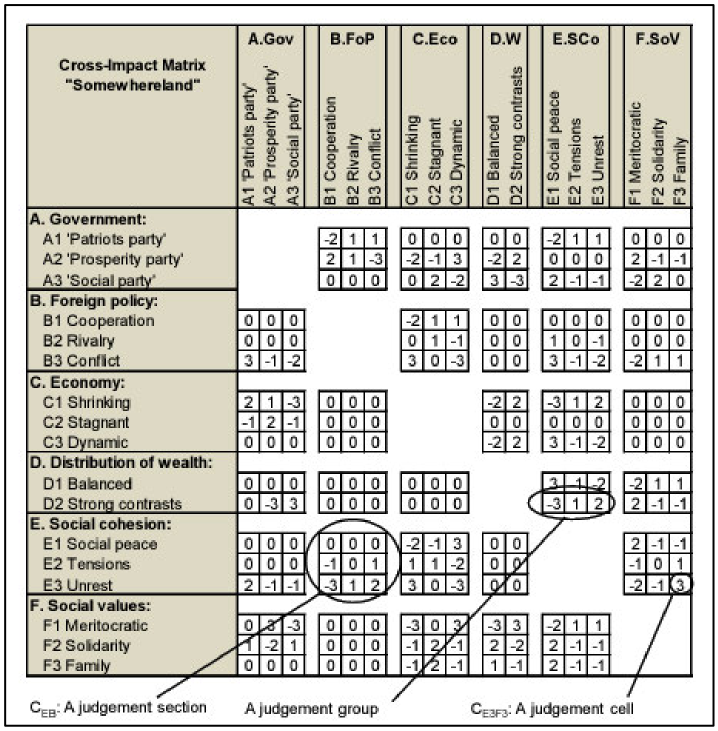


Figure 3: Example judgement matrix 1 (Source: Weimer-Jehle (2023b)

The pairwise effects that factor states have on each other are traditionally obtained from expert participants using a focus question (Weimer-Jehle 2006). Historically this cross-impact question has been in the form:

> *"If the only piece of information about the system is that Descriptor X has the state x, will you evaluate this due to the direct influence of X on Y as a hint that Descriptor Y has the state y (promoting influence, positive points assessed) or as a hint that Descriptor Y has not the state y (restricting influence, negative points assessed)?*" (Weimer-Jehle 2006: 339).

When answering the focus question on the influencing strength and direction that factor states have on other factor states, the expert usually selects a value from an integer scale, with negative values representing restricting direct effects and positive values being representative of promoting direct effects (Weimer-Jehle 2009). While a scale of [+3…-3] is frequently used, where +3 represents a strongly promoting direct influence and -3 represents a strongly restricting direct influence, other values are also permissible (Weimer-Jehle 2006). An integer scale of [+2…-2] (Table 9) was used by Stankov *et al.* (2021b) and Stankov *et al.* (2021a).

Table 9: Scale of impacts

Scale	Description
+2	Strong promoting influence
+1	Weak promoting influence
0	No significant influence
-1	Weak restrictive influence
-2	Strong restrictive influence

After all effects are obtained, a matrix similar to that of Figure 3 is obtained. The explanation of the matrix that follows is taken for Weimer-Jehle (2006) and Weimer-Jehle (2009).

The matrix of N factors is a hypermatrix (a matrix of matrices) of size $N \times N$. C_{ij}, which is a submatrix (or *"judgement section")* of the hypermatrix, is a matrix of size $s_i \times s_j$, where s_i and s_j are positive integers representing the number of states of factor i and j respectively. A *"cross-impact judgement"*, C_{ikjl}, is the entry in a judgement section for cell k, l of the judgement section i, j. This will be in the integer range [-2…+2]. Therefore, the judgement cell highlighted in Figure 3 has a value of 3 and is represented as: $C_{E3F3} = 3$.

A *"judgement group"* is a row in a submatrix or *"judgement section"* (see Figure 3). If the sum of the *cross-impact judgements* in each judgement group is 0, the group is called a "*standardized judgement group",* and if all groups in the hypermatrix are standardized, then the matrix is a *"standardized CIB matrix".* While standardization is not a requirement of the method, it does strengthen the internal consistency of the scenarios constructed and is recommended by the developers of the method (Weimer-Jehle 2009). A "*standardized judgement group"* with a zero sum is represented as:

$$\sum_{l=1}^{s_j} C_{ik\,jl} = 0. \tag{3.15}$$

For studies where only two states exist, the judgement group formula for ensuring standardization of factor i with state k, on factor j is:

$$C_{ikj1} + C_{ikj2} = 0 \tag{3.16}$$

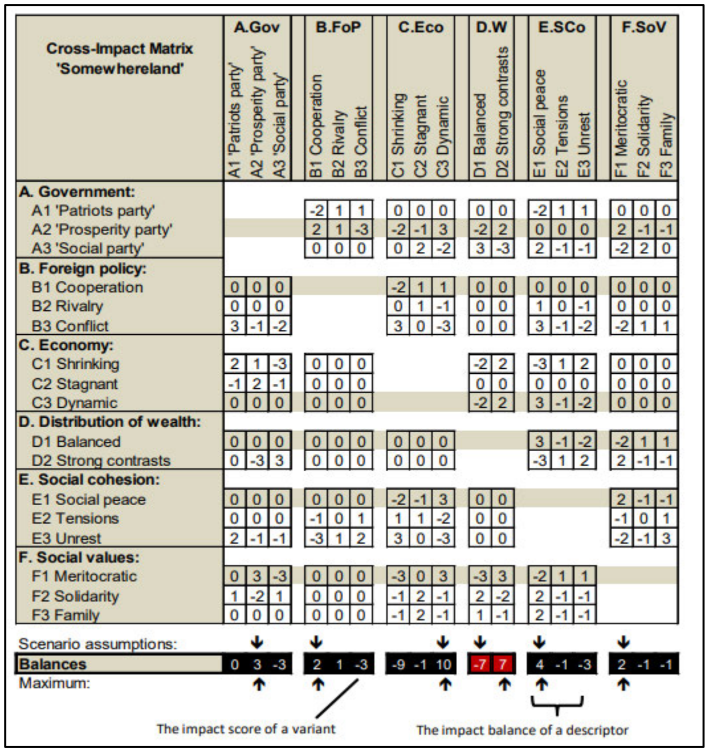
Therefore, judgements in a *"judgement group*" are merely the additive inverse of the other judgements represented as:

$$C_{ikj1} = -C_{ikj2} \tag{3.17}$$

It follows that when only two states exist, it is not necessary to gather both judgements from the participant as this can be calculated.

In the CIB analysis method, all possible system states that exist in a judgement matrix are checked for self-consistency. For the "*Somewhereland"* example judgement matrix in Figure 3, there are 486 possible scenarios (3*3*3*2*3*3). Checking the consistency of a scenario involves two steps: 1) investigating the factor as a source of an influence, and 2) investigating the factor as a target of an influence. If no contradiction exists between these two perspectives, then the scenario is deemed to be valid and consistent.

Consider the possible scenario highlighted in the example matrix in Figure 4. The rows that form part of the possible scenario are highlighted. The possible scenario consists of government party being the Prosperity party; foreign policy being cooperative; economy being dynamic; distribution of wealth being balanced; social cohesion being social peace; and social values being meritocratic. The impact scores for this possible scenario are calculated. These scores represent the net effect that the scenario has on the system and are calculated by performing a linear sum of all judgements in a columnar direction. For example, the impact score for "Foreign policy" being "conflict" (see column labelled "B. FoP", "B3 Conflict") is -3 (-3+0+0+0+0), and the impact score for "Social values" being "meritocratic" (see column labelled "F. SoV", "F1 Meritocratic") is 2 (2+0+0-2+2).



Cross-Impact Matrix 'Somewhereland'	A.Gov			B.FoP			C.Eco			D.W		E.SCo			F.SoV		
	A1 'Patriots party'	A2 'Prosperity party'	A3 'Social party'	B1 Cooperation	B2 Rivalry	B3 Conflict	C1 Shrinking	C2 Stagnant	C3 Dynamic	D1 Balanced	D2 Strong contrasts	E1 Social peace	E2 Tensions	E3 Unrest	F1 Meritocratic	F2 Solidarity	F3 Family
A. Government:																	
A1 'Patriots party'				-2	1	1	0	0	0	0	0	-2	1	1	0	0	0
A2 'Prosperity party'				2	1	-3	-2	-1	3	-2	2	0	0	0	2	-1	-1
A3 'Social party'				0	0	0	0	2	-2	3	-3	2	-1	-1	-2	2	0
B. Foreign policy:																	
B1 Cooperation	0	0	0				-2	1	1	0	0	0	0	0	0	0	0
B2 Rivalry	0	0	0				0	1	-1	0	0	1	0	-1	0	0	0
B3 Conflict	3	-1	-2				3	0	-3	0	0	3	-1	-2	-2	1	1
C. Economy:																	
C1 Shrinking	2	1	-3	0	0	0				-2	2	-3	1	2	0	0	0
C2 Stagnant	-1	2	-1	0	0	0				0	0	0	0	0	0	0	0
C3 Dynamic	0	0	0	0	0	0				-2	2	3	-1	-2	0	0	0
D. Distribution of wealth:																	
D1 Balanced	0	0	0	0	0	0	0	0	0			3	-1	-2	-2	1	1
D2 Strong contrasts	0	-3	3	0	0	0	0	0	0			-3	1	2	2	-1	-1
E. Social cohesion:																	
E1 Social peace	0	0	0	0	0	0	-2	-1	3	0	0				2	-1	-1
E2 Tensions	0	0	0	-1	0	1	1	1	-2	0	0				-1	0	1
E3 Unrest	2	-1	-1	-3	1	2	3	0	-3	0	0				-2	-1	3
F. Social values:																	
F1 Meritocratic	0	3	-3	0	0	0	-3	0	3	-3	3	-2	1	1			
F2 Solidarity	1	-2	1	0	0	0	-1	2	-1	2	-2	2	-1	-1			
F3 Family	0	0	0	0	0	0	-1	2	-1	1	-1	2	-1	-1			
Scenario assumptions:		↓		↓					↓	↓		↓			↓		
Balances	0	3	-3	2	1	-3	-9	-1	10	-7	7	4	-1	-3	2	-1	-1
Maximum:		↑		↑					↑		↑	↑			↑		

Figure 4: Example judgement matrix 2 (Source : Weimer-Jehle (2023b)

The impact balances at the bottom of the matrix show the comparisons of all the possible states for the possible scenario being examined. It can be seen that each group of factors (or descriptors) is balanced due to the principle of compensation. The focus is on the maximum impact score. This maximum represents the state of the system that is preferred because of the net effects of the possible scenario. The possible scenario is deemed to be consistent if the impact scores for the states of the factors in the possible scenario are the preferred state. For the example scenario the “Prosperity party” state from the “Government” factor, the “Conflict” state for the “Foreign policy” factor, the “Dynamic” state for the “Economy” factor, the “Balanced” state for the “Distribution of wealth” factor, the “Social peace” state for the “Social cohesion” factor, and the “Meritocratic” state for the “Social values” factor must all be the preferred states in their respective impact balance groups.

The “Prosperity party” state from the “Government” factor the preferred as it has the maximum impact score of 3. The “Conflict” state for the “Foreign policy” factor has an impact score of 2, making it the highest in the impact group and therefore preferred. With an impact score of 10, the “Dynamic” state for the “Economy” factor is also the preferred state. In a similar vein, the “Social peace” state for the “Social cohesion” factor, and the “Meritocratic” state for the “Social values” factor are preferred as they both have the highest impact scores. On the contrary, the “Balanced” state for the “Distribution of wealth” factor with an impact score of -7 is not the preferred factor state, as the “Strong contrast” state for the “Distribution of Wealth” factor has the highest impact score and is therefore the preferred state. For this possible scenario, the “Distribution of wealth” factor violates the rules of consistency, and the scenario is not consistent. The principle of consistency specifies that for internal consistency to exist, every factor state must be chosen such that no other state of the same factor is stronger when that factor state is supported by the influences of the states of the same factors (Weimer-Jehle 2023b). During CIB analysis the consistency of every combination of every factor state is evaluated according to the method explained so that a set of consistent scenarios is identified.

While the CIB analysis method serves as the computational engine of this study, its application is fundamentally underpinned by the integrated theoretical framework. Each theory provides a distinct and essential justification for its role, transforming CIB from a technical tool into a sophisticated instrument for foresight. CIB analysis is directly grounded in GST, which posits that a system's behaviour is an emergent property of the interactions between its components (Von Bertalanffy 1968). CIB applies this principle by taking a predefined set of factors and their pairwise influences as its input. Its algorithm identifies combinations of factor states (scenarios) that are internally consistent, meaning the mutual influences between them are non-contradictory and mutually reinforcing (Weimer-Jehle *et al.* 2020). This process ensures systemic coherence, fulfilling GST's imperative that scenarios must be analysed as interconnected wholes rather than as collections of independent trends.

CIB is powerfully informed by complexity theory, which emphasizes non-linearity, emergence, and the existence of multiple stable states in complex systems (Cilliers 2002). The method gives formal expression to these concepts. Unlike predictive models that seek a single outcome, CIB computationally explores the possibility space to identify multiple, equally plausible scenarios, each representing a distinct, internally consistent systemic state. This embodies the complexity theory principle of equifinality, acknowledging that different end states can arise from similar initial conditions through varied path dependencies, thereby preparing decision makers for a spectrum of plausible futures.

The entire CIB process is synthesized through a constructivist lens. The foundational input for the analysis, the judgement matrix, is itself a socially constructed artifact, built from the collective interpretations of experts. CIB does not claim to discover a pre-existing "true" future but computationally explores the logical implications of this co-constructed model of reality (Schultz 2006). The resulting scenarios are therefore structured narratives derived from a specific, interpreted social reality, making the method an exercise in transparent and rigorous sense-making rather than objective prediction.

PST adds a critical dimension to the interpretation of CIB's output. While CIB generates plausible scenarios, a PST lens encourages the researcher to scrutinize these scenarios for their surprising and disruptive potential (Shackle 2012). It shifts the focus from viewing scenarios merely as consistent possibilities to evaluating them as narratives that could fundamentally challenge incumbent mental models and strategies. PST ensures that the final set of scenarios is not just internally consistent but also imaginatively challenging, capturing futures that would constitute a genuine surprise and thus demand strategic resilience. In summary, CIB analysis is the point of synthesis for the entire theoretical framework: it is operationalized by GST, directed by complexity theory, legitimized by constructivism, and critically refined by PST. This multi-theoretical grounding ensures that the final scenarios are structurally robust, dynamically insightful, socially relevant, and imaginatively provocative.

3.4 Chapter Summary

Chapter 3 has established the integrated theoretical foundations for scenario construction, built on four complementary perspectives: GST, complexity theory, constructivism, and PST. Together, these theories form a robust, multi-dimensional framework that addresses the critical limitations of existing methods and justifies the development of a more rigorous and holistic methodology.

GST provides the essential structural lens, emphasizing systemic interdependencies, feedback loops, and holistic analysis. Complexity theory adds a dynamic lens, explaining the emergent, adaptive, and unpredictable behaviour of socio-technical systems and underscoring the need for methods that accommodate deep uncertainty and non-linearity. Constructivism contributes the interpretive lens, framing scenarios as socially constructed narratives and championing methodological transparency, inclusivity, and the co-creation of knowledge. Finally, PST introduces a crucial imaginative lens, shifting the focus from probabilistic forecasts to the exploration of plausible surprises and disruptive possibilities, thereby ensuring scenarios challenge entrenched mental models.

A central and critical contribution of this chapter is its detailed discussion of the rationale behind each methodological technique introduced in Chapter 4. For every technique, the chapter clearly explains why the specific technique was selected, directly linking it to the demands of the theoretical framework; and how the technique works, providing a conceptual explanation of the technique's operational principles.

In conclusion, Chapter 3 provides a theoretically coherent and actionable foundation. It demonstrates how the synergistic integration of GST, complexity theory, constructivism, and PST enables a scenario methodology that is structurally rigorous, dynamically sensitive, socially relevant, and imaginatively challenging, while explicitly justifying the choice and explaining the function of each constituent technique.

CHAPTER 4: MATERIALS AND METHODS

This chapter outlines the materials and methods employed in this study. It begins by describing the materials used, specifically the data collection and analysis tools that underpin the research process. Critically, the selection of these specific tools, including using secondary data, the ADVIAN® method, the crowdsourcing platform, and CIB analysis, was not only informed by the study's practical objectives but was fundamentally guided by the theoretical framework developed in Chapter 3. This ensures that the methodology directly operationalizes the principles of GST, complexity theory, constructivism, and PST, thereby guaranteeing methodological coherence, theoretical validity, and transparency from data collection through to analysis.

The second part of the chapter presents the six-step methodological process developed and implemented in this study. Unlike a linear approach that separates data collection and analysis, this methodology integrates both processes across different stages. Data collection is undertaken in Steps 1, 2, and 4, while data analysis is conducted in Steps 3, 5, and 6. Each step is presented with an explanation of its specific purpose, the rationale for the tools employed, and its contribution to the overall methodological framework.

The development of the automated application used to support data collection and processing which is informed by the Design Science Research (DSR) paradigm, and provides a structured approach for the design and evaluation of artefacts addressing identified research problem, is discuissed. This ensures that the tool is both methodologically grounded and fit for purpose within the overall framework.

The chapter concludes with a discussion on the validity and reliability of the methodology, highlighting the strategies employed to ensure the credibility, consistency, and robustness of the research process and its outcomes.

4.1 Materials used in the study

This study employs a range of tools and materials to support the systematic collection, reduction, and analysis of data for scenario construction. These tools are categorized into data collection and data analysis tools, reflecting their roles in the research methodology.

4.1.1 Data collection tools

Microsoft Excel was used to systematically record factors identified from secondary literature and to map relationships between these factors. This facilitated the creation of an initial impact matrix, providing a structured overview of the system and laying the groundwork for subsequent factor reduction and analysis.

The study utilized the social media platform **"X" (formerly Twitter)** to recruit experts for participation through crowdsourcing. "X" offers access to a large, professional user base of over 550 million active users and more than 500 million daily posts, with approximately 90% of accounts being public . Participants were recruited via a tweet containing a link to the survey tool (source code available at https://github.com/robyn-thompson/RE_Adop_files and https://github.com/robyn-thompson/AI_Adop_files) and relevant hashtags, which increase visibility, attract a diverse set of participants, and categorize the invitation into topical discussions (Howe 2006b; MacDermott *et al.* 2020).

Once expert judgements were collected through the researcher-developed survey tool (discussed in Section 4.2.5)**, Microsoft Excel** was again used to record and organize the aggregated judgement matrix, ensuring the data were systematically structured for subsequent CIB analysis.

4.1.2 Data analysis tools

After the factor matrix had been compiled, the **ADVIAN® method** (Linss and Fried 2010) was applied to reduce the factors to those most critical and uncertain. ADVIAN® classifies factors as driving, driven, or precarious, with the study focusing on highly driving and highly precarious factors. These are the factors that are most influential and uncertain in shaping systemic dynamics, while reactive, highly driven factors were not prioritized for scenario construction. ADVIAN® analyses both direct and indirect interactions in the factor matrix to systematically prioritize key drivers, ensuring that scenario construction is focused on the factors that matter most (Thompson, Olugbara and Singh 2018). The formulae and detailed procedures for ADVIAN® were discussed and presented in Chapter 3, Section 3.3.2.

The final stage of the methodology involves the construction of internally consistent scenarios using CIB analysis and is implemented with the assistance of the freeware tool **ScenarioWizard v4.54**. This software allows for the computational derivation of consistent scenarios from the judgement matrix generated through crowdsourcing. It operationalizes the relationships between factors in accordance with the method outlined by Weimer-Jehle (2006). The CIB method was discussed in Chapter 3, Section 3.3.4. The software and accompanying manuals are freely available for download (https://www.cross-impact.org/english/CIB_e_ScW.htm), ensuring transparency and replicability.

By clearly separating **data collection** and **data analysis tools**, the methodology highlights the sequential and theoretically aligned use of instruments throughout the study. Excel facilitated the systematic recording of factors, relationships, and the final aggregated judgement matrix. ADVIAN® and ScenarioWizard provide computationally rigorous mechanisms for factor prioritization and scenario synthesis. Together, these tools create a structured foundation for the study.

The following section builds on this foundation by detailing the research methodology, describing how these tools are used in a step-by-step process to construct internally consistent scenarios and address the study's research objectives.

4.2 Proposed Scenario Construction Methodology

The aim of the study was to construct an improved methodology for scenario construction based on advanced cross-impact analysis, CIB analysis and the crowdsourcing process. To achieve the aim, the study employed a sequential mixed methods approach, integrating qualitative techniques such as thematic analysis and crowdsourced judgements with quantitative methods, including ADVIAN® classification and CIB computation (Greene, Caracelli and Graham 1989; Johnson and Onwuegbuzie 2004). Each phase in the methodology builds on the previous one, ensuring that data collection and analysis are complementary and mutually informative (Tashakkori, Johnson and Teddlie 2020). A cross-sectional time horizon was adopted, capturing a "snapshot" of the methodology in application. The primary research strategy focuses on methodology development, aiming to design, articulate, and validate a novel multi-step methodology for scenario construction, rather than merely describing a phenomenon or testing a hypothesis.

The methodology adopted in this study and outlined in Figure 5 is closely aligned with the theoretical framework presented in Chapter 3, Section 3.3, ensuring coherence between the philosophical underpinnings, conceptual design, and practical execution of the research. The methodology is structured around six sequential phases, each operationalizing a distinct component of the integrated theoretical framework discussed in Chapter 3, Section 3.2. GST provides the structural rationale for systematically identifying factors and relationships from literature. Complexity theory informs the application of ADVIAN® to isolate critical uncertainties and emergent drivers. Constructivism grounds the crowdsourcing process, ensuring the integration of diverse perspectives and co-constructed judgements. PST further enriches this stage by specifically guiding the elicitation of judgements toward disruptive possibilities and plausibly surprising interactions. Finally, CIB analysis serves as the synthesizing mechanism, computationally deriving internally consistent scenarios from this structurally sound, dynamically sensitive, and imaginatively rich foundation. The development of this methodology achieves the third objective of the study: *to develop a theoretically grounded methodology for constructing consistent scenarios.*

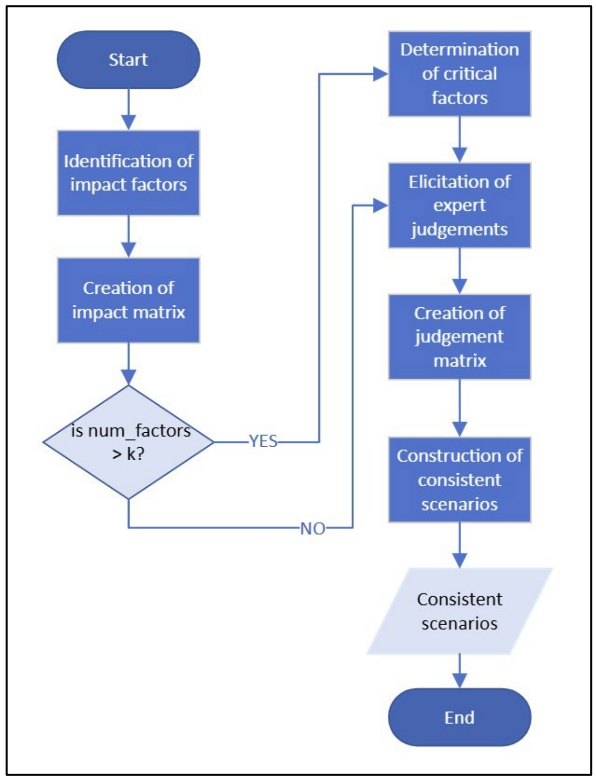


Figure 5: Flowchart for scenario construction methodology (Source: Researchers craft)

As can be seen, the research methodology unfolds in six steps: (1) identification of factors from existing literature; (2) creation of an impact matrix from systematically sourced secondary data; (3) application of ADVIAN® to identify and prioritize critical influencing factors; (4) elicitation of expert judgements through crowdsourcing strategies using a custom-designed online tool; (5) construction of a judgement matrix via a purpose-built application; and (6) generation of internally consistent scenarios through CIB analysis. This methodological structure ensures that each step is both theoretically justified and practically grounded, contributing to the development of a novel, transparent, and replicable scenario construction methodology. Table 10 below outlines the techniques and materials used for each step of the methodology.

Table 10: Data collection and analysis techniques

Step	Research Activity	Data Collection Technique	Data Analysis Technique	Tools used
1	Identification of impact factors	Systematic literature review (secondary data)	Content analysis to identify factors	Microsoft Excel
2	Creation of impact matrix	Systematic literature review (secondary data)	Content analysis to identify factor relationships through SEM	Microsoft Excel, SEM
3	Determination of critical factors	N/a	ADVIAN® to filter for the most critical and uncertain factors	Researcher-developed application, ADVIAN®, Microsoft Excel
4	Elicitation of expert judgements	Online Crowdsourcing Survey	N/a	Researcher-developed data gathering tool, “X”
5	Creation of judgement matrix	N/a	Descriptive statistics to synthesize individual judgements into a single, collective judgement matrix	Researcher-developed application, Microsoft Excel
6	Construction of consistent scenarios	N/a	CIB Analysis - computational identification of internally consistent scenarios	ScenarioWizard v4.54

The subsections that follow provide a detailed explanation of each phase of the methodology.

4.2.1 Step 1: Identification of impact factors

The first step of the methodology aims to identify impact factors from suitable data sources. The resultant set of factors or drivers are those that affect the “future” for which scenarios are being constructed. Literature relating to scenario construction describe these drivers as those elements of the macro-environment that exert an influence on the manner in which other factors operate (Phadnis *et al.* 2014).

As discussed in Chapter 3 Section 3.3.1, the use of secondary data for initial factor identification is grounded in the study's theoretical framework. For the current study, secondary data was obtained from published works that were discovered using the recommendations of the popular Preferred Reporting Items for Systematic Reviews and Meta-analysis (PRISMA) (Page *et al.* 2021) approach. The selected articles were subsequently subjected to content analysis. Content analysis encompasses a systematic investigation of natural language text and has been used by many authors for factor identification (Umble, Haft and Umble 2003; Finney and Corbett 2007; Thompson Mrs 2017; Epizitone and Olugbara 2019). During content analysis the researcher analysed the full text of the article with the aim of identifying factors affecting the environment being studied. The identified factors were analysed and synthesized to ensure that factors relating to the same concept are merged (Gupta and Mittal 2020). After examining each article, the researcher undertook a second scour of each paper to ensure that no factor had been omitted. The output from Step 1 was a list of *n* factors that affect the environment under consideration.

4.2.2 Step 2: Creation of the impact matrix

The second step of this methodology aimed to create an impact matrix that reflects the impacts that factors have on each other. Matrix creation relies on determining the strength of the relationships between pairs of impact factors. Criticisms on human-centred methods of obtaining data have been highlighted in Chapter 3 Section 3.3.1, but, in addition, it is difficult to realistically engage humans in creating the impact matrix when a large set of factors and complex higher order interdependent relationships need exploring. Therefore, as in Step 1, the alternative method of reviewing existing literature was employed to identify the strengths of the direct relationships. Secondary data from literature also increases reliability and credibility of the current study and reduces the complexity of collecting data from users multiple times.

The articles selected in Step 1 using the PRISMA protocol were, for this step, analysed to determine the direct relationships that exist between pairs of factors. The factors identified in Step 1 and the relationships between pairs of impacting factors were used to create an *n x n* impact matrix, where *n* is the total number of impact factors in the system. A cell in the matrix denotes the strength of a direct relationship between a factor pair (Gordon 1994). These relationships were obtained from reported structural equation modeling (SEM) of partial least squares statistical analyses. SEM is a powerful, quantitative tool for testing complex theories and establishing evidence for causal mechanisms while unveiling the strength of the relationships that exist between the factors of a system (Bollen 2014). Therefore, during article selection, only published works that applied SEM to unveil the relationships between factors and provided path coefficients to measure impact strengths were considered (Fan *et al.* 2016).

SEM is widely used to analyse complex relationships between a set of factors. SEM analysis is performed on data gathered from participants, where structured statements presented to participants are evaluated using a Likert scale (Bollen 2014). For example, to measure the perceived ease of use of a technology, participants may be presented with a question similar to the following: "*Please indicate your level of agreement with the following statements regarding the [Name of Software/Technology] on a scale from 1 to 5, where 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree. My interaction with [the system] is clear and understandable"* (Davis 1989). The strength and direction of SEM relationships is reported through the path coefficient, which assesses the direct or indirect effect within the network of multiple factors (Bollen 2014). A path coefficient from a factor *Fi* to a factor *Fj* quantifies how much a one standard deviation change in *Fi* is linked to a change in *Fj* while other factors in the system are controlled. Since path coefficients quantify both strength and direction, they are consistent with the impact assessment measurements required by CIB analysis (implemented in the final step of the methodology). A key difference between the two types of relationships is that relationships obtained from SEM analysis relate to factor relationships, while the relationships gathered for CIB analysis (discussed in Section 4.2.4) rather relate to the impact that factor **states** have on each other.

Traditional impact matrices report impact strengths using ordinal values of 0, 1, 2, or 3, representing "no impact", "weak impact", "medium impact", and "strong impact" respectively (Linss and Fried 2009). This study uses the path coefficients (βij) of direct relationships between pairs of factors (i and j) in the continuous interval [0, 1] to measure the pair strength. Should several articles include different path coefficients for the same pair of factors, the maximum path coefficient is included in the final impact matrix.

Once the matrix is created, a decision on whether to proceed to Step 2 or Step 3 must be made. This depends on the number of factors identified in Step 1. Because a smaller set of critical factors is desirable for scenario construction (Weimer-Jehle 2009), if the number of identified factors is more than k, the methodology continues to Step 2, which includes factor reduction. Otherwise, the methodology branches to Step 3, where factor reduction is not required. The choice of k's value is guided by literature, where most recently, Mehrolhassani, Mozhdehifard and Rahimisadegh (2024) contended that five factors should be subjected to CIB analysis, but Kurniawan *et al.* (2022) recommend seven factors. In contrast, Weimer-Jehle (2006) opines that nine to 15 factors are optimal for scenario analysis. The present researcher meticulously chose a threshold value of $k=10$ for further analysis after considering these differing opinions. It must be mentioned that should the number of factors be 10 or less, there would be no need to extract path coefficients and create the impact matrix. Some researchers may contend that the extraction of path coefficients may be time wasted, but this process is performed at the same time as the initial review of papers in Step 1. What is more, should the path coefficients not be extracted at the time of factor identification and the number of factors become more than 10, this would necessitate a second review of papers, which would be time intensive.

The output from Step 2 was a list of *n* factors represented as an *n x n* impact matrix of direct relationships between pairs of factors as determined by path coefficients and it served as input to Step 3 or Step 4, as may be required.

4.2.3 Step 3: Determination of critical factors

The third step of the methodology aimed to reduce the factors to only those that are most important or critical for scenario construction. In the context of scenario construction, ***critical factors*** refer to those influential elements or driving forces in a system that significantly affect the outcome of future scenarios (Amer, Daim and Jetter 2013). The creation of the impact matrix in this step achieved objective two of the study: *To identify and critically structure the key factors and their interdependencies from a set of factors derived from of a structured literature review, as a foundational analytical step informing scenario construction.*

The rationale behind reducing factors to those that are most critical is informed by the CIB analysis method, applied in Step 6. CIB analysis uses a matrix to represent the system of interrelationships between factors, with the rows representing factors as driving influences and columns being representative of the driven property of the factors (Weimer-Jehle 2006). Since the developers of the CIB method view scenarios as the different combinations of the varying states of factors that exist in a system, each influence in the matrix is dependent on the state of that factor. Participants of a study using CIB analysis evaluate an extensive number of pairwise comparisons of various factor states, therefore the exhaustive list of factors identified through content analysis in Step 1 has to be reduced.

If one considers all the possible combinations of the states of the factors, there is an exponential growth in the number of possible scenarios and in the number of interactions that participants would need to evaluate (Panula-Ontto *et al.* 2018). If there are two factors and each have three different states, there would be 30 *$((2x3)^2–(2x3))$* pairwise influences to evaluate, while having 10 factors with three possible states each would result in 870 *$((10x3)^2–(10x3))$* evaluations. This becomes challenging to analyse and often overwhelming for participants of the study. With the critical factors being only those that are most influential or driving, it becomes necessary to reduce the factors using a factor reduction method.

During this step the researcher applied ADVIAN® analysis to the factor matrix constructed in Step 2 for factor reduction. The ADVIAN® method not only reduces the number of factors but also compensates for the limitations of relying on SEM for factor relationship identification. The researcher acknowledges that not all factor relationships are represented in the selected papers identified in Step 2, and the papers reviewed are not a fully exhaustive or a complete list of all possible papers. Therefore, if there is a 0 relationship in the factor matrix it does not necessarily mean that no relationship exists between the factors. It rather indicates that the selected papers did not report on this relationship. ADVIAN®, through the discovery of indirect relationships, unveils additional hidden relationships that SEM does not report on (Linss and Fried 2010). CIB analysis (in Step 6) also has the ability to confirm these relationships that are unveiled by the ADVIAN® analysis.

Before ADVIAN® analysis is performed, the matrix is normalized by dividing all entries by the maximum of all impacts. Normalizing the matrix ensures that high impact values can be accommodated without the concern of numeric overflow occurring during matrix calculations that are required by the analysis method. The formulae for the various ADVIAN® measures and classifications are presented in Table 8, found in Chapter 3, Section 3.3.2.

While prior studies have relied on Excel spreadsheets to perform ADVIAN® calculations (Thompson, Olugbara and Singh 2018; Epizitone and

Olugbara 2019; Meara 2021), this approach necessitates extensive manual manipulation of formulae and matrix operations. Such adjustments are required so that variations in the number of factors across different applications can be accommodated, because each scenario study results in a matrix of differing dimensions. Consequently, users must manually verify formula ranges and ensure accurate matrix multiplication, which introduces the potential for human error and compromises the reliability of the final measures and classifications. To address these limitations, the researcher developed an algorithm (Figure 6) to automate the calculation of ADVIAN® constructs. This algorithm was implemented using Python, streamlining the process and eliminating the need for manual intervention.

The code for the algorithm, presented in Figure 6 and accessible at https://github.com/robyn-thompson/ADVIAN-app, was tested for accuracy and consistency using two established test cases (Linss and Fried 2010; Thompson, Olugbara and Singh 2018). (While the automated ADVIAN® application was tested to ensure accuracy, it was assumed that the input matrix has been validated prior to execution of the algorithm). Input data for these tests was provided in the form of CSV files (Figure 7 and Figure 8), and the outputs generated by the automated application were exported as Excel files (Figure 9 and Figure 10). Each test case was executed three times, yielding identical results across all runs. Furthermore, the outputs matched precisely with those reported in the respective published studies, thereby affirming the algorithm’s reliability. The test cases included the original dataset used by the developers of the ADVIAN® method (Figure 7), and a dataset previously validated in a peer-reviewed publication by the researcher (Figure 8). These results confirm that the developed application produces accurate and consistent calculations of ADVIAN® constructs.

Algorithm 1: advanced impact analysis
Input: $n \; x \; n$ impact matrix
Output: ADVIAN measures and classifications (PARAM) and system stability (STAB).

1. Declare and initialize variable arrays, PARAM{DAS← $0*n$, DPS← $0*n$, IAS← $0*n$, IPS← $0*n$, RDAS← $0*n$, RDPS← $0*n$, RIAS← $0*n$, RIPS← $0*n$, $CRI \leftarrow 0*n$, $INT \leftarrow 0*n$, $STA \leftarrow 0*n$, $PRE \leftarrow 0*n$, $DRI \leftarrow 0*n$, $DRE \leftarrow 0*n$};
2. Declare and initialize additional variables, MDS←0, MIS←0, STAB←0
3. Validate input matrix (Input).
4. Normalize input data, Input←Input /max(Input);
5. Copy the Input matrix, OMEGA←Input

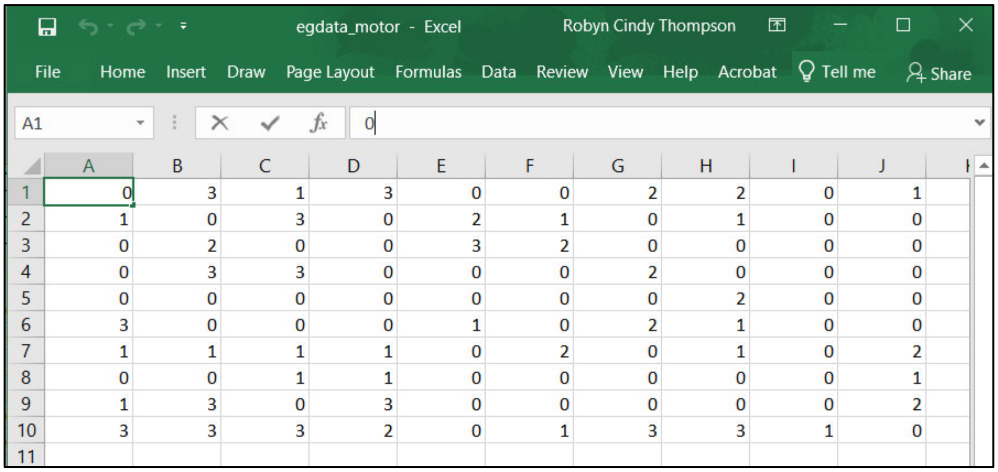
   Calculate: direct active sum and direct passive sum; initialize indirect active sum and indirect passive sum.
6. for i=1 to n do
7. for p=1 to n do
8. PARAM (i,DAS)← PARAM (i,DAS)+OMEGA(i,p);
9. PARAM (i,DPS)← PARAM (i,DPS)+OMEGA(p,i);
10. PARAM (i,IAS)← PARAM (i,IAS)+OMEGA(i,p);
11. PARAM (i,IPS)← PARAM (i,IPS)+OMEGA(p,i);
12. end p for loop
13. end i for loop

    Calculate maximum of direct sums and maximum of indirect sums.
14. MDS←max(PARAM (i,DAS), PARAM (i,DPS));
15. MIS←MDS;

    Calculate of indirect active and passive sums to an order of: $n - 1$
16. for k=2 to n-1 do
17. OMEGA←Input *OMEGA;
18. for i=1 to n do
19. for p=1 to n do
20. PARAM (i,IAS)← PARAM (i,IAS)+OMEGA(i,p);
21. PARAM (i,IPS)← PARAM (i,IPS)+OMEGA(p,i);
22. end p for loop
23. MIS←max(MIS PARAM (i,IAS), PARAM (i,IPS));
24. end i for loop
25. end k for loop

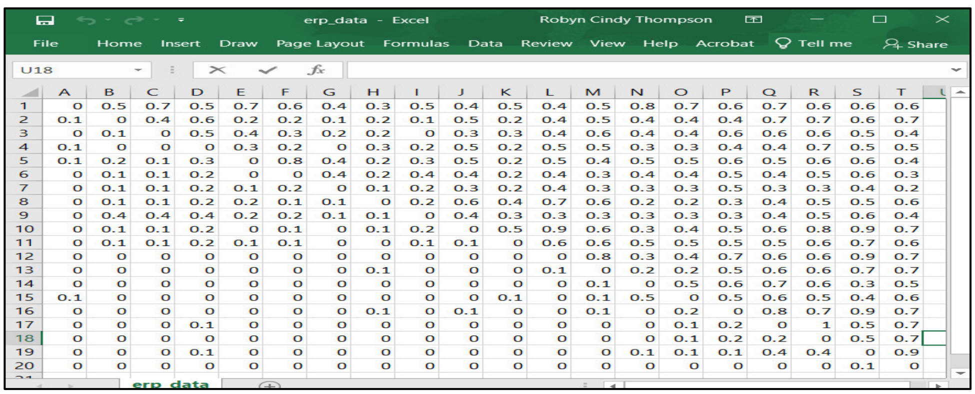
    Calculate measures and classifications
26. for i=1 to n do
27. PARAM (i,RDAS)← 100*(PARAM (i,DAS)/MDS);
28. PARAM (i,RDPS)← 100*(PARAM (i,DPS)/MDS);
29. PARAM (i,RIAS)← 100*(PARAM (i,IAS)/MIS);
30. PARAM (i,RIPS)← 100*(PARAM (i,IPS)/MIS);
31. PARAM (i,CRI)←sqrt(PARAM (i,RIAS)* PARAM (i,RIPS));
32. PARAM (i,INT)←0.5*(PARAM (i,RIAS)+ PARAM (i,RIPS));
33. PARAM (i,STA)← ABS(100-(2/(1/ PARAM (i,RIAS)+1/ PARAM (i,RIPS)));
34. PARAM (i,PRE)←sqrt(PARAM (i,CRI)* PARAM (i,RIAS));
35. PARAM (i,DRI)←sqrt((100- PARAM (i,CRI))* PARAM (i,RIAS));
36. PARAM (i,DRE)←sqrt((100- PARAM (i,CRI))* PARAM (i,RIPS));
37. end i for loop
38. STAB←mean(PARAM (:,STA));
39. Return PARAM and STAB

Figure 6: Algorithm 1: Advanced impact analysis algorithm



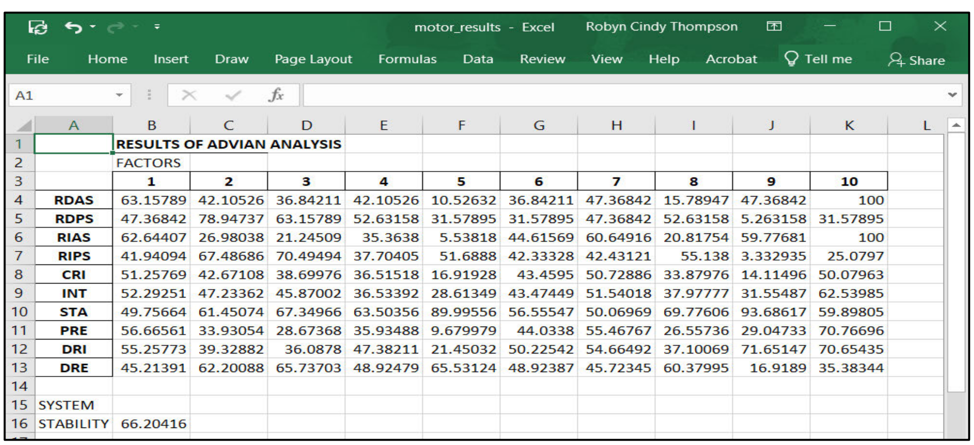
	A	B	C	D	E	F	G	H	I	J
1	0	3	1	3	0	0	2	2	0	1
2	1	0	3	0	2	1	0	1	0	0
3	0	2	0	0	3	2	0	0	0	0
4	0	3	3	0	0	0	2	0	0	0
5	0	0	0	0	0	0	0	2	0	0
6	3	0	0	0	1	0	2	1	0	0
7	1	1	1	1	0	2	0	1	0	2
8	0	0	1	1	0	0	0	0	0	1
9	1	3	0	3	0	0	0	0	0	2
10	3	3	3	2	0	1	3	3	1	0

Figure 7: Test case 1: Test data from Linss and Fried (2010)



	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T
1	0	0.5	0.7	0.5	0.7	0.6	0.4	0.3	0.5	0.4	0.5	0.4	0.5	0.8	0.7	0.6	0.7	0.6	0.6	0.6
2	0.1	0	0.4	0.6	0.2	0.2	0.1	0.2	0.1	0.5	0.2	0.4	0.5	0.4	0.4	0.4	0.7	0.7	0.6	0.7
3	0	0.1	0	0.5	0.4	0.3	0.2	0.2	0	0.3	0.3	0.4	0.6	0.4	0.4	0.6	0.6	0.6	0.5	0.4
4	0.1	0	0	0	0.3	0.2	0	0.3	0.2	0.5	0.2	0.5	0.5	0.3	0.3	0.4	0.4	0.7	0.5	0.5
5	0.1	0.2	0.1	0.3	0	0.8	0.4	0.2	0.3	0.5	0.2	0.5	0.4	0.5	0.5	0.6	0.5	0.6	0.6	0.4
6	0	0.1	0.1	0.2	0	0	0.4	0.2	0.4	0.4	0.2	0.4	0.3	0.4	0.4	0.5	0.4	0.5	0.6	0.3
7	0	0.1	0.1	0.2	0.1	0.2	0	0.1	0.2	0.3	0.2	0.4	0.3	0.3	0.3	0.5	0.3	0.3	0.4	0.2
8	0	0.1	0.1	0.2	0.2	0.1	0.1	0	0.2	0.6	0.4	0.7	0.6	0.2	0.2	0.3	0.4	0.5	0.5	0.6
9	0	0.4	0.4	0.4	0.2	0.2	0.1	0.1	0	0.4	0.3	0.3	0.3	0.3	0.3	0.3	0.4	0.5	0.6	0.4
10	0	0.1	0.1	0.2	0	0.1	0	0.1	0.2	0	0.5	0.9	0.6	0.3	0.4	0.5	0.6	0.8	0.9	0.7
11	0	0.1	0.1	0.2	0.1	0.1	0	0	0.1	0.1	0	0.6	0.6	0.5	0.5	0.5	0.5	0.6	0.7	0.6
12	0	0	0	0	0	0	0	0	0	0	0	0	0.8	0.3	0.4	0.7	0.6	0.6	0.9	0.7
13	0	0	0	0	0	0	0	0.1	0	0	0	0.1	0	0.2	0.2	0.5	0.6	0.6	0.7	0.7
14	0	0	0	0	0	0	0	0	0	0	0	0	0.1	0	0.5	0.6	0.7	0.6	0.3	0.5
15	0.1	0	0	0	0	0	0	0	0	0	0.1	0	0.1	0.5	0	0.5	0.6	0.5	0.4	0.6
16	0	0	0	0	0	0	0	0.1	0	0.1	0	0	0.1	0	0.2	0	0.8	0.7	0.9	0.7
17	0	0	0	0.1	0	0	0	0	0	0	0	0	0	0	0.1	0.2	0	1	0.5	0.7
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.1	0.2	0.2	0	0.5	0.7
19	0	0	0	0.1	0	0	0	0	0	0	0	0	0	0.1	0.1	0.1	0.4	0.4	0	0.9
20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.1	0

Figure 8: Test case 2: Test data from Thompson, Olugbara and Singh (2018)



	A	B	C	D	E	F	G	H	I	J	K
1		**RESULTS OF ADVIAN ANALYSIS**									
2		FACTORS									
3		**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
4	**RDAS**	63.15789	42.10526	36.84211	42.10526	10.52632	36.84211	47.36842	15.78947	47.36842	100
5	**RDPS**	47.36842	78.94737	63.15789	52.63158	31.57895	31.57895	47.36842	52.63158	5.263158	31.57895
6	**RIAS**	62.64407	26.98038	21.24509	35.3638	5.53818	44.61569	60.64916	20.81754	59.77681	100
7	**RIPS**	41.94094	67.48686	70.49494	37.70405	51.6888	42.33328	42.43121	55.138	3.332935	25.0797
8	**CRI**	51.25769	42.67108	38.69976	36.51518	16.91928	43.4595	50.72886	33.87976	14.11496	50.07963
9	**INT**	52.29251	47.23362	45.87002	36.53392	28.61349	43.47449	51.54018	37.97777	31.55487	62.53985
10	**STA**	49.75664	61.45074	67.34966	63.50356	89.99556	56.55547	50.06969	69.77606	93.68617	59.89805
11	**PRE**	56.66561	33.93054	28.67368	35.93488	9.679979	44.0338	55.46767	26.55736	29.04733	70.76696
12	**DRI**	55.25773	39.32882	36.0878	47.38211	21.45032	50.22542	54.66492	37.10069	71.65147	70.65435
13	**DRE**	45.21391	62.20088	65.73703	48.92479	65.53124	48.92387	45.72345	60.37995	16.9189	35.38344
14											
15	SYSTEM										
16	STABILITY	66.20416									

Figure 9: Test case 1: Results from the researcher-developed application.

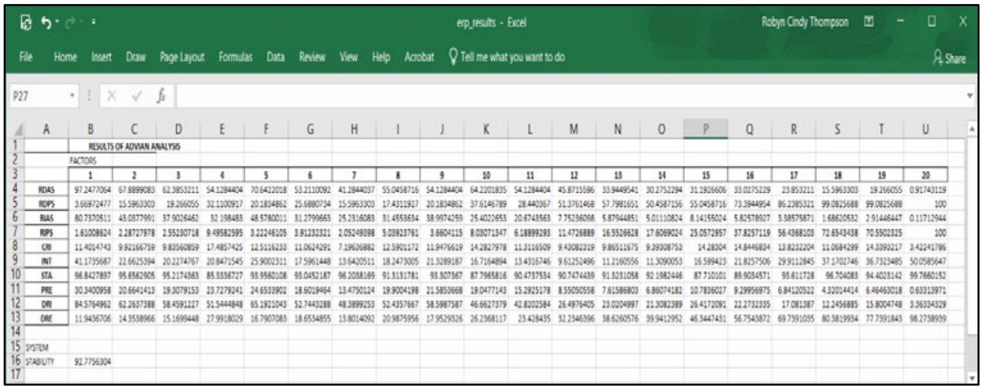


Figure 10: Test case 2: Results from the researcher-developed application.

As outlined in Section 3.3.2 of Chapter 3 and in the context of applying ADVIAN® to scenario construction, the method focuses specifically on identifying the most significant **driving** and most significant **uncertain** factors. These are represented respectively by the 12th row ("DRI") and the 11th row ("PRE") in the example Excel output shown in Figure 10. A factor is considered significant in either category if its value exceeds a predefined threshold, calculated as two-thirds above the average standard deviation (Guertler and Spinler 2015; Thompson, Olugbara and Singh 2018). Factors meeting this criterion in either the driving or uncertain category form the refined set of key factors.

The creation of the resultant refined set of driven and uncertain factors directly addresses objective two of the study: *to identify and critically structure the key factors and their interdependencies from a set of factors derived from of a structured literature review, as a foundational analytical step informing scenario construction*. These key factors represent the output of the current phase and serve as the input for Step 4 of the methodology.

4.2.4 Step 4: Elicitation of expert judgements

The primary aim of this step was to gather expert data required for the construction of the judgement matrix, which occurred in Step 5. Since CIB analysis, conducted in Step 6, relies on a judgement matrix, this step is a critical precursor. Step 3 of the methodology produced a refined set of key factors, which served as input to Step 4. It is these factors and their associated states that were presented to expert participants for evaluation.

To accomplish this data collection, a custom web-based tool was developed. Given that this artefact represents a methodological contribution of the study, its development is reported here using the DSR paradigm. DSR is a problem-solving framework concerned with creating and evaluating innovative artefacts. In this case, a software-based data collection instrument to address defined real-world problems (Peffers *et al.* 2007; Hevner *et al.* 2008). The following subsections document the design, development, and testing of the tool in accordance with DSR principles.

4.2.4.1 Problem identification

The elicitation of expert judgements and the construction of cross-impact matrices are traditionally carried out using participatory methods, such as interviews, focus group discussions, and facilitated workshops, typically involving a small group of experts and key stakeholders (Choi, Kim and Park 2007; Schweizer and Lazurko 2020). As discussed in Chapter 2, Section 2.6 and in Chapter 3, Section 3.3.1, these participatory approaches have been widely criticised for several limitations (Skinner *et al*. 2015), including:

- The need for true consensus, which is often difficult to achieve due to group dynamics and pressure;
- The absence of standardised procedures for achieving consensus;
- High time demands and participant fatigue due to repeated rounds of engagement;
- The potential for conformity rather than consistency across rounds;
- Time delays between rounds, making the process inefficient;
- The tendency for consensus processes to yield diluted, middle-ground judgements.

These limitations motivated the development of a web-based alternative that would enable the independent, anonymous collection of expert judgements without the constraints of synchronous, in-person engagement. Furthermore, given that the target expert population was geographically dispersed and could not be readily identified through traditional sampling frames, an online approach was necessary to access a sufficiently diverse and knowledgeable participant base.

4.2.4.2 Requirements definition

The requirements for the web-based data collection tool were derived from three primary sources:

Methodological Requirements: The CIB methodology, as outlined in Chapter 3, Sections 3.3.1 to 3.3.4, imposed specific functional requirements. These included:

- The ability to present factors and their associated states to expert participants;
- The capacity to collect pairwise impact judgements using a [+2 to –2] integer scale;
- The construction of judgement strings for subsequent matrix generation;
- The storage of individual participant judgement data to enable later aggregation.

Participant Recruitment Considerations: The study used the "X" platform to recruit expert participants through crowdsourcing. Participation via social media is voluntary, resulting in a self-selected, non-probabilistic sample consistent with purposive sampling, where inclusion probabilities cannot be calculated (Arbia *et al.* 2023). Given the logistical constraints of probability sampling in online contexts, non-probability surveys are widely accepted for capturing expert and public insights (Radford *et al*. 2022). Due to the exploratory nature of the study and the wild population reached through social media, elements of snowball sampling emerged as participants shared or retweeted the survey link (Winton and Sabol 2022). As the expert population is both unknown and dispersed, snowball sampling is considered a practical and valid approach (Naderifar, Goli and Ghaljaie 2017; Reagan *et al*. 2019). Based on prior research, a sample of at least 10 experts was deemed sufficient (Worrell, Di Gangi and Bush 2013; Emami-Naeini *et al*. 2020). This sample was drawn from the global community of approximately 556 million active X users as of November 2023 (Duarte 2023).

Expert Quality Control Requirements: To ensure the quality of responses, the tool needed to evaluate participant expertise prior to presenting the judgement tasks. Drawing on prior literature (Anguera *et al.* 2018; Emami-Naeini *et al.* 2020; Devaney and Henchion 2018), inclusion and exclusion criteria were established (see Table 11). These criteria formed the basis for the tool's screening functionality.

Table 11: Participant inclusion and exclusion criteria

INCLUSION CRITERIA (one of the following)	EXCLUSION CRITERIA
Authored a book, published an article, or presented at a conference in the field.	Less than five years' experience in the field.
Has, in the past three years, been an invited speaker at an event related to the field.	
Leads a corporate team in the field.	
Is actively involved in policy making in the field.	
Is a member of a committee in the field.	
Is a point of contact for the media on matters relating to the field.	
COMPULSORY INCLUSION CRITERIA	
Five years or more experience in the field.	

Usability Requirements: Recognising that participants would engage with the tool remotely and without facilitator support, usability requirements were identified through consultation with two user interface experts (a power engineering expert and a software engineering specialist). These requirements included: intuitive navigation, mobile responsiveness, clear instructions, and visual feedback on progress.

4.2.4.3 Design and development

Technology Stack: The web-based data collection tool was built using PHP, HTML, CSS, and a MySQL database, with data stored remotely. The website is hosted on a free service that ensures both security and database backup functionality. Furthermore, the data collected are stored in the cloud by the web host.

Database Population: Prior to distributing the tweet and sharing the online survey tool, the database tables storing the factors to be evaluated and their associated meanings were populated. The researcher created a script that reads text data from an Excel comma delimited file and inserts the relevant data into the database table. The algorithm for this task is presented in Figure 11, while the associated PHP code (getfactors.php) and EXCEL.csv files can be found at https://github.com/robyn-thompson/RE_Adop_files and https://github.com/robyn-thompson/AI_Adop_files.

Algorithm 2: Populating Factor data

Input: $n \; x \; n$ impact matrix

Output: CSV file with one row of factors

1. Open the .csv file for reading
2. Read cell entries into array DATA and array DESCRIPT
3. Count the number of factors, num← count(DATA)
4. Insert each factor into the database table
5.   for x=1 to num do
6.   insert into table factors values (x, DATA[x], DESCRIPT[x])
7. end loop
8. end algorithm

Figure 11: Algorithm 2: Populating factor data

Recruitment Mechanism: The study relied on "X" for the recruitment of participants and the distribution of the online survey tool. In an effort to recruit participants and gather data, the researcher created tweets on the "X" platform with links to the survey tool. It is recommended that to increase reach and attract participants, a combination of hashtags and mentions should be included in the tweet (MacDermott et al. 2020). Hashtags relevant to the application context are used as a catalyst to attract participants as well as requests for retweets (Cummings and Sibona 2017). As mentioned in Chapter 2, Section 2.7.5 and 2.7.7, hashtags are regularly used on social media to highlight and categorize pertinent items of discussion and provide an efficient search strategy by interested parties (Rana *et al.* 2023). A hashtag consists of a # symbol followed by a key term such as #EnergySaving #SavingThePlanet #Sustainability. If hashtags are added to posts, they are more easily found by other “X” users, as they are used in all searches. Mentions are used to target a particular “X” user. A mention consists of the @ symbol followed by their username (called a handle in “X”) such as @RobzThom, @Eskom_SA, @PhdStudy. “X” users can be targeted and asked to complete the survey as in the study by MacDermott et al. (2020). For this study, the researcher shared links to the surveys through the researcher's private “X” account and included hashtags relevant to the study. The initial recruitment was done in a similar manner to that of Pozzar *et al.* (2020), which is through a single tweet and reads: "*Assist with research on [include a brief application description] for my PhD study by completing the survey at [link to survey]. Many thanks.*"

The researcher was guided by these recommendations. Hashtags relevant to the application context were included in the tweet, and as suggested by MacDermott *et al.* (2020) and Wasilewski *et al.* (2019), retweets of the post were done in the early evening and later afternoons to improve the reach. The researcher also made every effort to increase their number of followers as per recommendations (Hendricks, Düking and Mellalieu 2016) and the tweet was pinned to the researcher's page. Screenshots of the tweets are shared in Chapter 5, Sections 5.1.1 and 5.2.1 as well as in the GitHub repository referred to in Chapter 5, Sections 5.1 and 5.2, where the two applications of the methodology are presented.

Participant Workflow: When a prospective participant clicked on the link in the tweet, they were directed to the online survey tool. The tool first evaluated the level of expertise of the participant using the inclusion and exclusion criteria provided in Table 11 above. Those participants considered experts according to the criteria listed were presented with a series of input screens to elicit the judgements of factor states. These judgements related to pairwise assessments of the effects that the states of factors have on the states of other factors. This study used 'low' and 'high' states for each factor. The reasoning for this selection complies with the binary state representation used in other CIB studies (Stankov *et al.* 2021b; Stankov *et al.* 2021a; Tori, Te Boveldt and Keseru 2023).

Focus Question Format: Judgement data is traditionally obtained from expert participants through the use of a structured focus question, as outlined in Chapter 3, Section 3.3.4 (Weimer-Jehle 2006). Stankov *et al.* (2021b) and Stankov *et al.* (2021a) rather employed cause-effect graphs as visual prompts to elicit expert input, but their approach assumes a level of familiarity with graph interpretation that may not be universally shared among all experts. Given the anonymity of participants in the present study, the researcher could not assess participants' competence in graph-based reasoning prior to data collection. Excluding participants on this basis might have unjustifiably disqualified knowledgeable experts in the relevant domain. For this reason, the current study rather adopted the traditional focus question format to elicit expert judgements. The question posed to expert participants was:

When considering {project x} in the future if there exists an {x} state of {factor j}, how will that impact a {y} state of {factor k}?

The expert had to answer the focus question using an integer scale, where negative values represented restricting (inhibitory) direct impacts and positive values indicated promoting (enabling) direct impacts (Weimer-Jehle 2009). This study adopted a [+2 to –2] integer scale, according to Table 9 in Chapter 3, Section 3.3.4, and is consistent with the approach used by Stankov *et al.* (2021b) and Stankov *et al.* (2021a).

Data Storage Mechanism: During the process of the participant selecting impact judgements, a string of the corresponding quantitative measures, separated by the "~" character, was built. To illustrate this, assume the judgements selected by a participant evaluating a system of three factors corresponds with those in Table 12. The diagonals (in red) are automatically populated with 0's by the online tool because factors do not affect themselves. Two impact judgement strings are built, one for the effects that the "high" states of the factors have on "high" states of other factors (referred to as highstr), and a further string to store the effect that the "low" states of the factors have on "high" states of other factors (referred to as lowstr). Each judgement string consists of n^2 values. Considering Table 12, string highstr will store "0~+2~-2~+1~0~-1~-1~+2~0" (impacts for the "high" state of each factor) and string lowstr will store "0~+1~+1~+2~0~-2~+1~-2~0" (impacts for the "low" state of each factor). It is these strings that were stored in the database for each expert participant and were used to create the cross-impact matrix in Step 5, which was needed for CIB analysis in Step 6. This data form the output from Step 4 of the methodology and input to Step 5.

Table 12: Example CIM for illustration

Factors		F1 (High)	F2 (High)	F3 (High)
F1	High	0	+2	-2
	Low	0	+1	+1
F2	High	+1	0	-1
	Low	+2	0	-2
F3	High	-1	+2	0
	Low	+1	-2	0

4.2.4.4 Design and development

The tool was tested through a multi-phase process to ensure technical reliability, usability, and validity of the data captured.

Technical Testing: The researcher tested the tool using a few laptops and mobile devices that run various operating systems to verify cross-platform compatibility. The researcher also consulted with two user interface experts, which included an expert in power engineering and a software engineering specialist, who provided technical and usability feedback.

User Acceptance Testing: The application was piloted and tested by 10 social media users. These users shared their input data with the researcher, so that this data along with other test data that were entered by the researcher could be used to test the application to ensure it produced an accurate and valid matrix.

Refinements Following Testing: From input received from the users and experts, the following improvements were made:

1. Factors were reworded to use more simple terms.
2. Tooltips were included to provide extra clarity.
3. Fields were increased in size as truncation had occurred.
4. A status bar indicating the percentage complete was included.
5. The inclusion of an option for users to indicate that they do not comply with any of the expert inclusion criteria.
6. Inclusion of an SSL certificate.
7. Additional formatting for mobile devices included.
8. Inclusion of a "back" button between screens.

4.2.4.5 Contribution of the developed artifact

Researcher-developed web-based tools for data collection have proven to be efficient and effective alternatives to traditional methods such as interviews, questionnaires, and group discussions (Cooper *et al.* 2006). These tools offer the advantage of eliciting the collective wisdom of an anonymous crowd, comprising diverse experts from various locations (O'Reilly 2009; Raford 2015). Gathering data through online tools ensures access to a large and diverse participant base, has real-time characteristics and ensures that rapid feedback is obtained (Kayser and Shala 2020). Furthermore, the web-based tool and the subsequent automated generation of a final matrix ensures that the number of participants is not restricted. Moreover, web-based tools have been developed and successfully used for the collection of diverse data by many researchers. The CIMgen tool was used to gather preference chains from expert participants (Epizitone and Olugbara 2019; Thompson, Olugbara and Singh 2020) while the tool developed by Cooper *et al.* (2006) gathered data for the assessment of students' health status and work efficiency over a two-year period. To the best of the researcher's knowledge, no other publication has developed an online application specifically designed to gather expert judgements for scenario construction. The tool developed in this study therefore constitutes a novel methodological contribution, enabling the efficient, scalable, and rigorous collection of expert judgement data for CIB-based scenario construction.

Having established the design, development, and testing of the web-based data collection tool, it is necessary to process the data it generated. The judgement strings stored in the database for each expert participant form the output of Step 4 and provide the necessary input for Step 5, wherein these individual strings are aggregated to construct the cross-impact matrix that underpins the CIB analysis in Step 6.

4.2.5 Step 5: Creation of the judgement matrix

The aim with this step of the methodology was to create a matrix of judgements from the judgements gathered from expert participants in Step 4. The resulting judgement matrix followed the structure illustrated in Figure 3 as required for CIB analysis in Step 6 (Section 3.3.4 of Chapter 3).

The researcher developed a software tool to convert judgement strings to a judgement matrix that can be used as input to the CIB analysis method. The automated tool reads strings from the database and produces a judgement matrix in EXCEL format. The algorithm for the automation is provided in Figure 12, while the code (toexcel.php) is available at https://github.com/robyn-thompson/RE_Adop_files and https://github.com/robyn-thompson/AI_Adop_files. The algorithm reads each of the expert judgement strings from the database and increments the count of the corresponding category (-2,-1,0,+1,+2). Once all the expert judgements from the database have been read and processed, the count for each judgement category for each impact is stored in two matrices, one for all high state judgements and the other for low state judgements. While traditional methods often attempt to reach consensus about the judgements from participants through repeated rounds, it has already been established in Chapter 2, Section 2.6 that those techniques have been subject to several criticisms. This study therefore did not attempt to establish consensus and rather used statistical measures of median and mean to obtain a single judgement for each impact and ultimately develop a single judgement matrix.

The construction of the final judgement matrix relied on measures of central tendency. The algorithm determines the median of the expert judgements and uses this measure in the final matrix. The median is an appropriate measure when identifying the "typical" selection made by participants and is more relevant and more accurate that the mean when the distribution of data may not be normal and when outliers may be present (Lydersen 2020). Finding the median of a dataset with an odd number of entries is simple as the middle element has an equal number of evaluations above and below it. But, when the dataset has an even number of entries, the standard practice is to use the mean of the middle two values (McCluskey and Lalkhen 2007). Since the current judgement data were ordinal categorical data, finding the mean of the two middle values could have resulted in a value from the set (-1.5, -0.5, +0.5, +1.5) that did not correspond with any of judgement categories. It is for this reason that had the number of entries been even and the two middle entries be from different categories, then the category closest to the mean of the dataset would have been used in the judgement matrix.

The resultant matrix consists of the judgements as determined above as well as the additive inverse of these judgements. The judgements gathered from expert participants were only with respect to the impact that a *high* state has on the states of other factors. Therefore, the additive inverse of these determined the judgement that a *low* factor state has on the states of other factors. The automated application that applied the algorithm was developed by the researcher using php code. The output from the application is an EXCEL.csv file that contains a matrix of all judgements as shown in the example matrix in Figure 13. The matrix that was the output from this fifth step became input for the sixth and final step of the methodology: Construction of consistent scenarios.

```
Algorithm 3: judgement_matrix_creation
Input: Table of expert judgement strings
Output: judgement matrix
    Open .csv file for output
    num← count of factors
    Create and write header lines to .csv file
    Create 2Dim matrices to store the final judgements for the high and low states: finalHmatrix, finalLmatrix
    Create 2Dim matrices to store a count of each judgement type for the high and low states: highmatrix, lowmatrix
    Initialize each element in the highmatrix and lowmatrix matrices to an array [0,0,0,0,0]. Initialize each entry in the finalHmatrix and finalLmatrix to [-1,-1].
    For each entry in each judgement string in the database, increment the relevant judgement count for the corresponding judgement in the highmatrix and lowmatrix.
    for each database row do
        explode the strings for the high and low judgements into arrays
            for each judgement in the array increment the count for the corresponding judgement
            end loop
    end loop
    Find each judgement find the median of the expert evaluations. If there are an even count of judgements and the category of median +1 is different to the category of the median then select the judgement category closest to the average. Store the additive inverse of each judgement in the final matrix
    for i=1 to num do
        for j=1 to num do
            if number of judgements is even then
                even ← true
            end if
            medposn ← median of highmatrix[i][j]
            if even is true and the judgement category at (medposn +1) is in a new category then
                avg ← average of highmatrix[i][j]
                if the category at (medposn+1) is closest to avg then
                    medposn ← (medianposn +1)
                end if
            end if
            med ← category at medposn
            finalHmatrix[i][j*2] ← med
            finalHmatrix[i][(j*2)+1] ← 0-med
            medposn ← median of lowmatrix[i][j]
            if even is true and the judgement category at (medposn +1) is in a new category then
                avg ← average of lowmatrix[i][j]
                if the category at (medposn+1) is closest to avg then
                    medposn ← (medianposn +1)
                end if
            end if
            med ← category at medposn
            finalLmatrix[i][j*2] ← med
            finalLmatrix[i][(j*2)+1] ← 0-med
        end loop j
    end loop i
    Write each row from finalHmatrix and finalLmatrix to the csv file
    Return csv file
```

Figure 12: Algorithm 3: Judgement matrix creation

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
1	"Cross Impact Balance Matrix"															
2																
3			F1		F2		F3		F4		F5		F6		F7	
4			H	L	H	L	H	L	H	L	H	L	H	L	H	L
5	F1	H	0	0	1	-1	2	-2	2	-2	2	-2	2	-2	1	-1
6		L	0	0	-1	1	-1	1	-1	1	0	0	-1	1	-1	1
7	F2	H	2	-2	0	0	2	-2	1	-1	1	-1	2	-2	1	-1
8		L	-1	1	0	0	-1	1	-1	1	-1	1	-1	1	0	0
9	F3	H	1	-1	2	-2	0	0	2	-2	1	-1	2	-2	2	-2
10		L	-1	1	-1	1	0	0	-1	1	0	0	-1	1	-1	1
11	F4	H	1	-1	1	-1	1	-1	0	0	1	-1	1	-1	2	-2
12		L	-1	1	-1	1	0	0	0	0	-1	1	-1	1	-1	1
13	F5	H	2	-2	1	-1	2	-2	1	-1	0	0	2	-2	1	-1
14		L	-1	1	-1	1	-1	1	-1	1	0	0	-1	1	-1	1
15	F6	H	1	-1	1	-1	1	-1	2	-2	1	-1	0	0	2	-2
16		L	-1	1	-1	1	-1	1	-1	1	-1	1	0	0	-1	1
17	F7	H	1	-1	1	-1	1	-1	2	-2	1	-1	1	-1	0	0
18		L	-1	1	-1	1	-1	1	-1	1	-1	1	-1	1	0	0
19																

Figure 13: Example of a judgement matrix (Source: Researcher-developed tool)

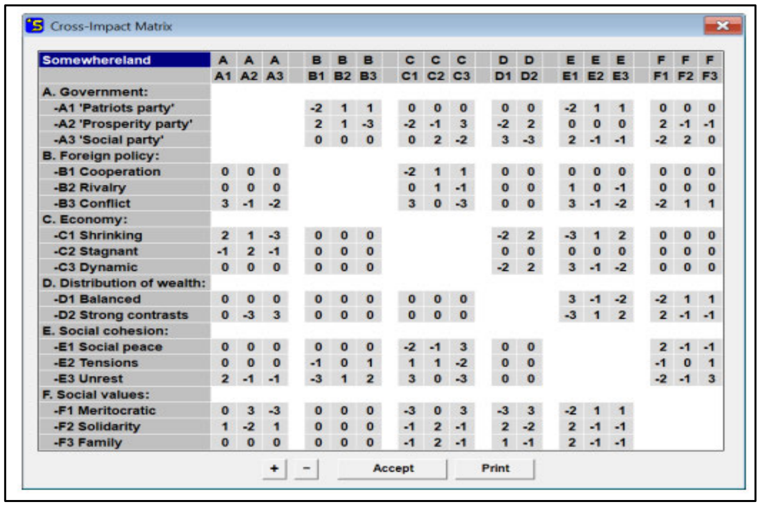
4.2.6 Step 6: Construction of consistent scenarios

The aim of this final step of the methodology was to construct consistent scenarios using CIB analysis. The judgement matrix created in the prior step was used as input to this sixth step of the methodology.

CIB analysis can be performed manually, following the workings of the method as outlined by Weimer-Jehle (2006), or by using ScenarioWizard v4.54 open-source software (Weimer-Jehle 2023a). The software tool automates the analysis of the interdependencies that exist between the alternate futures to produce a set of scenarios that the CIB analysis technique deems plausible and consistent. The software's reliability and validity have been proven through its' successful implementation and application in a number of scenario projects (Weimer-Jehle *et al.* 2020). After installing the ScenarioWizard software, as indicated by Weimer-Jehle (2023b), a new project can be created and the steps outlined below followed to construct a set of consistent scenarios:

1. Create the analysis structure, which consists of the factor names and states.
2. Capture the judgements using the *"cross-impact matrix"* option under the *"edit"* menu (Figure 14).
3. Check that each judgement group is standardized (consistent), by executing the "*standardization"* option in the *"edit"* menu and correcting any anomalies.

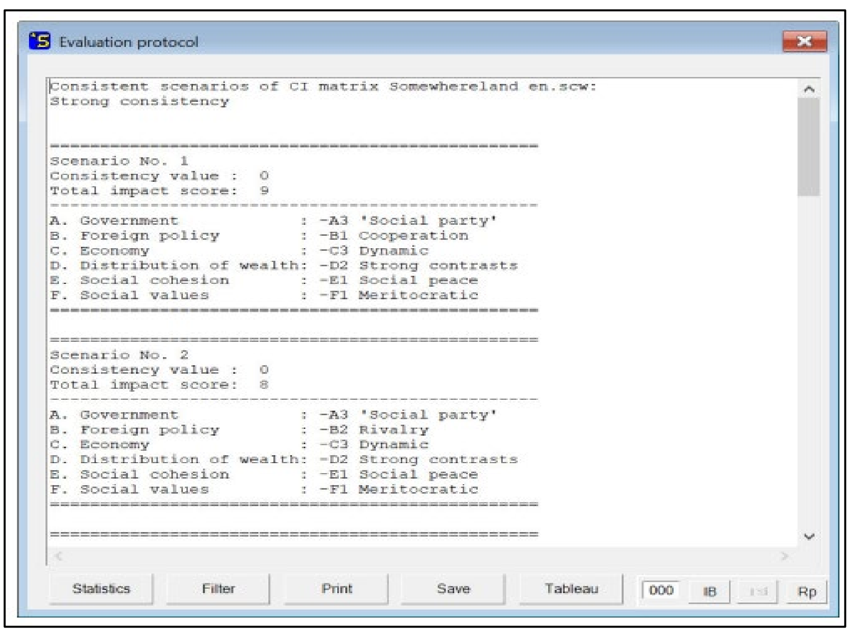
4. Compute the consistency of all scenarios and obtain a list of consistent scenarios in an evaluation protocol report by selecting the *“Consistent Scenarios*” option under the *“analyse”* menu (Figure 15*).*
5. A tabular representation of all consistent scenarios can be generated by selecting the “Tableau” button on the “evaluation protocol report” (Figure 16).
6. The scenarios in the table can be sorted manually so that those that align in a meaningful way are grouped together. This can be performed in the *“Tableau”* screen.



Cross-Impact Matrix

Somewhereland	A	A	A	B	B	B	C	C	C	D	D	E	E	E	F	F	F
	A1	A2	A3	B1	B2	B3	C1	C2	C3	D1	D2	E1	E2	E3	F1	F2	F3
A. Government:																	
-A1 'Patriots party'				-2	1	1	0	0	0	0	0	-2	1	1	0	0	0
-A2 'Prosperity party'				2	1	-3	-2	-1	3	-2	2	0	0	0	2	-1	-1
-A3 'Social party'				0	0	0	0	2	-2	3	-3	2	-1	-1	-2	2	0
B. Foreign policy:																	
-B1 Cooperation	0	0	0				-2	1	1	0	0	0	0	0	0	0	0
-B2 Rivalry	0	0	0				0	1	-1	0	0	1	0	-1	0	0	0
-B3 Conflict	3	-1	-2				3	0	-3	0	0	3	-1	-2	-2	1	1
C. Economy:																	
-C1 Shrinking	2	1	-3	0	0	0				-2	2	-3	1	2	0	0	0
-C2 Stagnant	-1	2	-1	0	0	0				0	0	0	0	0	0	0	0
-C3 Dynamic	0	0	0	0	0	0				-2	2	3	-1	-2	0	0	0
D. Distribution of wealth:																	
-D1 Balanced	0	0	0	0	0	0	0	0	0			3	-1	-2	-2	1	1
-D2 Strong contrasts	0	-3	3	0	0	0	0	0	0			-3	1	2	2	-1	-1
E. Social cohesion:																	
-E1 Social peace	0	0	0	0	0	0	-2	-1	3	0	0				2	-1	-1
-E2 Tensions	0	0	0	-1	0	1	1	1	-2	0	0				-1	0	1
-E3 Unrest	2	-1	-1	-3	1	2	3	0	-3	0	0				-2	-1	3
F. Social values:																	
-F1 Meritocratic	0	3	-3	0	0	0	-3	0	3	-3	3	-2	1	1			
-F2 Solidarity	1	-2	1	0	0	0	-1	2	-1	2	-2	2	-1	-1			
-F3 Family	0	0	0	0	0	0	-1	2	-1	1	-1	2	-1	-1			

Figure 14: Example of cross-impact matrix capturing judgements (Source: Weimer-Jehle (2023b))



Evaluation protocol

```
Consistent scenarios of CI matrix Somewhereland en.scw:
Strong consistency


=================================================
Scenario No. 1
Consistency value :  0
Total impact score:  9
-------------------------------------------------
A. Government             : -A3 'Social party'
B. Foreign policy         : -B1 Cooperation
C. Economy                : -C3 Dynamic
D. Distribution of wealth: -D2 Strong contrasts
E. Social cohesion        : -E1 Social peace
F. Social values          : -F1 Meritocratic
=================================================

=================================================
Scenario No. 2
Consistency value :  0
Total impact score:  8
-------------------------------------------------
A. Government             : -A3 'Social party'
B. Foreign policy         : -B2 Rivalry
C. Economy                : -C3 Dynamic
D. Distribution of wealth: -D2 Strong contrasts
E. Social cohesion        : -E1 Social peace
F. Social values          : -F1 Meritocratic
=================================================

=================================================
```


Figure 15: Evaluation protocol example (Source: Weimer-Jehle (2023b))

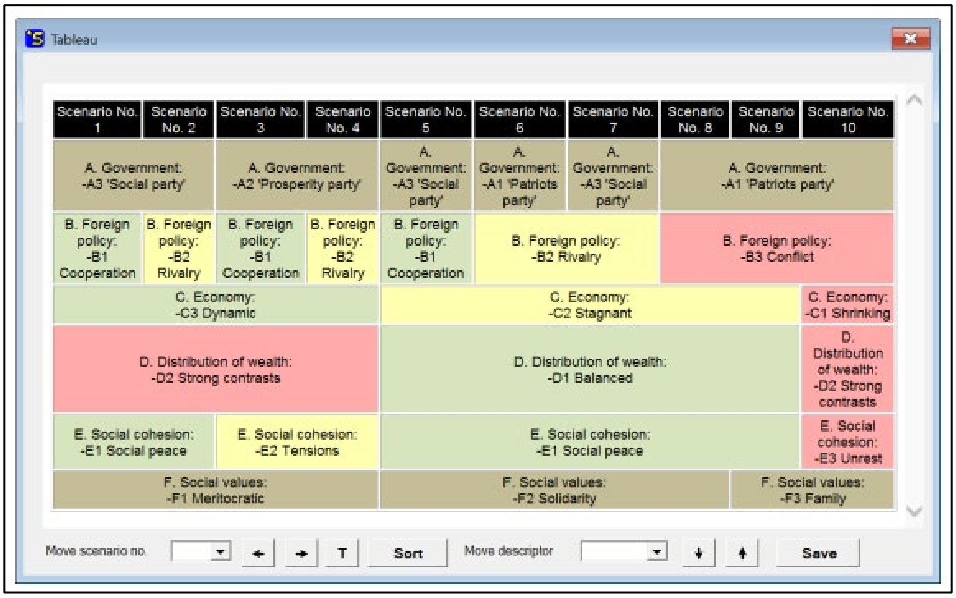


Figure 16: "Somewhereland's" tableau of consistent scenarios (Source: Weimer-Jehle (2023b))

Figure 15 above shows an example of the details of all consistent scenarios that might be constructed using the ScenarioWizard software. These scenarios are produced after evaluating all possible scenarios for consistency. The report and the brief narrative that is developed becomes the output for this final step of the methodology. The development of the methodology achieves the third objective of the study: *to develop a theoretically grounded methodology for constructing consistent scenarios.*

Scenario construction projects usually continue to a final phase that involves developing full narratives for each of the scenarios. Qualitative scenario narratives are not the focus of this paper; it is rather the methodology developed for the construction of consistent scenarios that is the focus. It is for this reason that only brief narratives for each of the scenarios are provided in the experimental results chapter. These brief narratives then form the foundation for a team of subject matter specialists to develop the full narratives associated with each scenario (Chermack 2011). This is in line with other researchers who have also sought to publish novelty in the methodology, leaving the creative writing of narratives to specialists in that area (Schweizer and Lazurko 2020; Stankov *et al.* 2021b; Kurniawan *et al.* 2022).

4.3 Ethical and Methodological Considerations

This study acknowledges the methodological and ethical challenges inherent in using social media platforms such as “X” for expert recruitment and data collection. To address these, several safeguards and design strategies were implemented to ensure ethical integrity, data reliability, and methodological rigour.

The “X” platform tends to attract a more educated and professionally engaged user base (Wojcik and Hughes 2019), and this was an advantage for the current study as participants had be experts in their respective domains. The survey design includes a set of screening questions to determine participant expertise before granting access to the main survey. This inclusion and exclusion process eliminated non-expert responses, thereby ensuring data integrity, which is cited as a concern (Kramer *et al.* 2014; Teitcher *et al.* 2015). Data integrity was further maintained through the use of Likert-type scales for all questions, avoiding narrative or open-ended responses that could introduce subjective interpretation or irrelevant content. Since participation was entirely voluntary and no incentives were offered, the likelihood of compromised responses was reduced. The study follows established “X”-based recruitment strategies as recommended by Hendricks, Düking and Mellalieu (2016), Wasilewski *et al.* (2019) and MacDermott *et al.* (2020), including optimal post timing, reposting, tagging domain specialists, and leveraging relevant hashtags to enhance reach and participation.

Reliance on expert participants introduces additional methodological concerns such as anonymity, cognitive bias, and expert selection. While Sackman (1975) argues that anonymity may reduce accountability, it was viewed as a strength for this study. The fact that participants had no direct contact with the researcher and responses were collected anonymously, encouraged honesty and objectivity.

Cognitive bias in this study was minimized through the structured survey design for judgement gathering and the methodological framework adopted from Weimer-Jehle (2006). The questions posed to experts were intentionally neutral, avoiding any leading or restrictive phrasing. The survey was also pilot-tested with both subject-matter specialists and user interface experts to ensure clarity and eliminate potential bias. Furthermore, the systematic analytical approach of ADVIAN® and CIB contributed to objectivity and minimized subjective interpretation (Schweizer and Lazurko 2020).

Expert selection was managed using a transparent and unbiased process. Since experts were not handpicked by the researcher but rather self-select through the screening process, selection bias was reduced. The screening criteria, presented in Table 11, clearly define the inclusion and exclusion requirements. Although Worrell, Di Gangi and Bush (2013) caution against generalizing expert opinions, they emphasize that experts offer deeper domain insights than the general population. The diverse backgrounds of participating experts enhance the richness and representativeness of the study's findings.

The study adhered to institutional ethics standards (ethics clearance was obtained from the researcher's academic institution before data collection commenced – ethics clearance number IREC 067/24) and did not mine or analyse any data directly from "X" tweets or user content, a practice that would require further consideration of ethics (Gold 2020). Instead, all data were collected via a researcher-developed online survey, which serves as the sole data collection instrument. Informed consent was obtained digitally through the survey platform and participants were presented with a Letter of Information and Consent prior to beginning the survey, outlining the study's purpose, voluntary nature, and data privacy measures. Consent was confirmed when participants chose to proceed with the survey, and participants could exit at any time with no data stored upon withdrawal. To ensure the anonymity of participants, the survey did not collect usernames, personal identifiers, or demographic data beyond what was necessary to determine expertise. Contributions were anonymized at source and immediately transformed during analysis, ensuring that raw data were neither stored nor traceable.

Given that participation was online at a time and place chosen by the participant, and that no sensitive or personal data were collected, the study poses no foreseeable risk of harm. Moreover, participation was voluntary, anonymous, and non-intrusive, fully aligning with contemporary ethics standards for digital and crowdsourced research (Pozzar *et al.* 2020).

4.4 Methodology Validity and Reliability

The validity of critical factors and of the expert judgements, the reliability of the factor matrices, and the consistency of the CIB results were examined to ensure the methodological robustness and credibility of the constructed scenarios.

Validity indicates how accurately a method measures something, and how closely the results relate to real-world measures (Anastasi and Urbina 1997). Construct validity indicates the adequacy of an instrument to measure the indicators under investigation (Sjøberg and Bergersen 2022). In this study construct validity is demonstrated firstly by the fact that the factors that were used to build the scenarios are secondary data as they were derived from factors that had already been empirically validated in published papers. Secondly, the applications developed and implemented in the methodology were derived from the algorithms of previously published methods that had been tested and validated in published papers (Asan and Asan 2007; Thompson, Olugbara and Singh 2018; Epizitone and Olugbara 2019). Lastly, the study relied on expert participants for the evaluation of measures, which further ensures construct validity.

Content validity refers to the extent to which the measuring instrument fully represents all aspects of the phenomenon being measured (Bollen 1989). Content validity was ensured since the initial set of factors were secondary data. The subsequent refinement of factors was done through ADVIAN® analysis, which is a published and well cited method for the extraction of critical factors. The subsequent CIB analysis method had already been established as valid by the developers of the technique (Linss and Fried 2010; Weimer-Jehle *et al.* 2020). Furthermore, these techniques have been tested successfully in other cross-impact and scenario construction projects. The expert participants' evaluation of strengths between states of factors further strengthened the methodology's content validity (Sürücü and Maslakci 2020). In addition, the study's validity was ensured by constructing consistent scenarios across two distinct application contexts, with consistency verified using the widely recognised CIB analysis method.

Reliability relates to the consistency of an instrument so that it produces the same results repeatedly under the same conditions over time (Sürücü and Maslakci 2020). Since the factors being used for data analysis were obtained from studies where the internal consistency had already been determined and measured, it follows that the factors extracted and analysed in this study would also have internal consistency. The researcher ensured reliability during the development of the applications that were implemented in the proposed methodology using the "test-retest" method (Berchtold 2016). This was done by using sample datasets from other studies and comparing the results from the developed application to the published results from the datasets. It follows that the reliability of the instruments has been determined scientifically. In addition, CIB analysis and the ScenarioWizard software that had been made available for use, have been used by researchers in numerous studies. The developers of the method and the application had already measured the reliability of the model and application (Weimer-Jehle 2006). Furthermore, if the input data is not reliable and contains inconsistencies, the software will not provide any consistent scenarios and will report an error to indicate the existence of inconsistent data (Mohammad Ganji Nik *et al.* 2023).

The reliability and validity of the expert judgements and scenario outputs can also be substantiated by the study's integrated theoretical framework. GST ensured structural validity by providing a rigorous, holistic model of systemic relationships. Complexity theory supported dynamic validity, ensuring the methodology is sensitive to uncertainty, emergence, and adaptive behaviour. Constructivism established interpretive validity through a transparent, participatory process that legitimizes the co-construction of knowledge. Finally, PST contributed exploratory validity by ensuring the methodology is capable of generating scenarios that challenge incumbent mental models and capture plausibly disruptive futures. Collectively, these theoretical pillars ensured that the methodology is both valid and reliable for constructing robust scenarios in complex environments.

4.5 Chapter Summary

This chapter presented the materials used and the methodology the researcher followed while conducting the experiments presented in Chapter 5. Data gathering relied on secondary data and surveys distributed through “X”. The surveys were completed using the researcher-developed online tool, with expert participants recruited by means of the crowdsourcing process and “X” used for survey distribution. Throughout the methodology, Microsoft Excel was used to capture and store matrix data. The ADVIAN® cross-impact analysis technique was selected as the method best suited to refine factors and to only identify those that were most driving and most uncertain. The researcher developed a software tool so that the ADVIAN® method could be automated and in doing so, human error and the time associated with performing the ADVIAN® analysis were reduced. The construction of the consistent scenarios was performed using the tried and tested CIB method of analysis using the ScenarioWizard software tool. The judgement matrix required for CIB analysis was generated by a researcher-developed online tool from the judgements elicited from expert participants. Since the researcher used algorithmic development for the various tools, it follows that the results are both valid and reliable.

The methodology was implemented for two applications. These are presented and discussed in the following chapter.

CHAPTER 5: EXPERIMENTAL RESULTS

This chapter reports on the implementation of the methodology outlined in Chapter 4, achieving the study's final objective: *to validate the methodology through the practical implementation and application to renewable energy adoption and AI adoption in higher education*. The chapter begins with the implementation of the methodology for the first application: **consistent scenarios for the adoption of renewable energy systems**. The discussion first provides an overview of the research area, followed by a step-by-step implementation of the methodology and a presentation of results. This is followed by the second application, namely **consistent scenarios for the adoption of AI in higher education**, discussed in the same structured format.

The domains of renewable energy and AI in higher education is particularly relevant for scenario construction, as scenario methods are well-suited for fields undergoing significant transformation (Schoemaker 1995). Both areas are currently experiencing rapid growth and development, underscoring the timeliness and importance of this methodology. Each of two discussions on the different implementations starts with an overview of the context area. This is followed by a detailed walkthrough of the methodology, with each step discussed in a separate sub-section.

The figures that show the various screens and pages that are referenced in the following sections and sub-sections are available in the GitHub repository at *https://github.com/robyn-thompson/Robyn-Phd/blob/main/Supporting%20Material.pdf*.

5.1 Consistent Renewable Energy Adoption Scenarios

Recent years have seen a significant global shift towards renewable energy as a more sustainable alternative to traditional, non-renewable sources (Murdock *et al.* 2021). However, this transition is not without its challenges: A

2022 report highlights public resistance and policy limitations as substantial obstacles to renewable energy adoption (REN21 2022). Despite advancements in the energy sector, the integration of renewables has progressed slowly, with renewables accounting for only 12.5% of total final energy consumption in 2022, an increase of just 2.5% since 2015 (Diesendorf 2022). This slow uptake is particularly concerning given the United Nations' Sustainable Development Goals (SDGs), specifically goals 7, 9, 11, and 13, which directly advocate for a broader adoption of renewable energy. These goals emphasize the need to "ensure access to affordable, reliable, sustainable and modern energy for all" (SDG7); "build resilient infrastructure, promote inclusive and sustainable industrialization, and foster innovation" (SDG9); "make cities inclusive, safe, resilient, and sustainable" (SDG11); and "take urgent action to combat climate change and its impacts" (SDG13). The 2024 sustainable goals report indicates that with only six years remaining to meet the SDG aims and only 17% of the SDGs on track, current progress is not at the level required to meet all SDGs (UN DESA 2024). The 2024 Sustainable Goals Report underscores that accelerated action is urgently needed, especially in the area of renewable energy adoption (UN DESA 2024). While significant strides have been made in providing access to energy, the 2024 Sustainable Goals Report states that significant acceleration is needed in terms of adopting more renewable, sustainable energy sources to meet the 2030 goals (UN DESA 2024).

A wealth of research has explored the factors that influence renewable energy adoption. Some studies examine the possible integration of renewable systems into existing infrastructure (Nkundabanyanga *et al.* 2020), while others focused on the adoption of the technology in rural areas (Majid 2020). Additionally, studies have focused their attention on a specific country or area. Research has also concentrated on specific countries, particularly in Asia, such as Pakistan (Irfan *et al.* 2021a; Irfan *et al.* 2021b), Bangladesh (Masukujjaman *et al.* 2021), Nepal (Bhattarai, Somanathan and Nepal 2018), Malaysia (Zahari and Esa 2018), Indonesia (Wijaya and Kokchang 2023), and India (Majid 2020). In other regions the focus includes Ghana (Asante *et al.* 2021), Nigeria (Ashinze *et al.* 2021), China (Zhu 2023), and Iran (Shahangian *et al.* 2022). However, few studies have comprehensively assessed adoption across multiple types of renewable energy in a single analysis, with most focusing on solar energy alone (Rana *et al.* 2022; Kar, Harichandan and Prakash 2024). Thus, a global study that considers multiple renewable technologies and spans diverse regions would provide a valuable, holistic view of adoption factors.

Researchers have used various theoretical models to assess renewable energy adoption, including the diffusion of innovation theory (Alwedyan 2021), the technology acceptance model (Yang, Bashiru Danwana and Yassaanah 2021), the unified theory of acceptance and use (Lau *et al.* 2020), the theory of planned behaviour (Aslam, Farhat and Arif 2021), the theory of reasoned action (Nketiah *et al.* 2022), the behavioural finance and institutional theory (Parsad, Mittal and Krishnankutty 2020), the technology-organizational-environmental model (Maqbool 2018), or combinations of these (Ashinze *et al.* 2021; Bekti *et al.* 2021; Fatoki 2022; Kar, Harichandan and Prakash 2024). These frameworks highlight a range of factors that affect adoption, yet no single study consolidates these findings into a set of cohesive scenarios to guide policymakers in achieving improved adoption rates. Furthermore, few studies have adopted a methodology that leverages the combined power of SEM, ADVIAN® analysis, and crowdsourcing. By constructing comprehensive scenarios for enhanced renewable energy adoption using an innovative methodology, this implementation of the novel methodology aims to provide actionable insights for policymakers. These scenarios can help identify common threads across different adoption paths, serving as a foundation for future policy planning and development. The insights gained would directly contribute to energy efficiency policies and support the achievement of global sustainable development goals.

5.1.1 Renewable energy adoption scenario results

In the first step of the methodology, key factors influencing the adoption of renewable energy were identified through a comprehensive review of existing literature. To ensure robust coverage, articles were sourced from two major databases, Web of Science Core Collection (WoSCC) and Scopus. These databases were used as they are both commonly recommended for systematic reviews due to their complementary data scopes (Kasaraneni and Rosaline 2024). This literature search followed the PRISMA guidelines (Page *et al.* 2021), with the database search conducted on May 20, 2024. A detailed search strategy targeting the title, abstract, and keywords in each paper was applied using the string: TITLE-ABS-KEY((*factor* OR *driver*) AND "*renewable energy*" AND "*structural equation model*ing*") AND PUBYEAR > 2013. The search string included logical operators to identify studies relevant to specific contexts, ensuring that only papers mentioning factors (or drivers) of renewable energy adoption and employing SEM techniques were selected. Given the variations in SEM terminology (e.g., "modeling" vs. "modelling"), a wildcard was included to the search term to capture all relevant publications. The scope of the search was further refined to include only works published in the past decade.

The initial search yielded 306 entries from both databases (175 from WoSCC and 131 from Scopus). After eliminating duplicates (98) and studies with inaccessible full texts (2), 206 articles remained for eligibility screening. After applying inclusion and exclusion criteria, a final set of 81 studies that focused specifically on renewable energy adoption factors was discovered for analysis. Studies were excluded if they addressed tangential topics, such as electric vehicles, renewable energy policies, biowaste, or financial aspects unrelated to adoption drivers (Manutworakit and Choocharukul 2022; Fu and Moeckel 2023; Guo *et al.* 2023; Nguyen and Hoang 2023). Other studies that investigated and reported on renewable energy policies were also eliminated (Doblinger, Dowling and Helm 2016; Liu *et al.* 2021; Shahangian *et al.* 2022). Papers that examined farming, forestry, biogas and biowaste (Sutherland *et al.* 2016; Ali *et al.* 2023b; Ugarte Lucas, Lund and Gamborg 2023) and those investigating the role that corporate social responsibility plays in renewable energy (Mory, Wirtz and Göttel 2016; Xu *et al.* 2022; Panda 2023) were also excluded. Other significant reasons for exclusion were reporting on sustainability goals (Jaber 2020; Poudel, Parton and Morrison 2022; Haldar *et al.* 2023; Mahmood *et al.* 2024), and on financial implications and financial planning for renewable energy systems (Sangroya and Nayak 2017; Chen, Zhuo and Lin 2023; Umamaheswaran *et al.* 2023). The inclusion and exclusion criteria used are outlined in Table 13, and a PRISMA flowchart detailing the search and selection process appears in Figure 17.

Table 13: Inclusion and exclusion criteria for factor identification for renewable energy adoption

ID	Inclusion Criterion	ID	Exclusion Criterion
IC1	Articles published in the English language.	**EC1**	Articles with no full text available.
IC2	Articles that reported certain specific information such as path coefficients.	**EC2**	Retracted articles.
IC3	Articles related to certain specific projects or factors affecting the adoption of renewable energy.	**EC3**	Articles marked as “in press”.
		EC4	Duplicate records.
		EC5	Articles not available in the English language.
		EC6	Gray articles like reviews, newsletters, or conference proceedings.
		EC7	Articles that do not report on specific information such as path coefficients.
		EC8	Articles that do not relate to specific projects or factors affecting the adoption of renewable energy.

Content analysis was used to ensure a comprehensive extraction of relevant factors. While scouring the papers, it was evident that different authors refer to the same factor using different terms. The researcher was mindful of this, merging factors that referred to the same construct by examining the description of the factor that the author provided, e.g., “effort efficacy” and “ease of use” were combined, “social influence”, “social pressure” and “social norm” were amalgamated, “facilitating conditions” and “perceived level of support” were also merged. Ultimately, 36 unique factors were identified, achieving factor saturation after 51 articles. These factors, shown in Table 14, represent a synthesized view from the literature and formed the basis for subsequent scenario-building in the study.

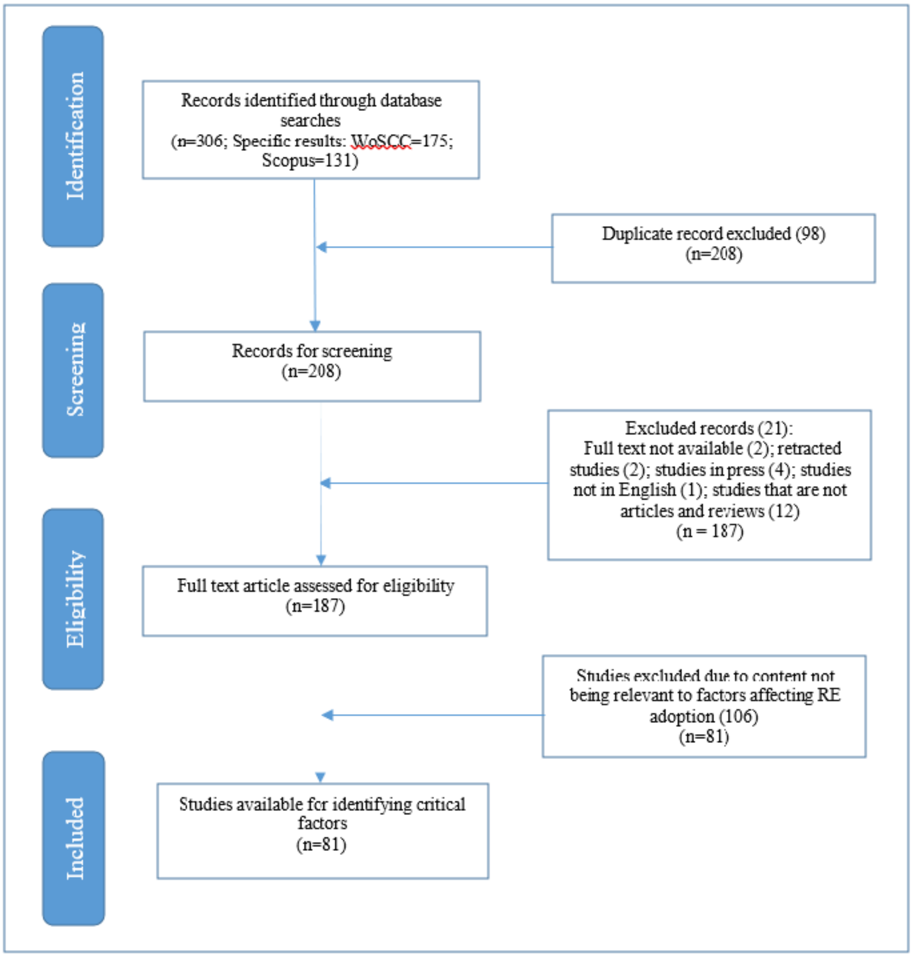


Figure 17: PRISMA protocol for renewable energy adoption studies

Table 14: Factors identified for renewable energy adoption

Factor	Factor Name	References
F1	Perceived performance expectancy	(Kim *et al.* 2014; Yazdanpanah *et al.* 2015; Amin *et al.* 2017; Bozorgparvar *et al.* 2018; Kotilainen and Saari 2018; Rezaei and Ghofranfarid 2018; Akroush *et al.* 2019; Park 2019; Yasmin and Grundmann 2019; Ali *et al.* 2020a; Parsad, Mittal and Krishnankutty 2020; Alwedyan 2021; Angowski *et al.* 2021; Asante *et al.* 2021; Ashinze *et al.* 2021; Bekti *et al.* 2021; Cheam, Lau and Wei 2021; Irfan *et al.* 2021a; Irfan *et al.* 2021b; Jabeen, Ahmad and Zhang 2021; Khalid *et al.* 2021; Marrero *et al.* 2021; Mostafaeipour *et al.* 2021; Wall *et al.* 2021; Yang, Bashiru Danwana and Yassaanah 2021; Chen, Chen and Hsiao 2022; Fatima *et al.* 2022; Fatoki 2022; Mularczyk *et al.* 2022; Nazir and Tian 2022; Nketiah *et al.* 2022; Rana *et al.* 2022; Zeng *et al.* 2022; Ahmad *et al.* 2023a; Ali, Esposito and Gatto 2023; Ali *et al.* 2023a; Asif *et al.* 2023; Harorli and Erciş 2023; Le-Anh *et al.* 2023; Lupoae *et al.* 2023; Muwanga, Mwiru and Watundu 2023; Rahmani and Naeini 2023)
F2	Perceived ease of use	(Yazdanpanah *et al.* 2015; Kotilainen and Saari 2018; Yasmin and Grundmann 2019; Ali *et al.* 2020a; Alwedyan 2021; Ashinze *et al.* 2021; Cheam, Lau and Wei 2021; Khalid *et al.* 2021; Mostafaeipour *et al.* 2021; Tanveer *et al.* 2021; Yang, Bashiru Danwana and Yassaanah 2021; Fatoki 2022; Mularczyk *et al.* 2022; Nazir and Tian 2022; Wang, Mao and Li 2022; Yazdanpanah, Komendantova and Zobeidi 2022; Zeng *et al.* 2022; Rahmani and Naeini 2023; Yin *et al.* 2023; Kumar and Nayak 2024; Wong *et al.* 2024)

F3	Perceived self-efficacy	(Yazdanpanah, Komendantova and Ardestani 2015; Bozorgparvar *et al.* 2018; Rezaei and Ghofranfarid 2018; Shakeel 2018; Jabeen *et al.* 2019; Irfan *et al.* 2020; Ashinze *et al.* 2021; Aslam, Farhat and Arif 2021; Bekti *et al.* 2021; Conradie *et al.* 2021; Irfan *et al.* 2021a; Irfan *et al.* 2021b; Wall *et al.* 2021; Fatima *et al.* 2022; Fatoki 2022; Nketiah *et al.* 2022; Zhang, Chou and Chen 2022; Zobeidi, Komendantova and Yazdanpanah 2022; Asif *et al.* 2023; Fathima MS, Batcha and Alam 2023; Gumasing *et al.* 2023; Le-Anh *et al.* 2023; Nagy, Molnár and Hajdú 2023; Ud Din *et al.* 2023; Wijaya and Kokchang 2023; Wong *et al.* 2024)
F4	Social influence	(Ashinze *et al.* 2021); (Ud Din *et al.* 2023); (Irfan *et al.* 2021a); (Bozorgparvar *et al.* 2018) ; (Zhang, Chou and Chen 2022); (Kesari, Atulkar and Pandey 2021); (Irfan *et al.* 2021b); (Fatoki 2022); (Gumasing *et al.* 2023); (Tanveer *et al.* 2021); (Nketiah *et al.* 2022); (Le-Anh *et al.* 2023); (Yazdanpanah, Komendantova and Zobeidi 2022); (Vu, Nguyen and Nguyen 2023); (Cheraghi, Choobchian and Abbasi 2019);(Alwedyan 2021); (Ahmad *et al.* 2023a); (Emmann, Arens and Theuvsen 2013); (Asif *et al.* 2023); (Lau *et al.* 2020);(Wang *et al.* 2023b); (Kumar and Nayak 2024); (Jabeen, Ahmad and Zhang 2021); (Wang *et al.* 2022a); (Wong *et al.* 2024); (Irfan *et al.* 2020); (Higueras-Castillo *et al.* 2019); (Shakeel 2018); (Nagy, Molnár and Hajdú 2023); (Conradie *et al.* 2021); (Aslam, Farhat and Arif 2021); (Asante *et al.* 2021)
F5	Awareness	(Ashinze *et al.* 2021); (Mostafaeipour *et al.* 2021); (Yang, Bashiru Danwana and Yassaanah 2021); (Irfan *et al.* 2021a); (Irfan *et al.* 2021b); (Jabeen *et al.* 2019); (Fatoki 2022); (Akroush *et al.* 2019); (Wang *et al.* 2020); (Nketiah *et al.* 2022);(Ali, Esposito and Gatto 2023); (Ali *et al.* 2022); (Lupoae *et al.* 2023); (Cheraghi, Choobchian and Abbasi 2019); (Angowski *et al.* 2021); (Wall *et al.* 2021); (Fatima *et al.* 2022); (Ahmad *et al.* 2023a); (Muwanga, Mwiru and Watundu 2023); (Mularczyk *et al.* 2022); (Lau *et al.* 2020); (Zeng *et al.* 2022); (Rahmani and Naeini 2023); (Rezaei and Ghofranfarid 2018); (Marrero *et al.* 2021); (Zobeidi, Komendantova and Yazdanpanah 2022); (Nazir and Tian 2022); (Yin *et al.* 2023); (Shakeel 2018); (Amin *et al.* 2017); (Fathima MS, Batcha and Alam 2023); (Wijaya and Kokchang 2023); (Maqbool 2018); (Rana *et al.* 2022); (Ali *et al.* 2023a)
F6	Perceived cost value	(Ashinze *et al.* 2021); (Yang, Bashiru Danwana and Yassaanah 2021); (Kim *et al.* 2014); (Irfan *et al.* 2021a); (Bozorgparvar *et al.* 2018) ; (Irfan *et al.* 2021b); (Chen, Chen and Hsiao 2022); (Akroush *et al.* 2019); (Bekti *et al.* 2021); (Tanveer *et al.* 2021); (Ali *et al.* 2022); (Vu, Nguyen and Nguyen 2023); (Angowski *et al.* 2021);(Fatima *et al.* 2022); (Lau *et al.* 2020);(Jabeen, Ahmad and Zhang 2021) ;(Yasmin and Grundmann 2019); (Park 2019); (Kumar and Nayak 2024); (Irfan *et al.* 2020); (Nazir and Tian 2022); (Shakeel 2018); (Parsad, Mittal and Krishnankutty 2020); (Harichandan *et al.* 2023)
F7	Attitude	(Ashinze *et al.* 2021); (Yang, Bashiru Danwana and Yassaanah 2021); (Kim *et al.* 2014); (Ud Din *et al.* 2023); (Bozorgparvar *et al.* 2018) ; (Zhang, Chou and Chen 2022); (Kesari, Atulkar and Pandey 2021); (Jabeen *et al.* 2019); (Fatoki 2022); (Akroush *et al.* 2019); (Bekti *et al.* 2021); (Gumasing *et al.* 2023); (Ali *et al.* 2020a); (Nketiah *et al.* 2022); (Le-Anh *et al.* 2023); (Ali, Esposito and Gatto 2023); (Harorli and Erciş 2023); (Lupoae *et al.* 2023); (Vu, Nguyen and Nguyen 2023); (Cheraghi, Choobchian and Abbasi 2019); (Agarwal *et al.* 2023); (Yazdanpanah, Komendantova and Ardestani 2015); (Asif *et al.* 2023); (Mularczyk *et al.* 2022); (Kumar and Nayak 2024); (Kotilainen and Saari 2018); (Rahmani and Naeini 2023); (Zobeidi, Komendantova and Yazdanpanah 2022); (Wong *et al.* 2024); (Irfan *et al.* 2020); (Nazir and Tian 2022);(Higueras-Castillo *et al.* 2019); (Nagy, Molnár and Hajdú 2023); (Conradie *et al.* 2021); (Harichandan *et al.* 2023); (Amin *et al.* 2017); (Fathima MS, Batcha and Alam 2023); (Wijaya and Kokchang 2023); (Rana *et al.* 2022); (Aslam, Farhat and Arif 2021); (Asante *et al.* 2021); (Genç and Akilli 2019)
F8	Geographic and environmental factors	(Mostafaeipour *et al.* 2021)
F9	Behavioural intention	(Ashinze *et al.* 2021);(Mostafaeipour *et al.* 2021); (Yang, Bashiru Danwana and Yassaanah 2021); (Kim *et al.* 2014); (Ud Din *et al.* 2023); (Irfan *et al.* 2021a); (Zhang, Chou and Chen 2022); (Kesari, Atulkar and Pandey 2021); (Chen, Chen and Hsiao 2022); (Fatoki 2022); (Akroush *et al.* 2019); (Bekti *et al.* 2021); (Gumasing *et al.* 2023); (Ali *et al.* 2020a); (Wang *et al.* 2020); (Tanveer *et al.* 2021); (Nketiah *et al.* 2022); (Le-Anh *et al.* 2023); (Ali *et al.* 2022); (Khalid *et al.* 2021); (Harorli and Erciş 2023); (Yazdanpanah, Komendantova and Zobeidi 2022) ; (Vu, Nguyen and Nguyen 2023); (Cheraghi, Choobchian and Abbasi 2019); (Angowski *et al.* 2021); (Agarwal *et al.* 2023); (Wall *et al.* 2021); (Alwedyan 2021); (Kar, Harichandan and Prakash 2024); (Cheam, Lau and Wei 2021); (Yazdanpanah, Komendantova and Ardestani 2015); ;(Fatima *et al.* 2022); (Ahmad *et al.* 2023a); ; (Muwanga, Mwiru and Watundu 2023); (Asif *et al.* 2023); (Mularczyk *et al.* 2022); (Lau *et al.* 2020); (Wang *et al.* 2023b); (Zeng *et al.* 2022);(Kumar and Nayak 2024); (Jabeen, Ahmad and Zhang 2021); (Yasmin and Grundmann 2019; Rahmani and Naeini 2023); (Rezaei and Ghofranfarid 2018); (Marrero *et al.* 2021); (Zobeidi, Komendantova and Yazdanpanah 2022); (Wang *et al.* 2022a); (Wong *et al.* 2024); (Kumar and Nayak 2024); (Irfan *et al.* 2020); (Nazir and Tian 2022); (Higueras-Castillo *et al.* 2019); (Yin *et al.* 2023); (Shakeel 2018); (Nagy, Molnár and Hajdú 2023); (Conradie *et al.* 2021); (Van Dael *et al.* 2017); (Parsad, Mittal and Krishnankutty 2020); (Harichandan *et al.* 2023); (Wijaya and Kokchang 2023); (Zhu 2023); (Maqbool 2018); (Rana *et al.* 2022); (Aslam, Farhat and Arif 2021); (Ali *et al.* 2023a); (Asante *et al.* 2021)
F10	Usage behaviour	(Ashinze *et al.* 2021); (Le-Anh *et al.* 2023); (Conradie *et al.* 2021); (Wijaya and Kokchang 2023); (Zhu 2023)
F11	Infrastructure readiness	(Mostafaeipour *et al.* 2021); (Rahmani and Naeini 2023); (Harichandan *et al.* 2023)
F12	Financial support	(Mostafaeipour *et al.* 2021); (Kesari, Atulkar and Pandey 2021); (Khalid *et al.* 2021); (Vu, Nguyen and Nguyen 2023); (Kar, Harichandan and Prakash 2024); (Ahmad *et al.* 2023a); (Jabeen, Ahmad and Zhang 2021); (Kotilainen and Saari 2018); (Rahmani and Naeini 2023); (Parsad, Mittal and Krishnankutty 2020); (Zhu 2023); (Asante *et al.* 2021)
F13	Facilitating conditions	(Mostafaeipour *et al.* 2021); (Bekti *et al.* 2021); (Ali *et al.* 2022); (Rahmani and Naeini 2023); (Yin *et al.* 2023); (Parsad, Mittal and Krishnankutty 2020)
F14	Hedonic motivation	(Ud Din *et al.* 2023); (Bozorgparvar *et al.* 2018); (Bozorgparvar *et al.* 2018); (Harorli and Erciş 2023)
F15	Perceived environmental awareness	(Yang, Bashiru Danwana and Yassaanah 2021); (Ud Din *et al.* 2023); (Irfan *et al.* 2021a); (Zhang, Chou and Chen 2022); (Irfan *et al.* 2021b); (Jabeen *et al.* 2019); (Fatoki 2022); (Gumasing *et al.* 2023); (Wang *et al.* 2020); (Khalid *et al.* 2021); (Harorli and Erciş 2023); (Lupoae *et al.* 2023); (Angowski *et al.* 2021); (Wall *et al.* 2021); (Kar, Harichandan and Prakash 2024); (Cheam, Lau and Wei 2021); (Lau *et al.* 2020); (Wang *et al.* 2023b); (Zeng *et al.* 2022); (Kumar and Nayak 2024); (Irfan *et al.* 2020); (Higueras-Castillo *et al.* 2019); (Yin *et al.* 2023); (Shakeel 2018); (Nagy, Molnár and Hajdú 2023); (Conradie *et al.* 2021); (Grębosz-Krawczyk *et al.* 2021); (Van Dael *et al.* 2017); (Parsad, Mittal and Krishnankutty 2020); (Fathima MS, Batcha and Alam 2023); (Wijaya and Kokchang 2023); (Aslam, Farhat and Arif 2021); (Ali *et al.* 2023a); (Genç and Akilli 2019)
F16	Perceived system quality	(Kim *et al.* 2014); (Jabeen, Ahmad and Zhang 2021); (Park 2019); (Yin *et al.* 2023)

F17	Perceived trust	(Kim *et al.* 2014); (Yasmin and Grundmann 2019); (Rahmani and Naeini 2023); (Amin *et al.* 2017); (Fathima MS, Batcha and Alam 2023)
F18	Perceived satisfaction	(Kim *et al.* 2014); (Bozorgparvar *et al.* 2018); (Wang *et al.* 2020); (Ali *et al.* 2022); (Jabeen, Ahmad and Zhang 2021); (Yasmin and Grundmann 2019); (Marrero *et al.* 2021)
F19	Perceived risk	(Ud Din *et al.* 2023); (Bozorgparvar *et al.* 2018); (Tanveer *et al.* 2021); (Yazdanpanah, Komendantova and Zobeidi 2022); (Angowski *et al.* 2021); (Kar, Harichandan and Prakash 2024); (Fatima *et al.* 2022); (Jabeen, Ahmad and Zhang 2021); (Yasmin and Grundmann 2019); (Marrero *et al.* 2021); (Park 2019); (Zobeidi, Komendantova and Yazdanpanah 2022); (Wang *et al.* 2022a); (Harichandan *et al.* 2023); (Amin *et al.* 2017)
F20	Moral obligations	(Ud Din *et al.* 2023); (Bozorgparvar *et al.* 2018); (Kesari, Atulkar and Pandey 2021); (Wang *et al.* 2020); (Yazdanpanah, Komendantova and Ardestani 2015); (Rezaei and Ghofranfarid 2018); (Yin *et al.* 2023)
F21	Access to electricity	(Jabeen *et al.* 2019)
F22	Personal innovativeness	(Zhang, Chou and Chen 2022); (Tanveer *et al.* 2021); (Vu, Nguyen and Nguyen 2023); (Angowski *et al.* 2021); (Agarwal *et al.* 2023); (Zeng *et al.* 2022); (Park 2019); (Amin *et al.* 2017); (Maqbool 2018)
F23	Environmental knowledge	(Jabeen *et al.* 2019); (Vu, Nguyen and Nguyen 2023); (Cheam, Lau and Wei 2021); (Fatima *et al.* 2022); (Asif *et al.* 2023); (Park 2019); (Higueras-Castillo *et al.* 2019); (Van Dael *et al.* 2017); (Parsad, Mittal and Krishnankutty 2020); (Aslam, Farhat and Arif 2021); (Genç and Akilli 2019)
F24	Perceived authoritative support	(Gumasing *et al.* 2023); (Wang *et al.* 2023b)
F25	Government policy and propaganda	(Ali *et al.* 2020a); (Nketiah *et al.* 2022); (Cheraghi, Choobchian and Abbasi 2019); (Mularczyk *et al.* 2022); (Kotilainen and Saari 2018); (Dalaeen 2023); (Harichandan *et al.* 2023); (Zhu 2023); (Ali *et al.* 2023a)
F26	Social media influence	(Wang *et al.* 2020); (Zobeidi, Komendantova and Yazdanpanah 2022); (Nazir and Tian 2022); (Ali *et al.* 2023a)
F27	Moral norm	(Wang *et al.* 2020); (Aslam, Farhat and Arif 2021)
F28	Reason for adoption	(Asif *et al.* 2023); (Le-Anh *et al.* 2023)
F29	Socio-demographic factors	(Ali, Esposito and Gatto 2023); (Kar, Harichandan and Prakash 2024);
F30	Perceived compatibility	(Ahmad *et al.* 2023a); (Park 2019); (Kumar and Nayak 2024)
F31	Personal financial commitments	(Conradie *et al.* 2021)
F32	Perceived relevance (usefulness)	(Yasmin and Grundmann 2019); (Marrero *et al.* 2021); (Park 2019); (Wang *et al.* 2022a); (Wong *et al.* 2024); (Kumar and Nayak 2024); (Yin *et al.* 2023); (Conradie *et al.* 2021); (Grębosz-Krawczyk *et al.* 2021); (Harichandan *et al.* 2023); (Maqbool 2018)
F33	Trialability	(Kumar and Nayak 2024)
F34	Pro-environmental behaviour	(Conradie *et al.* 2021)
F35	Perceived community identity	(Conradie *et al.* 2021)
F36	Homeownership	(Conradie *et al.* 2021)

While analysing each paper, the researcher also recorded the path coefficients from each study's SEM analysis (Step 2), as this presents the strength of the relationships between the factors. An Excel spreadsheet was used to record and organize the factors and the corresponding path coefficients from each paper. The factors were arranged as both row and column labels, forming a matrix where each cell represented the influence (path coefficient) one factor has on another. The path coefficient reflects the strength of the relationship between two factors, with the independent factor represented in the row and the dependent factor in the column.

Given that multiple papers reported on the same factor pair relationships, the Excel matrix was coded so that only the highest path coefficient for each of the relationships across studies was displayed in each cell. Table 15 shows the resultant matrix, summarizing all reported path coefficients after reviewing each paper. The matrix's diagonal cells contain zeros, as factors do not affect themselves. All other cells display a single path coefficient. The researcher relied on Excel's MAX function to retrieve the highest coefficient for each relationship. For instance, the intersection of the row labelled "F18" and the column labelled "F9" (0.787) represents the maximum influence that F18 (perceived satisfaction) has on F9 (behavioural intention). The formula in the cell, "=MAX(0.787, 0.119, 0.543, 0.328, 0.24, 0.32)," indicates that six papers examined the F18-F9 relationship. The resulting path coefficient for that cell is 0.787, reported by Kim *et al.* (2014), as it is the highest measure. The final matrix is the output from the second step of the methodology. Since more than 10 impact factors were extracted from the published papers (Figure 5), factors had to be refined in Step 3 so that the most critical could be determined. This matrix of factors therefore served as input to the next step of the methodology.

Table 15: Matrix of factor relationships for renewable energy adoption

Factor	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15	F16	F17	F18
F1	0.000	0.698	0.820	0.620	0.640	0.900	1.000	0.000	0.840	0.000	0.710	0.000	0.450	0.380	0.670	0.000	0.000	0.000
F2	0.520	0.000	0.000	0.610	0.400	0.319	1.000	0.000	0.700	0.000	0.000	0.000	0.000	0.000	0.370	0.000	0.000	0.000
F3	0.310	0.000	0.000	0.370	0.446	0.380	0.400	0.000	0.660	0.408	0.000	0.000	0.000	0.000	0.220	0.000	0.000	0.000
F4	0.610	0.610	0.370	0.000	0.390	0.390	0.596	0.000	0.705	0.363	0.000	0.000	0.400	0.000	0.759	0.000	0.000	0.000
F5	0.905	0.400	0.000	0.390	0.000	0.370	0.517	0.000	0.900	0.000	0.000	0.260	0.430	0.000	0.413	0.000	0.000	0.320
F6	0.377	0.319	0.380	0.431	0.370	0.000	1.000	0.000	0.840	0.000	0.000	0.000	0.000	0.000	0.390	0.250	0.000	0.000
F7	0.530	0.000	0.400	0.400	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.390	0.000	0.000	0.000
F8	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.730	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F9	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.520	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.180
F10	0.000	0.000	0.000	0.000	0.000	0.000	0.168	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F11	0.710	0.000	0.000	0.000	0.000	0.000	0.235	0.730	0.950	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F12	0.392	0.421	0.000	0.000	0.000	0.000	0.349	0.000	0.610	0.585	0.000	0.000	0.000	0.000	0.000	0.000	0.502	0.000
F13	0.450	0.421	0.904	0.400	0.430	0.000	0.235	0.000	0.491	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.502	0.000
F14	0.000	0.421	0.000	0.480	0.000	0.000	0.780	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.880	0.000	0.502	0.000
F15	0.540	0.370	0.399	0.610	0.413	0.390	0.447	0.000	0.465	0.247	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F16	0.820	0.000	0.000	0.000	0.000	0.000	0.660	0.000	0.571	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F17	0.370	0.000	0.000	0.000	0.000	0.000	0.362	0.000	0.201	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F18	0.300	0.000	0.000	0.306	0.349	0.000	0.380	0.000	0.787	0.000	0.000	0.000	0.000	0.000	0.037	0.000	0.000	0.000
F19	0.370	0.520	0.170	0.600	0.190	0.300	0.530	0.000	0.600	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F20	0.538	0.000	0.000	0.690	0.000	0.000	0.261	0.000	0.540	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F21	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.291	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F22	0.430	0.300	0.000	0.370	0.301	0.390	0.277	0.000	0.560	0.000	0.000	0.000	0.000	0.000	0.399	0.000	0.000	0.000
F23	0.290	0.000	0.410	0.270	0.310	0.250	0.800	0.000	0.520	0.000	0.000	0.000	0.000	0.000	0.250	0.000	0.000	0.000
F24	0.000	0.000	0.000	0.206	0.000	0.000	0.244	0.000	0.322	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.450
F25	0.318	0.520	0.000	0.541	0.000	0.000	0.359	0.000	1.000	0.375	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F26	0.000	0.000	0.000	0.000	0.000	0.000	0.442	0.000	0.437	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F27	0.000	0.000	0.261	0.213	0.000	0.000	0.262	0.000	0.202	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F28	0.000	0.000	0.451	0.340	0.000	0.000	0.556	0.000	0.215	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F29	0.108	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.169	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F30	0.390	0.000	0.270	0.000	0.300	0.000	0.000	0.000	0.536	0.000	0.000	0.000	0.500	0.000	0.000	0.000	0.000	0.000
F31	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F32	0.410	0.000	0.000	0.000	0.000	0.000	0.458	0.000	0.677	0.215	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.300
F33	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.750	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F34	0.000	0.000	0.000	0.000	0.000	0.000	0.184	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F35	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F36	0.000	0.000	0.206	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Factor	F19	F20	F21	F22	F23	F24	F25	F26	F27	F28	F29	F30	F31	F32	F33	F34	F35	F36
F1	0.370	0.550	0.000	0.410	0.290	0.000	0.000	0.000	0.000	0.628	0.000	0.390	0.000	0.672	0.000	0.000	0.000	0.000
F2	0.520	0.000	0.000	0.300	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.602	0.000	0.000	0.000	0.000
F3	0.170	0.000	0.000	0.000	0.410	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F4	0.600	0.655	0.000	0.370	0.270	0.000	0.000	0.000	0.000	0.000	0.000	0.270	0.000	0.322	0.000	0.000	0.000	0.000
F5	0.180	0.186	0.000	0.301	0.310	0.000	0.000	0.000	0.000	0.000	0.000	0.300	0.000	0.300	0.000	0.000	0.000	0.000
F6	0.300	0.260	0.000	0.390	0.250	0.000	0.139	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F7	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F8	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F9	0.000	0.000	0.000	0.080	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.280	0.000	0.000	0.000	0.000
F10	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F11	0.000	0.000	0.000	0.000	0.000	0.000	0.538	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F12	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F13	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.500	0.000	0.000	0.000	0.000	0.000	0.000
F14	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F15	0.523	0.126	0.000	0.399	0.646	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F16	0.552	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F17	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F18	0.000	0.162	0.000	0.000	0.000	0.131	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F19	0.000	0.000	0.000	0.210	0.450	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.141	0.000	0.000	0.000	0.000
F20	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.598	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F21	0.000	0.410	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F22	0.380	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F23	0.450	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F24	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F25	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F26	0.270	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F27	0.000	0.311	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F28	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F29	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F30	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F31	0.000	0.000	0.000	0.161	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F32	0.308	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F33	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F34	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F35	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F36	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.287	0.000

The third step of the methodology aims to determine the most critical factors. This is only done if the number of factors exceeds 10 (refer to the flowchart in Figure 5). The most critical factors are determined by refining the factor set, that is only retaining the most influential and uncertain factors. As outlined in Chapter 4, Section 4.2.3, ADVIAN® analysis was applied to the matrix from Step 2 to classify the factors and ascertain the most influential and most uncertain. This section details the use of an automated ADVIAN® tool developed by the researcher to analyse Step 2's matrix and presents the classification results.

The custom tool, *advian_analysis.py*, which was validated with test datasets (see Chapter 4, Section 4.2.3), was run using the matrix from Table 15 as input. Figure 18 shows a screenshot of the input screen, where the user specifies the file containing the matrix, along with feedback indicating that 36 rows of data were processed. The output from the tool is an Excel file containing the ADVIAN® analysis results (see Figure 19).

```
Please enter source data filename (csv file): energy_data
36  rows processing

Process finished with exit code 0
```

Figure 18: Screenshot of input screen to researcher-developed tool for renewable energy data analysis

RESULTS OF ADVIAN ANALYSIS

FACTORS

	1	2	3	4	5	6	7	8	9	10	11	12
RDAS	66.739	32.293	22.819	46.436	39.192	34.44	16.446	4.4138	6.4091	1.0158	19.124	17.286
RDPS	58.577	30.232	30.479	47.445	27.444	22.305	75.591	4.4138	100	16.404	8.7067	1.572
RIAS	76.971	44.36	29.266	59.127	52.174	43.905	22.771	3.0146	2.3862	0.8928	17.695	14.733
RIPS	61.176	37.017	40.639	54.953	38.203	38.076	75.008	1.7786	100	25.199	10.44	2.3181
CRI	68.62	40.522	34.487	57.002	44.645	40.887	41.328	2.3155	15.447	4.7431	13.592	5.8441
INT	69.073	40.688	34.953	57.04	45.189	40.991	48.889	2.3966	51.193	13.046	14.067	8.5257
STA	31.829	59.643	65.973	43.036	55.891	59.216	65.064	97.763	95.339	98.276	86.868	95.994
PRE	72.676	42.398	31.769	58.055	48.263	42.369	30.677	2.642	6.0713	2.0578	15.508	9.2792
DRI	49.146	51.366	43.787	50.422	53.741	50.945	36.552	17.16	14.204	9.2219	39.102	37.246
DRE	43.814	46.922	51.598	48.609	45.986	47.443	66.339	13.181	91.952	48.993	30.035	14.774

	13	14	15	16	17	18	19	20	21	22	23	24
RDAS	26.199	18.52	33.708	15.739	5.6412	14.826	24.675	15.884	4.2385	20.6	21.464	7.3886
RDPS	10.762	2.2976	28.889	1.5116	9.1058	7.5579	27.952	16.083	0	15.847	15.878	0.7921
RIAS	33.866	26.167	48.804	23.083	8.682	17.775	35.149	22.387	2.3041	33.042	29.151	6.1853
RIPS	16.986	5.4253	43.841	2.2215	2.8971	9.1365	36.324	21.856	0	27.069	26.901	0.2793
CRI	23.984	11.915	46.256	7.161	5.0153	12.744	35.732	22.12	0	29.907	28.004	1.3144
INT	25.426	15.796	46.322	12.652	5.7896	13.456	35.736	22.121	1.1521	30.056	28.026	3.2323
STA	77.376	91.013	53.811	95.947	95.655	87.931	64.273	77.882	95.392	70.241	72.019	99.465
PRE	28.5	17.657	47.513	12.857	6.5987	15.051	35.439	22.253	0	31.435	28.572	2.8513
DRI	50.738	48.01	51.215	46.293	28.717	39.383	47.529	41.755	15.179	48.125	45.812	24.706
DRE	35.933	21.861	48.541	14.361	16.589	28.235	48.316	41.257	0	43.559	44.009	5.2503

	25	26	27	28	29	30	31	32	33	34	35	36
RDAS	18.822	6.9472	7.5518	9.4443	1.6748	12.068	0.9735	14.318	4.5347	1.1125	0	2.9808
RDPS	4.0934	0	0	7.4128	0	8.8276	0	14.009	0	0	1.7353	0
RIAS	21.104	4.807	7.8514	10.846	2.0341	16.753	1.2415	13.992	0.4177	0.9778	0	1.407
RIPS	2.5459	0	0	12.016	0	13.687	0	29.329	0	0	5E-22	0
CRI	7.33	0	0	11.416	0	15.143	0	20.257	0	0	0	0
INT	11.825	2.4035	3.9257	11.431	1.0171	15.22	0.6208	21.66	0.2088	0.4889	3E-22	0.7035
STA	95.456	90.386	84.297	88.599	95.932	84.934	97.517	81.055	99.165	98.044	100	97.186
PRE	12.437	0	0	11.128	0	15.927	0	16.835	0	0	0	0
DRI	44.223	21.925	28.02	30.997	14.262	37.704	11.142	33.403	6.4627	9.8884	0	11.862
DRE	15.36	0	0	32.626	0	34.081	0	48.361	0	0	2E-10	0

SYSTEM STABILITY 81.902

Figure 19: Screenshot of the excel output file containing the ADVIAN® results for renewable energy factors

The software tool provides results for all ADVIAN® measures and classifications, making it applicable not only to the current study but to any application of the ADVIAN® method. The first column lists abbreviations for each measure or classification, corresponding to those defined in the algorithm in Chapter 4, Section 4.2.3: RDAS (relative direct active sum); RDPS (relative direct passive sum); RIAS (relative indirect active sum); RIPS (relative indirect passive sum); CRI (criticality); INT (integration); STA (stability); PRE (precarious); DRI (driving); and DRE (driven). For this scenario construction study, only the “driving” and “precarious” classifications were relevant, as the goal was to identify factors that are highly uncertain and that are strongly driving.

Factors advancing to the next step of the methodology were those that exceeded the average by two-thirds of the standard deviation (threshold) in the precarious and driving categories, as established by Guertler and Spinler (2015). For this study, the threshold for precarious measures was 37.605 and 49.173 for the driving category. The most precarious factors included perceived performance expectancy (72.676), social influence (58.055), awareness (48.263), perceived environmental awareness (47.513), perceived ease of use (42.398), and perceived cost value (42.369). While those classified as most driving included awareness (53.741), perceived ease of use (51.366), perceived environmental awareness (51.215), perceived cost value (50.945), facilitating conditions (50.738), and social influence (50.422). This refined set of factors, highlighted in Table 16 and described in

Table 17, served as the output from Step 3 and input to Step 4 of the methodology.

Table 16: ADVIAN® classification of factors for renewable energy adoption

Factor	Factor Name	Precarious	Driving	Factor	Factor Name	Precarious	Driving
F1	Perceived performance expectancy	72.676	49.146	F19	Perceived risk	35.439	47.529
F2	Perceived ease of use	42.398	51.366	F20	Moral obligations	22.253	41.755

F3	Perceived self-efficacy	31.769	43.787	F21	Access to electricity	0.000	15.179
F4	Social influence	58.055	50.422	F22	Personal innovativeness	31.435	48.125
F5	Awareness	48.263	53.741	F23	Environmental knowledge	28.572	45.812
F6	Perceived cost value	42.369	50.945	F24	Perceived authority support	2.851	24.706
F7	Attitude	30.677	36.552	F25	Government policy and propaganda	12.437	44.223
F8	Geographic and environmental factors	2.642	17.160	F26	Social media influence	0.000	21.925
F9	Behavioural intention	6.071	14.204	F27	Moral norm	0.000	28.020
F10	Usage behaviour	2.058	9.222	F28	Reason for adoption	11.128	30.997
F11	Infrastructure readiness	15.508	39.102	F29	Socio-demographic factors	0.000	14.262
F12	Financial support	9.279	37.246	F30	Perceived compatibility	15.927	37.704
F13	Facilitating conditions	28.500	50.738	F31	Personal financial commitments	0.000	11.142
F14	Hedonic motivation	17.657	48.010	F32	Perceived relevance (usefulness)	16.835	33.403
F15	Perceived environmental awareness	47.513	51.215	F33	Trialability	0.000	6.463
F16	Perceived system quality	12.857	46.293	F34	Pro-environmental behaviour	0.000	9.888
F17	Perceived trust	6.599	28.717	F35	Perceived community identity	0.000	0.000
F18	Perceived satisfaction	15.051	39.383	F36	Homeownership	0.000	11.862
Average + 2/3 std dev		**37.605**	**49.173**			**37.605**	**49.173**

Table 17: Refined set of driving and uncertain factors for renewable energy adoption

Factor Name	Factor Description	Reference
Perceived performance expectancy	The degree to which an individual perceives that using a particular system will enhance performance.	Yang, Bashiru Danwana and Yassaanah (2021)
Perceived ease of use	The extent to which a technology is perceived as being difficult to use.	Ashinze *et al.* (2021)
Social influence	The sensed societal influence to engage in or refrain from a certain behaviour.	Yazdanpanah *et al.* (2015)
Awareness	The extent to which individuals understand the technology, including its benefits and drawbacks, and their ability to stay updated with new technological advancements.	Ashinze *et al.* (2021)
Perceived cost value	An individual's assessment of the expenses associated with acquiring, using, or maintaining a product or service.	Ashinze *et al.* (2021)
Facilitating conditions	The extent to which an individual believes that resources, technical support, and organizational readiness are available to help them achieve their usage goals.	Nguyen and Hoang (2023)
Perceived environmental awareness	The level of awareness and concern regarding the resolution of environmental issues.	Irfan *et al.* (2021a)

The primary objective of the fourth step of the methodology was to elicit factor judgements from experts so that a judgement matrix could be created in the subsequent step. Experts for elicitation of the judgements were recruited via crowdsourcing through the “X” platform, where the researcher shared a link to a researcher-developed online tool through a tweet. Before collecting data from experts and in response to feedback from experts during the pilot study, factors were rephrased to provide better clarity (Table 18).

Table 18: Factor rephrasing for renewable energy adoption experiment

Factor	Rephrased Factor
Perceived performance expectancy	Expectancy in terms of the performance of renewable energy systems
Perceived ease of use	Expectancy in terms of user-friendliness
Social influence	Level of pressure from society regarding renewable energy technology
Awareness	Level of renewable energy awareness
Perceived cost value	Expectancy in terms of value for money of renewable technologies
Facilitating conditions	Expectancy in terms of the amount of support available for renewable energy technologies
Perceived environmental awareness	Level of environmental awareness that people have

Before data gathering commenced, an online database and relevant tables for data storage were created (database details are available at https://github.com/robyn-thompson/Robyn-Phd/blob/main/Supporting%20Material.pdf). After creating and populating the database tables, the researcher, on 21 October 2024, released a tweet using their private X account. The tweet was posted at 17:00 that evening as part of the crowdsourcing strategy to attract study participants. The tweet, shown in Figure 20, followed the structure recommended in the literature and outlined in Chapter 4, Section 4.2.4.

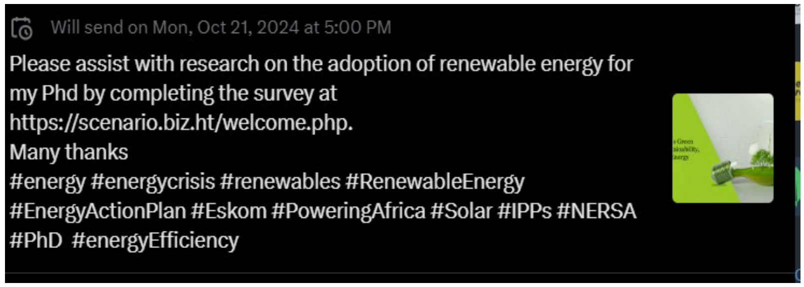


Figure 20: "X" post for distribution of survey link for renewable energy data collection

When participants clicked on the link to the researcher-developed data gathering tool (available at https://scenario.biz.ht/welcome.php), they were presented with the welcome page (Figure 21). This page included a link to the letter of information and consent, which opened in a separate window. If participants chose not to continue with the survey and clicked on "No", they were redirected to an exit screen (Figure 22). For those who agreed to participate, the survey proceeded to the background information form (Figure 23). This form gathered data relating to the participant's expertise in renewable energy, ensuring compliance with the inclusion criteria outlined in Chapter 4, Section 4.2.4 (Table 11). If a participant did not meet the expert criteria, a form thanking them for their interest was displayed (Figure 24).

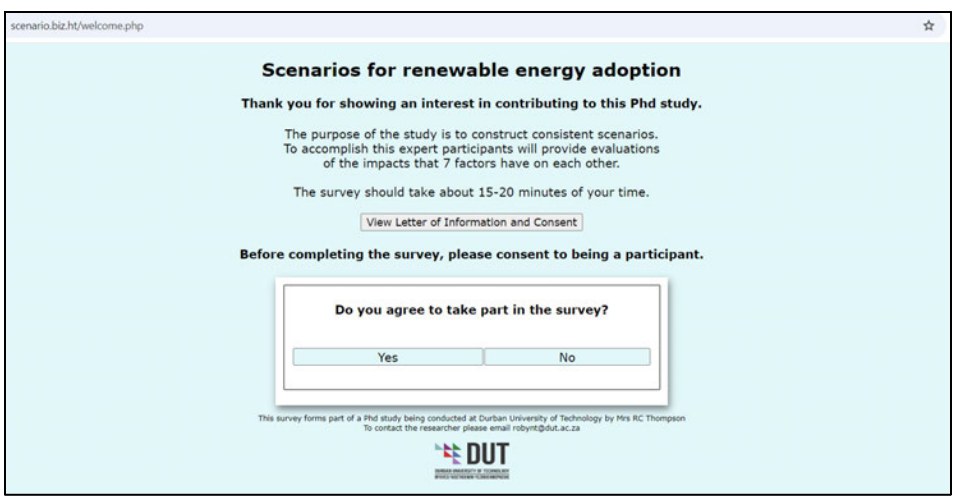


Figure 21: Welcome page (Source: Researcher-developed tool)

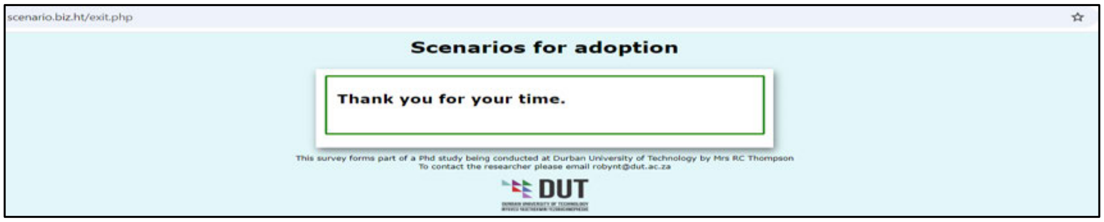


Figure 22: Exit page (Source: Researcher-developed application)

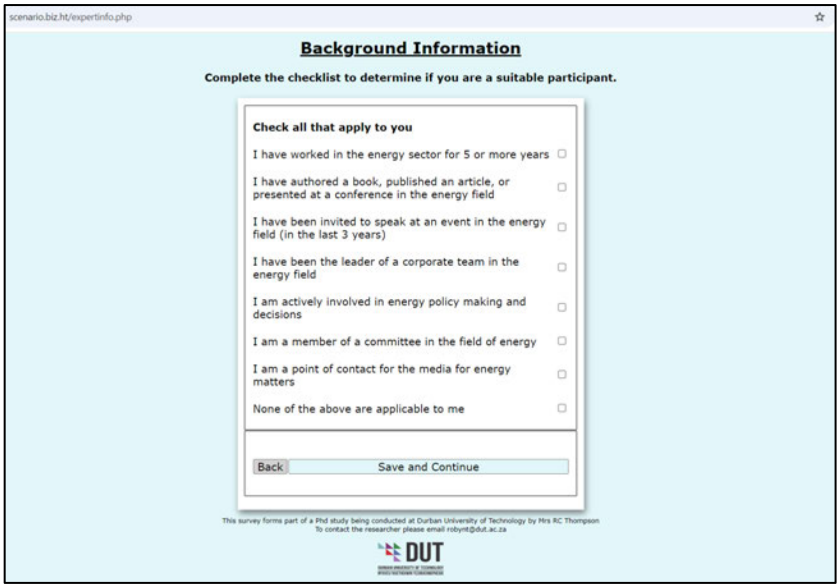


Figure 23: Participant background information page (Source: Researcher-developed application)

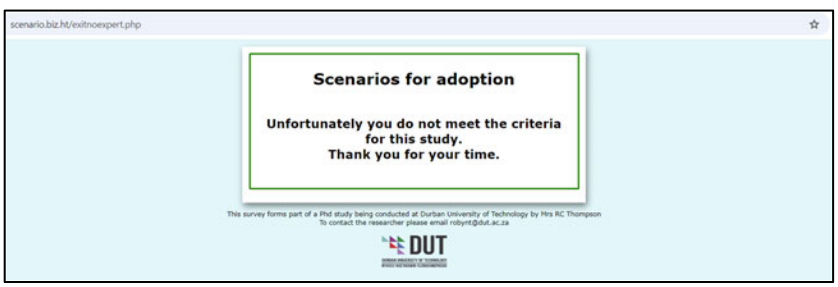


Figure 24: Non-expert exit page (Source: Researcher-developed application)

Participants who were successfully identified as experts in the domain were directed to a set of pages where they provided individual judgements. Each judgement screen required the participant to assess the impact of one independent factor on another dependent factor in both the "high" and "low" state categories. In the context of this renewable energy study, with seven factors being evaluated, each participant completed 42 judgement screens (calculated as n*(n-1)). Example judgement screens from a PC version of the tool are shown in Figure 25, while Figure 26 shows the mobile version of the same screen.

On PC, tooltips were available, providing participants with additional factor information. The information was extracted from the FACTORS_ENERGY table in the database. Tooltips were not available on the mobile version due to the limitations of mobile devices, but a link to a glossary was provided (Figure 27). After completing all judgement screens, the expert's selections were stored in the RELATIONSHIP table in the database. The final screen thanked the participant for their time and provided the researcher's contact e-mail address (Figure 28). This concluded the data gathering process for each participant.

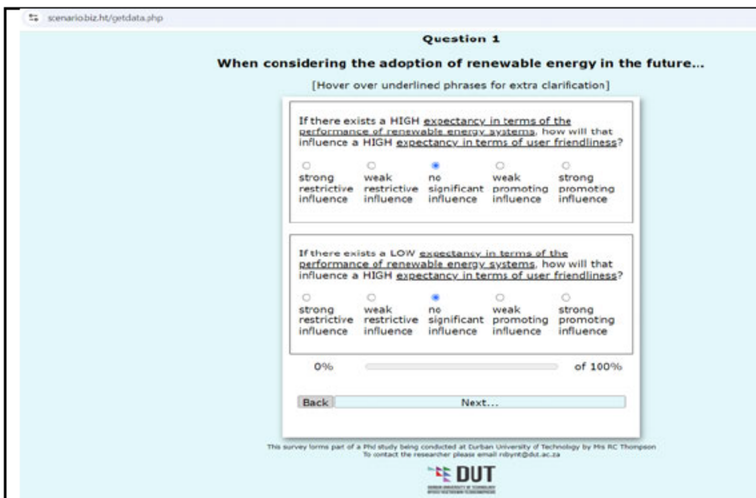


Figure 25: Judgement page for renewable energy application on PC (Source: Researcher-developed tool available at: https://scenario.biz.ht/welcome.php)

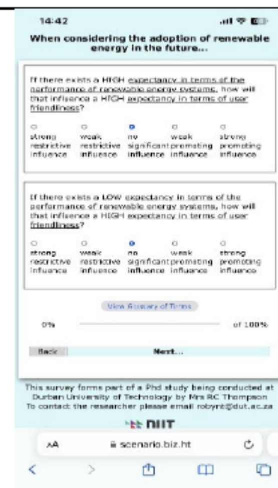


Figure 26: Judgement page for renewable energy application on mobile device (Source: Researcher-developed tool available at: https://scenario.biz.ht/welcome.php)

Glossary

Term	Definition
Environmental awareness	The extent of an individual's awareness and concern regarding the resolution of issues that relate to the environment.
Expected performance of renewable systems	The extent to which individuals believe that renewable energy technologies or systems can enhance their performance or achievements.
Renewable energy awareness	The extent to which individuals understand renewable energy technology, including its benefits and drawbacks, and to some extent how it works and what problems it can solve.
Resource support available	The extent to which an individual believes that resources, technical support, and organizational readiness are available to help them achieve their usage goals.
Social pressure	The sensed societal influence to engage in or refrain from a certain behaviour.
User friendliness	An individual's perception of the expected level of difficulty associated with using a tool or technology.
Value for money expectancy	An individual's expectations of the expenses associated with acquiring, using, or maintaining a product, service or technology versus the benefits and value it provides.

Figure 27: Glossary of terms pop-up (Source: Researcher-developed application)

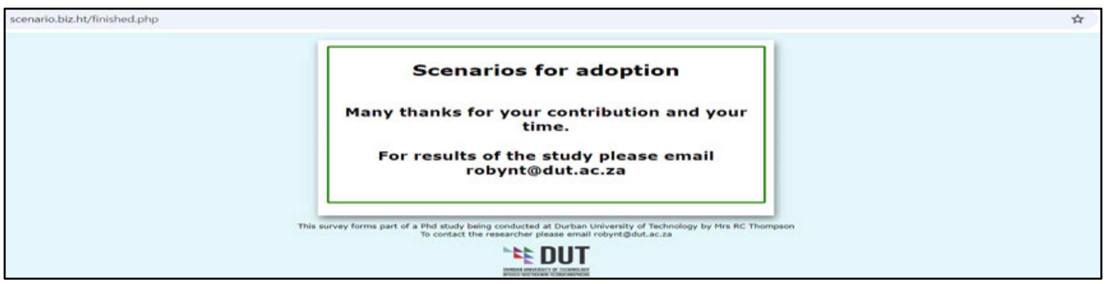


Figure 28: Final page of thanks (Source: Researcher-developed application)

On 11 November 2024, data was extracted from the online database for analysis. While no personal information was collected from expert participants, the researcher did store the responses to the qualifying criteria for all those who met the inclusion criteria. As shown in Table 19, a total of 31 respondents qualified for inclusion in the study. Of these, four respondents met the minimum requirement of two out of the seven criteria, while seven met three of the criteria, and ten respondents satisfied four of the requirements. Five respondents fulfilled five of the criteria, three met six, and two participants met all seven criteria. Consistent with the study's minimum requirements, all participants had at least five years of experience in the renewable energy domain. Furthermore, 81% of the respondents had been invited to speak at renewable energy events, and 71% had published academic works in the field. In terms of leadership roles, 58% of the experts had led a team in the renewable energy sector, while 43% had served on renewable energy committees. Only 42% of respondents had been involved in groups that inform policy decisions. Notably, media engagement appeared to be limited, as only 16% of experts served as points of contact for the media. However, all five of these media contacts met at least four of the other criteria.

Table 19: Inclusion criteria for renewable energy experts

Expert ID	5 years' experience	Published in books, journals etc	Invited Speaker	Leader of a team	Informs Policy	Member of a Committee	Media contact	Number of criteria
E1	✓	✓	✓	✓	✓	✓	✓	7
E2	✓	✓	✓	✓		✓	✓	6
E3	✓	✓	✓	✓		✓		5
E4	✓	✓	✓	✓				4
E5	✓	✓	✓	✓			✓	5
E6	✓		✓	✓				3
E7	✓	✓	✓					3
E8	✓	✓	✓	✓				4
E9	✓		✓	✓				3
E10	✓	✓				✓		3
E11	✓	✓	✓	✓				4
E12	✓		✓		✓			3
E13	✓	✓	✓		✓			4
E14	✓	✓	✓					3
E15	✓	✓	✓		✓			4
E16	✓				✓			2
E17	✓	✓	✓	✓	✓	✓		6
E18	✓	✓	✓	✓				4
E19	✓			✓	✓	✓		4
E20	✓	✓	✓			✓		4
E21	✓	✓	✓		✓	✓		5
E22	✓	✓	✓		✓			4
E23	✓	✓	✓	✓				4
E24	✓			✓				2
E25	✓			✓				2
E26	✓		✓	✓		✓	✓	5
E27	✓	✓	✓		✓	✓		5
E28	✓		✓			✓		3
E29	✓	✓	✓	✓	✓	✓		6
E30	✓	✓	✓	✓	✓	✓	✓	7
E31	✓	✓						2
Total	31	22 (71%)	25 (81%)	18 (58%)	12 (39%)	13 (42%)	5 (16%)	

While 31 respondents met the expert criteria, only 14 completed the survey and provided a complete set of factor judgements. This equates to a 55% dropout rate among eligible participants, which is in line with the dropout rates reported by McConnell, Finetto and Heise (2024) and Esch, Mylonopoulos and Theoharakis

(2025), who advise that these can be from 2% to 75%. The judgement data from these expert participants, which was stored in the database tables, was the output from this step and was used to create a final judgement matrix in the next step of the methodology. The expert judgements collected from these experts were stored in the database table and were the output from Step 4 of the methodology. It was used as input to Step 5.

It is in Step 5 that the final consolidated judgement matrix was created from the judgements gathered in Step 4. This final matrix was generated through the researcher-developed PHP script (toexcel.php), which is available in the GitHub repository. The script processed the expert judgements and produced a .csv file, as shown in Figure 29. The output matrix contained the evaluated data, which served as the output from this fifth step and the foundation for the subsequent and final step of the methodology.

"Cross Impact Balance Matrix"

		F1		F2		F4		F5		F6		F13		F15	
		H	L	H	L	H	L	H	L	H	L	H	L	H	L
F1	H	0	0	1	-1	2	-2	2	-2	2	-2	2	-2	1	-1
	L	0	0	-1	1	-1	1	-1	1	0	0	-1	1	-1	1
F2	H	2	-2	0	0	2	-2	1	-1	1	-1	2	-2	1	-1
	L	-1	1	0	0	-1	1	-1	1	-1	1	-1	1	0	0
F4	H	1	-1	2	-2	0	0	2	-2	1	-1	2	-2	2	-2
	L	-1	1	-1	1	0	0	-1	1	0	0	-1	1	-1	1
F5	H	1	-1	1	-1	1	-1	0	0	1	-1	1	-1	2	-2
	L	-1	1	-1	1	0	0	0	0	-1	1	-1	1	-1	1
F6	H	2	-2	1	-1	2	-2	1	-1	0	0	2	-2	1	-1
	L	-1	1	-1	1	-1	1	-1	1	0	0	-1	1	-1	1
F13	H	1	-1	1	-1	1	-1	2	-2	1	-1	0	0	2	-2
	L	-1	1	-1	1	-1	1	-1	1	-1	1	0	0	-1	1
F15	H	1	-1	1	-1	1	-1	2	-2	1	-1	1	-1	0	0
	L	-1	1	-1	1	-1	1	-1	1	-1	1	-1	1	0	0

Figure 29: Judgement matrix for renewable energy study (Source: Researcher-developed tool available at: https://scenario.biz.ht/toexcel.php)

The sixth and final phase of the methodology focused on generating consistent scenarios using the judgement matrix from the prior step as input. The ScenarioWizard software tool, as outlined by Weimer-Jehle (2023b), was used for the construction of consistent scenarios according to the following tasks:

1 The analysis structure was created, capturing both the long descriptions and abbreviations of the factors (Figure 30 and Figure 31).

2 The expert judgements were captured in the matrix (Figure 32).

3 The consistency of each judgement group was checked, with no anomalies detected during this process.

4 Consistency measures for all possible scenario options were computed. The report in Figure 33 highlights the scenarios with the highest consistency values, and the tabular representation of the scenarios shown in Figure 34.

Edit analysis structure

Descriptors:	variant [1]	variant [2]
F1: Perceived performance expectancy	High	Low
F2: Perceived Ease of Use	High	Low
F4: Social Influence	High	Low
F5: Awareness	High	Low
F6: Perceived Cost Value	High	Low
F13: Facilitating Conditions	High	Low
F15: Perceived Environmental Awareness	High	Low

Figure 30: The matrix structure for renewable energy study with factor names

Edit analysis structure

Descriptors:	variant [1]	variant [2]
F1	H	L
F2	H	L
F4	H	L
F5	H	L
F6	H	L
F13	H	L
F15	H	L

Figure 31: The matrix structure for renewable energy study with abbreviated factor names

Cross-Impact Matrix

REscenarios	F1 H	F1 L	F2 H	F2 L	F4 H	F4 L	F5 H	F5 L	F6 H	F6 L	F13 H	F13 L	F15 H	F15 L
F1: Perceived performance expectancy:														
High			1	-1	2	-2	2	-2	2	-2	2	-2	1	-1
Low			-1	1	-1	1	-1	1	0	0	-1	1	-1	1
F2: Perceived Ease of Use:														
High	2	-2			2	-2	1	-1	1	-1	2	-2	1	-1
Low	-1	1			-1	1	-1	1	-1	1	-1	1	0	0
F4: Social Influence:														
High	1	-1	2	-2			2	-2	1	-1	2	-2	2	-2
Low	-1	1	-1	1			-1	1	0	0	-1	1	-1	1
F5: Awareness:														
High	1	-1	1	-1	1	-1			1	-1	1	-1	2	-2
Low	-1	1	-1	1	0	0			-1	1	-1	1	-1	1
F6: Perceived Cost Value:														
High	2	-2	1	-1	2	-2	1	-1			2	-2	1	-1
Low	-1	1	-1	1	-1	1	-1	1			-1	1	-1	1
F13: Facilitating Conditions:														
High	1	-1	1	-1	1	-1	2	-2	1	-1			2	-2
Low	-1	1	-1	1	-1	1	-1	1	-1	1			-1	1
F15: Perceived Environmental Awareness:														
High	1	-1	1	-1	1	-1	2	-2	1	-1	1	-1		
Low	-1	1	-1	1	-1	1	-1	1	-1	1	-1	1		

+ - Accept Print

Figure 32: Final judgement matrix for the renewable energy study

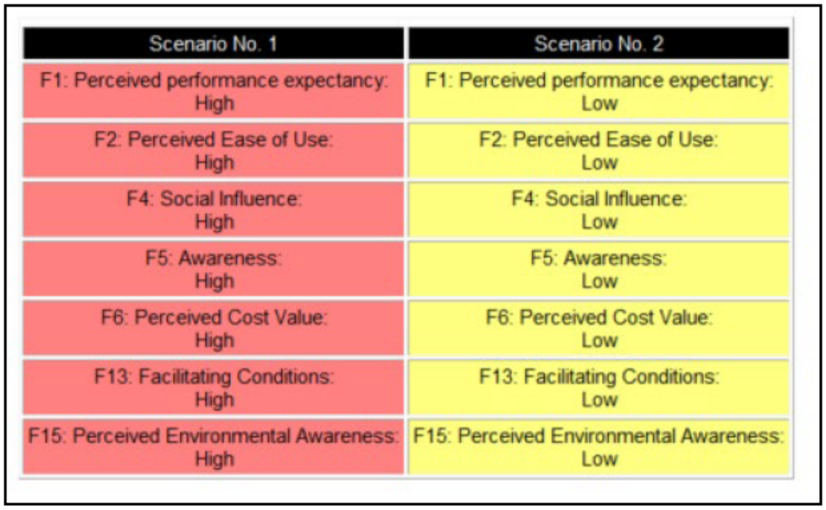
Evaluation protocol

```
Consistent scenarios of CI matrix REscenarios:
Strong consistency


==============================================
Scenario No. 1
Consistency value :  14
Total impact score:  60
----------------------------------------------
F1: Perceived performance expectancy  : High
F2: Perceived Ease of Use             : High
F4: Social Influence                  : High
F5: Awareness                         : High
F6: Perceived Cost Value              : High
F13: Facilitating Conditions          : High
F15: Perceived Environmental Awareness: High
==============================================

==============================================
Scenario No. 2
Consistency value :  8
Total impact score:  38
----------------------------------------------
F1: Perceived performance expectancy  : Low
F2: Perceived Ease of Use             : Low
F4: Social Influence                  : Low
F5: Awareness                         : Low
F6: Perceived Cost Value              : Low
F13: Facilitating Conditions          : Low
F15: Perceived Environmental Awareness: Low
==============================================
```

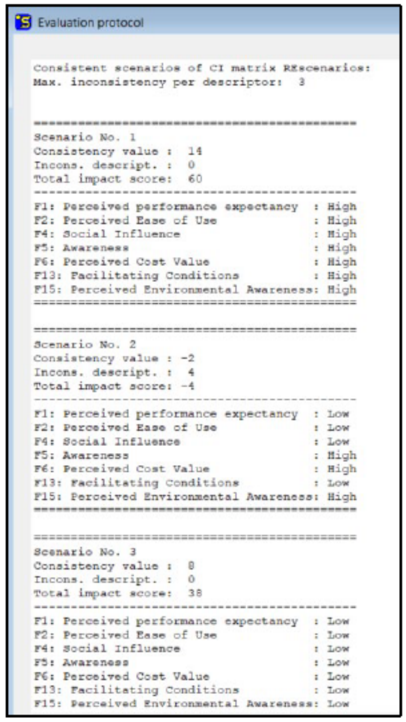
Figure 33: Fully consistent scenarios generated for the adoption of renewable energy



Scenario No. 1	Scenario No. 2
F1: Perceived performance expectancy: High	F1: Perceived performance expectancy: Low
F2: Perceived Ease of Use: High	F2: Perceived Ease of Use: Low
F4: Social Influence: High	F4: Social Influence: Low
F5: Awareness: High	F5: Awareness: Low
F6: Perceived Cost Value: High	F6: Perceived Cost Value: Low
F13: Facilitating Conditions: High	F13: Facilitating Conditions: Low
F15: Perceived Environmental Awareness: High	F15: Perceived Environmental Awareness: Low

Figure 34: Tableau of consistent scenarios for the adoption of renewable energy study

The ScenarioWizard tool identifies only fully consistent scenarios. According to Lindgren and Bandhold (2009), the optimal number of scenarios for scenario building is between three and five, while Finlay (1998) suggests that three is the ideal number. The analysis produced only two consistent scenarios. However, additional scenarios can be generated by lowering the consistency threshold (Tori, Te Boveldt and Keseru 2023). By adjusting the threshold to three, where the difference between the chosen factor's impact value and the highest possible impact value was no more than three, one additional scenario was created, bringing the total to three consistent scenarios. Further adjustments to the threshold revealed that reducing it to one or two did not generate any additional scenarios, while increasing it to four resulted in the generation of 17 different scenarios. Despite this, literature indicates that three scenarios are both manageable and optimal. Therefore, the final set of scenarios, which meets the study's objective of applying the novel methodology to develop consistent and time-sensitive scenarios, consisted of the three scenarios generated with a threshold value of three. These scenarios are presented in Figure 35 and Table 20.



```
Evaluation protocol

Consistent scenarios of CI matrix REscenarios:
Max. inconsistency per descriptor:  3


============================================
Scenario No. 1
Consistency value :  14
Incons. descript. :  0
Total impact score:  60
--------------------------------------------
F1: Perceived performance expectancy  : High
F2: Perceived Ease of Use             : High
F4: Social Influence                  : High
F5: Awareness                         : High
F6: Perceived Cost Value              : High
F13: Facilitating Conditions          : High
F15: Perceived Environmental Awareness: High
============================================

============================================
Scenario No. 2
Consistency value : -2
Incons. descript. :  4
Total impact score: -4
--------------------------------------------
F1: Perceived performance expectancy  : Low
F2: Perceived Ease of Use             : Low
F4: Social Influence                  : Low
F5: Awareness                         : High
F6: Perceived Cost Value              : High
F13: Facilitating Conditions          : Low
F15: Perceived Environmental Awareness: High
============================================

============================================
Scenario No. 3
Consistency value :  8
Incons. descript. :  0
Total impact score:  38
--------------------------------------------
F1: Perceived performance expectancy  : Low
F2: Perceived Ease of Use             : Low
F4: Social Influence                  : Low
F5: Awareness                         : Low
F6: Perceived Cost Value              : Low
F13: Facilitating Conditions          : Low
F15: Perceived Environmental Awareness: Low
```

Figure 35: Scenarios generated for the adoption of renewable energy with a consistency threshold of three

Table 20: Table of scenarios generated for the renewable energy adoption project

Scenario	Best-case scenario	Base-case scenario	Worst-case scenario
Perceived Performance Expectancy	High	Low	Low
Perceived Ease of Use	High	Low	Low
Social Influence	High	Low	Low
Awareness	High	High	Low
Perceived Cost Value	High	High	Low
Facilitating Conditions	High	Low	Low
Perceived Environmental Awareness	High	High	Low
	Promotes renewable energy adoption	Moderate renewable energy adoption	Restricts renewable energy adoption

Table 20 shows the consistently constructed scenarios with the rows presenting the most critical factors for renewable energy adoption. The scenario are labelled '**Best-case**' (Optimized Adoption); **'Base-case'** (Value-Driven Awareness); and '**Worst-case**' (Systemic Resistance), with these labels representing the promoting, moderating or restricting states of each of the factors. While there are seven descriptors in each of the scenarios, they can be reduced to three by applying the principle of relatedness to these descriptors. The principle of relatedness refers to the grouping or classifying objects based on their meaningful connections, similarities, or contextual relationships (Palmer, 1992). Therefore, the seven factors can be grouped into three constructs according to their functional similarities and conceptual connections in the context of technology adoption models. The first construct can be named **perceived value**. This includes the factors' perceived performance expectancy, perceived ease of use, and perceived cost value. The factors are related because they influence whether individuals, businesses, and government organizations see renewable energy as a viable investment based on effort, usability, and cost savings. The second is **awareness** and includes awareness, social influence, and perceived environmental awareness. These factors affect public opinion and the motivation to adopt renewable energy technologies. The last construct, **perceived support,** includes facilitating conditions and perceived ease of use, both of which influence how easily users of renewable energy can transition to the new technology given the support in place and resources available.

Considering these groupings, the '**best-case**' scenario characterized by high perceived value, high awareness, and high perceived support. This scenario can enhance the adoption of renewable energy technology and greatly increase the chances of attaining some of the SDGs. This scenario portrays an idealistic but possibly unrealistic future. In contrast, the '**worst-case**' scenario has low states for all impact factors. This scenario would not promote renewable energy adoption but would rather hinder progress. This is also not a realistic scenario and would impede the attainment of the SDGs. The '**base-case**' scenario has a mixture of high and low states for the impact factors. The construct states for this scenario are low for perceived value and perceived support, while awareness is high when considering the individual factors in Table 20. The scenario with a mixture of states can provide a more realistic view of the future and offer decision makers useful insights into renewable energy adoption issues and areas that need intervention strategies to enhance and accelerate its use.

5.2 Consistent Artificial Intelligence in Higher Education Adoption Scenarios

In recent decades, technological advancements have sparked a global surge in the use of AI across a wide range of sectors, including higher education (Cambra-Fierro *et al.* 2024; Sanusi, Ayanwale and Chiu 2024). AI, defined as the development of systems capable of performing human-like tasks (Du-Harpur *et al.* 2020), has rapidly integrated with higher education systems (Ahmad *et al.* 2023b). This adoption is reflected in various educational applications, such as tutoring systems, personalized learning platforms, adaptive assessment tools, and automation of tasks for educators. Additionally, AI-assisted content creation has gained popularity in academic settings (Mousavinasab *et al.* 2021; Bhutoria 2022; Xieling *et al.* 2022). AI-based speech recognition technologies are aiding language development, while machine learning algorithms are enhancing the personalization of learning environments for students (Gao 2023). With AI becoming an integral part of educational systems, numerous opportunities for innovation have emerged (Cheng, Sun and Zarifis 2020). To remain competitive and at the forefront of educational advancements, higher education institutions must ensure the adoption of state-of-the-art teaching, learning, and assessment strategies, embracing AI technology as a key enabler (Adamson and Sloan 2023).

Among the most notable in recent AI adoption is the rise of generative AI, particularly the ChatGPT platform. Researchers have increasingly focused on its potential in education, with studies by Li *et al.* (2024a) and Maheshwari (2024), exploring its applications, while Demeke (2023) examined educators' acceptance of ChatGPT for fostering metacognitive self-regulated learning. The adoption of ChatGPT by both students and educators has also been a subject of research, with academics such as Qu and Wu (2024), Cortez *et al.* (2024), Polyportis and Pahos (2024), and Grassini, Aasen and Møgelvang (2024). Chen *et al.* (2023) and Lin, Jhang and Wang (2024) also reported on the acceptance of AI robots as educators in higher education settings. Despite the growing interest in AI, there are concerns regarding its effective use. Hwang *et al.* (2020) argue that AI remains a highly technical, cross-disciplinary field, with many education practitioners lacking the knowledge and skills to effectively incorporate AI into their teaching practices. Developing AI-based learning activities has been identified as particularly challenging for educators. Additionally, students have expressed anxiety about the effect of AI on their learning process and potential future job prospects, with some fearing that it may limit their career opportunities (Wang *et al.* 2022b). Sanusi, Ayanwale and Chiu (2024) contend that equipping students with foundational AI knowledge is essential for preparing them for an AI-enabled future. This idea is supported by Paré *et al.* (2022), who report that although medical students demonstrated a strong intention to adopt AI, barriers such as a lack of competence and anxiety prevented them from putting this intention into practice.

Researchers have employed various models and theories to better understand the adoption and integration of AI in education. These include the technology acceptance model (TAM) (Demeke 2023; Ni and Cheung 2023); task-technology fit model (Chen, Zhuo and Lin 2023), theory of planned behaviour (Jatileni *et al.* 2023; Sanusi, Ayanwale and Chiu 2024); the hedonic motivation system adoption model (Qu and Wu 2024); unified theory of acceptance and use of technology (Raffaghelli *et al.* 2022; Salifu *et al.* 2024); the uses and gratification framework (Gao 2023); and theory of reasoned action (Beyari and Garamoun 2022). These models have also been used in various combinations to examine the factors influencing the adoption of AI in educational settings (Chen *et al.* 2023; Du *et al.* 2024).

Despite this extensive body of literature, research that systematically extracts and integrates the factors across these diverse models to construct comprehensive scenarios for the future adoption of AI in education remains lacking. This implementation of the methodology aims to fill this gap by applying a novel methodology to examine the factors identified in existing studies, and to develop scenarios that consider all relevant models and theories for the future of AI adoption in higher education.

5.2.1 Artificial intelligence in higher education adoption results

In order to create the impact matrix, which is the starting point for the methodology, empirically tested factors relevant to the adoption of AI in higher education were extracted from published studies. The WoSCC and SCOPUS databases were searched as they both include the most prominent journals in the fields of AI, computer science, statistics, engineering, mathematics (Khosravi _et al._ 2024) and education (Maral 2024). A search of the databases was conducted on 2 August 2024 following the PRISMA guidelines and the reporting checklist (Page _et al._ 2021). The search string used was: TITLE-ABS-KEY ("_structural equation model*ing"_ AND _("AI" OR "artificial intelligence" OR "robot_") AND ("_university_" OR "_school_" OR "_tertiary_" OR "_education_" OR "_learning_") AND ("_intent*_" OR "_accept*_" OR "_use_" OR "_adopt*_") AND PUBYEAR > 2013). This search string consisted of five sections, each separated by the 'AND' operator, ensuring the retrieval of studies specifically relevant to the context of the research.

1. The first section focused on studies using the SEM method, with a wildcard used to account for variations in spelling (e.g., "modeling" vs. "modelling").

2. The second section aimed to include papers referencing "artificial intelligence" (or its variations like "AI" or "robotics") in their title, abstract, or keywords.

3. The third section targeted studies related to "higher education" and its variations (e.g., "university", "school", "tertiary", "education", "learning").

4. The fourth section ensured that papers addressing adoption practices were captured, with wildcards to include variations like "adoption" or "adopted".

5. The final part limited the search to works published after 2013, ensuring a ten-year scope.

The search identified 439 papers (WoSCC = 175, SCOPUS = 259). After excluding duplicates across databases (63), 371 papers were available for screening. Further papers were excluded due to full texts not being available (147); papers being retracted (2); articles not being in English (2); papers being listed as "in press" (43); and studies that were neither articles nor review papers (57). This resulted in 120 papers that were eligible for inclusion. After reviewing papers according to the inclusion criteria (Table 21), 66 articles and review papers were identified for final analysis. The 54 excluded studies were removed for the following reasons: four papers did not report the path coefficients of the relationships, while 50 studies did not focus specifically on the factors affecting AI adoption in higher education. Other papers were excluded as the context of the study was not relevant to the experiment: AI in preschool education (Ayanwale *et al.* 2024), AI for combating cyberbullying (Sánchez-Medina, Galván-Sánchez and Fernández-Monroy 2020; Khan *et al.* 2024), the promotion of physical activity through AI (Catellani *et al.* 2023), and where "AI" referred to "alcohol intoxication" (rather than artificial intelligence) (Stamates, Lau-Barraco and Linden-Carmichael 2016; Glenn *et al.* 2019; Swaim and Stanley 2019). The criteria for inclusion and exclusion are detailed in Table 21 while the flowchart illustrating the systematic literature search process is shown in Figure 36.

Table 21: Inclusion and exclusion criteria for factor identification for AI adoption

ID	Inclusion Criterion	ID	Exclusion Criterion
IC1	Articles published in the English language.	**EC1**	Articles with no full text available.
IC2	Articles that reported specific information such as path coefficients.	**EC2**	Retracted articles.
IC3	Articles related to specific projects or factors impacting the adoption of AI in higher education.	**EC3**	Articles marked as “in the press”.
		EC4	Duplicate records.
		EC5	Articles not available in the English language.
		EC6	Gray articles like reviews, newsletters, or conference proceedings.
		EC7	Articles that do not report on specific information such as path coefficients.
		EC8	Articles that do not relate to specific projects or factors affecting the adoption of AI in higher education.

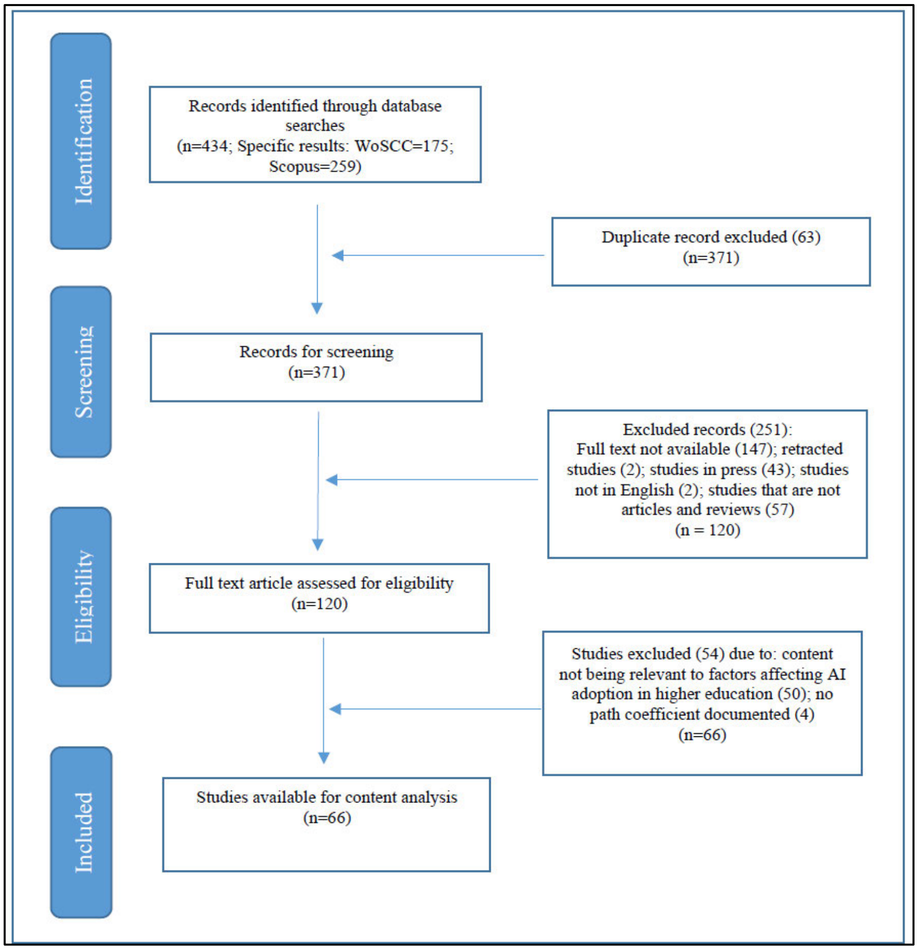


Figure 36: PRISMA protocol for AI adoption study

Factors influencing the adoption of AI in higher education were identified through content analysis. To ensure thoroughness, each paper was reviewed twice, with attention given to variations in terminology across authors for the same underlying factors. Where necessary, terms were consolidated; for instance, “hedonic motivation” and “perceived enjoyment” were unified under a single construct, as were “perceived value” and “perceived cost value.” Upon completion of content analysis and merging synonymous terms, 27 distinct factors were finalized for further analysis. It was observed that factor saturation occurred after reviewing 56 research papers. Table 22 presents the final set of factors along with citations relevant to each, and was the output from Step 1 of the methodology.

Table 22: Factors identified for AI adoption in higher education

Factor	Factor Name	References
F1	Behavioural intention	(Demeke 2023); (Ni and Cheung 2023); (Chen *et al.* 2023); (Sanusi, Ayanwale and Chiu 2024); (Jatileni *et al.* 2023); (Qu and Wu 2024); (Cambra-Fierro *et al.* 2024); (Ayanwale *et al.* 2022); (Lai, Cheung and Chan 2023); (Segbenya *et al.* 2023); (Sanusi, Ayanwale and Tolorunleke 2024); (Raffaghelli *et al.* 2022); (McLean and Osei-Frimpong 2019); (Mukuka 2024); (Cortez *et al.* 2024); (Dahri *et al.* 2024); (Almulla 2024); (Yao and Wang 2024); (Jo and Bang 2023); (Gao 2023); (Du *et al.* 2024); (Polyportis and Pahos 2024); (Grassini, Aasen and Møgelvang 2024); (Li 2024); (Wang *et al.* 2022b); (Adelana, Ayanwale and Sanusi 2024); (Salifu *et al.* 2024); (Kar, Harichandan and Prakash 2024); (Chen *et al.* 2020); (Paraskevi, Saprikis and Avlogiaris 2023); (Zhu, Wang and Pu 2022); (Paré *et al.* 2022); (Chai *et al.* 2024); (Wang *et al.* 2023a); (Zhang *et al.* 2023); (Islam *et al.* 2024); (Li, Gao and Liao 2024); (Sánchez-Holgado and Arcila-Calderón 2024); (Wu *et al.* 2024);(Wen *et al.* 2024); (Sîrghi *et al.* 2024); (Alrishan 2023); (Huang, Kumarasinghe and Jayarathna 2024); (Naidoo 2023); (Yu, Yan and Cai 2024); (García de Blanes Sebastián, Sarmiento Guede and Antonovica 2022); (Tian *et al.* 2024); (Van Phuoc 2022); (Al-Abdullatif 2023); (Sobaih, Elshaer and Hasanein 2024); (Yuduang *et al.* 2022); (Li *et al.* 2022); (Cheng, Li and Xu 2022); (Chai, Wang and Xu 2020); (Milicevic *et al.* 2024); (Masadeh *et al.* 2024); (Alzyoud *et al.* 2024); (Di Battista *et al.* 2023); (Elstad and Eriksen 2024)
F2	Perceived relevance (usefulness)	(Demeke 2023); (Sanusi, Ayanwale and Chiu 2024); (Ayanwale *et al.* 2022); (Zhang *et al.* 2023) ; (Sanusi, Ayanwale and Tolorunleke 2024); (Jo and Bang 2023); (Kar, Harichandan and Prakash 2024); (Paré *et al.* 2022); (Chai *et al.* 2024); (Sîrghi *et al.* 2024); (Alrishan 2023); (Li *et al.* 2022); (Yu, Yan and Cai 2024); (Tian *et al.* 2024); (Naidoo 2023); (Wang *et al.* 2022b)
F3	Perceived system quality	(Demeke 2023); (Almulla 2024); (Jo and Bang 2023); (Paraskevi, Saprikis and Avlogiaris 2023); (Sîrghi *et al.* 2024); (Naidoo 2023); (Yu, Yan and Cai 2024);
F4	Perceived self-efficacy	(Ni and Cheung 2023); (Ayanwale *et al.* 2022) ; (Sanusi, Ayanwale and Tolorunleke 2024); (Dahri *et al.* 2024); (Yao and Wang 2024);(Li *et al.* 2024b); (Du *et al.* 2024); (Wang *et al.* 2022b); (Chai *et al.* 2024); (Wang *et al.* 2023a); (Zhang *et al.* 2023); (Li, Gao and Liao 2024); (Yuduang *et al.* 2022); (Li *et al.* 2022); (Chai, Wang and Xu 2020); (Elstad and Eriksen 2024); (Cortez *et al.* 2024);
F5	Perceived anxiety	(Ni and Cheung 2023); (Chen *et al.* 2023); (Sanusi, Ayanwale and Chiu 2024); Jatileni et al., 2023; (Cambra-Fierro *et al.* 2024); (Sanusi, Ayanwale and Tolorunleke 2024); (Li *et al.* 2024b); (Li 2024); (Wang *et al.* 2022b); (Kar, Harichandan and Prakash 2024); (Zhang *et al.* 2023); (Wen *et al.* 2024); (Chai, Wang and Xu 2020); (Wang *et al.* 2022b);
F6	Hedonic motivation	(Ni and Cheung 2023); (Qu and Wu 2024) ; (Cambra-Fierro *et al.* 2024); (Lai, Cheung and Chan 2023); (Dahri *et al.* 2024); (Lin, Jhang and Wang 2024); (Cambra-Fierro *et al.* 2024); (Habibi *et al.* 2023); (Gao 2023); (Salifu *et al.* 2024); (Paraskevi, Saprikis and Avlogiaris 2023); (Zhu, Wang and Pu 2022); (Zhang *et al.* 2023); (Islam *et al.* 2024); (Li, Gao and Liao 2024); (Sánchez-Holgado and Arcila-Calderón 2024); (Sîrghi *et al.* 2024); (Al-Abdullatif 2023); (Masadeh *et al.* 2024); (Di Battista *et al.* 2023)
F7	Facilitating conditions	(Ni and Cheung 2023); (Segbenya *et al.* 2023); (Habibi *et al.* 2023); (Raffaghelli *et al.* 2022); (Cortez *et al.* 2024); (Jo and Bang 2023); (Polyportis and Pahos 2024); (Li 2024); (Salifu *et al.* 2024); (Chen *et al.* 2020); (Paraskevi, Saprikis and Avlogiaris 2023); (Zhu, Wang and Pu 2022); (Paré *et al.* 2022); (Chai *et al.* 2024); (Wang *et al.* 2023a); (Islam *et al.* 2024); (Sánchez-Holgado and Arcila-Calderón 2024); (Wen *et al.* 2024); (Alrishan 2023); (Yu, Yan and Cai 2024); (Chai, Wang and Xu 2020)
F8	Perceived performance expectancy	(Ni and Cheung 2023); (Chen *et al.* 2023); (Sanusi, Ayanwale and Chiu 2024); (Cambra-Fierro *et al.* 2024); (Ayanwale *et al.* 2022) ; (Lai, Cheung and Chan 2023); (Segbenya *et al.* 2023)Habibi et al., 2023; (Raffaghelli *et al.* 2022); (Mukuka 2024); (Cortez *et al.* 2024); (Dahri *et al.* 2024); (Almulla 2024); (Yao and Wang 2024); (Li *et al.* 2024b); (Lin, Jhang and Wang 2024); (Almulla 2024); (McLean and Osei-Frimpong 2019); (Gao 2023); (Polyportis and Pahos 2024); (Li 2024); (Adelana, Ayanwale and Sanusi 2024); (Chen *et al.* 2020); (Salifu *et al.* 2024); (Kar, Harichandan and Prakash 2024); (Paraskevi, Saprikis and Avlogiaris 2023); (Zhu, Wang and Pu 2022); (Paré *et al.* 2022); (Wang *et al.* 2023a); (Zhang *et al.* 2023); (Islam *et al.* 2024); (Li, Gao and Liao 2024); (Wen *et al.* 2024); (Choudhury and Shamszare 2024); (Sîrghi *et al.* 2024); (Alrishan 2023); (Huang, Kumarasinghe and Jayarathna 2024); (Naidoo 2023); (Yu, Yan and Cai 2024);(Van Phuoc 2022); (Al-Abdullatif 2023); (Sobaih, Elshaer and Hasanein 2024); (Yuduang *et al.* 2022); (Cheng, Li and Xu 2022); (Chai, Wang and Xu 2020); (Milicevic *et al.* 2024); (Masadeh *et al.* 2024); (Alzyoud *et al.* 2024); (Di Battista *et al.* 2023); (Demeke 2023)
F9	Perceived ease of use	(Ni and Cheung 2023); (Chen *et al.* 2023); (Cambra-Fierro *et al.* 2024); (Lai, Cheung and Chan 2023); (Segbenya *et al.* 2023); (Habibi *et al.* 2023); (Raffaghelli *et al.* 2022); (Mukuka 2024); (Almulla 2024); (Yao and Wang 2024); (Jo and Bang 2023); (Li *et al.* 2024b); (Gao 2023); (Polyportis and Pahos 2024); (Grassini, Aasen and Møgelvang 2024); (Li 2024); (Chen *et al.* 2020; Adelana, Ayanwale and Sanusi 2024); (Paraskevi, Saprikis and Avlogiaris 2023); (Zhang *et al.* 2023); (Li, Gao and Liao 2024); (Sánchez-Holgado and Arcila-Calderón 2024); (Wen *et al.* 2024); (Choudhury and Shamszare 2024); (Sîrghi *et al.* 2024); (Alrishan 2023); (Yu, Yan and Cai 2024); (Van Phuoc 2022); (Al-Abdullatif 2023); (Sobaih, Elshaer and Hasanein 2024); (Yuduang *et al.* 2022); (Cheng, Li and Xu 2022); (Milicevic *et al.* 2024); (Masadeh *et al.* 2024); (Alzyoud *et al.* 2024); (Salifu *et al.* 2024); (Zhu, Wang and Pu 2022);
F10	Perceived cost value	(Ni and Cheung 2023); (Al-Abdullatif 2023)
F11	Moral norm	(Du *et al.* 2024); (Paraskevi, Saprikis and Avlogiaris 2023)
F12	Technological autonomy	(Lin, Jhang and Wang 2024); (Di Battista *et al.* 2023)
F13	Social attractiveness	(Lin, Jhang and Wang 2024); (Polyportis and Pahos 2024); (Gao 2023); (Di Battista *et al.* 2023)
F14	Personal innovativeness	(Lin, Jhang and Wang 2024); (Sanusi, Ayanwale and Chiu 2024); (Jatileni *et al.* 2023); (Ayanwale *et al.* 2022); (Li *et al.* 2024b); (Kar, Harichandan and Prakash 2024); (Chen *et al.* 2020); (Chai *et al.* 2024); (Wu *et al.* 2024); (Alrishan 2023); (García de Blanes Sebastián, Sarmiento Guede and Antonovica 2022); (Qu and Wu 2024); (Zhu, Wang and Pu 2022)
F15	Attitude	(Sanusi, Ayanwale and Chiu 2024); (Jatileni *et al.* 2023); (Ayanwale *et al.* 2022); (Dahri *et al.* 2024); (Li *et al.* 2024b); (Polyportis and Pahos 2024); (Adelana, Ayanwale and Sanusi 2024); (Chai *et al.* 2024); (Li, Gao and Liao 2024); (Sîrghi *et al.* 2024); (Al-Abdullatif 2023); (Yuduang *et al.* 2022); (Chai, Wang and Xu 2020); (Masadeh *et al.* 2024); (Di Battista *et al.* 2023)

F16	Perceived use for social good	(Jatileni *et al.* 2023); (Ayanwale *et al.* 2022) ; (Sanusi, Ayanwale and Tolorunleke 2024); (Du *et al.* 2024); (Chai *et al.* 2024);
F17	Focused immersion	(Qu and Wu 2024); (Sîrghi *et al.* 2024)
F18	Social influence	(Habibi *et al.* 2023); (Sanusi, Ayanwale and Tolorunleke 2024); (McLean and Osei-Frimpong 2019); (Raffaghelli *et al.* 2022); (Dahri *et al.* 2024); (Polyportis and Pahos 2024); (Li 2024); (Adelana, Ayanwale and Sanusi 2024); (Salifu *et al.* 2024); (Kar, Harichandan and Prakash 2024); (Chen *et al.* 2020); (Chai *et al.* 2024); (Wang *et al.* 2023a); (Zhang *et al.* 2023); (Sánchez-Holgado and Arcila-Calderón 2024); (Wu *et al.* 2024); (Wen *et al.* 2024); (Sobaih, Elshaer and Hasanein 2024); (Yuduang *et al.* 2022); (Li *et al.* 2022); (Cheng, Li and Xu 2022); (Chai, Wang and Xu 2020); (Milicevic *et al.* 2024); (Alzyoud *et al.* 2024)
F19	Habit	(Habibi *et al.* 2023); (Cortez *et al.* 2024); (Grassini, Aasen and Møgelvang 2024); (Salifu *et al.* 2024); (García de Blanes Sebastián, Sarmiento Guede and Antonovica 2022)
F20	Awareness	(Sanusi, Ayanwale and Tolorunleke 2024); (Mukuka 2024); (Yao and Wang 2024); (Du *et al.* 2024); (Chai *et al.* 2024); (Wu *et al.* 2024); (Van Phuoc 2022); (Yuduang *et al.* 2022); (Li *et al.* 2022); (Chai, Wang and Xu 2020)
F21	Perceived trust	(Raffaghelli *et al.* 2022); (Dahri *et al.* 2024); (Polyportis and Pahos 2024); (Salifu *et al.* 2024); (Paraskevi, Saprikis and Avlogiaris 2023); (Wu *et al.* 2024); (Choudhury and Shamszare 2024); (García de Blanes Sebastián, Sarmiento Guede and Antonovica 2022); (Cheng, Li and Xu 2022); (Masadeh *et al.* 2024); (Alzyoud *et al.* 2024); (Di Battista *et al.* 2023)
F22	Perceived intelligence of AI	(Dahri *et al.* 2024); (Gao 2023)
F23	Organizational culture	(Jo and Bang 2023); (Van Phuoc 2022)
F24	Intrinsic motivation	(Li *et al.* 2024b); (Yuduang *et al.* 2022)
F25	User interface design	(Li *et al.* 2024b); (Paraskevi, Saprikis and Avlogiaris 2023)
F26	Perceived satisfaction	(Li *et al.* 2024b); (Gao 2023); (Choudhury and Shamszare 2024); (Yu, Yan and Cai 2024);
F27	Perceived risk	(Li 2024); (Chen *et al.* 2020); (Choudhury and Shamszare 2024); (Alzyoud *et al.* 2024)

The SEM path coefficients were stored in an Excel spreadsheet with rows representing independent factors, column-dependent factors, and each cell containing the strength of the relationship as determined by the extracted path coefficients. The matrix diagonal was set to zero, as factors do not influence themselves. An excel function was applied to each cell ensuring only the strongest relationships (those with the highest path coefficient) were retained. The resulting matrix, shown in Table 23, provides a consolidated view of the most significant relationships. This matrix was the output of the methodology's second step and served as the foundational input for Step 3.

Table 23: Matrix of factor relationships for adoption of AI in higher education

Factor	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15	F16	F17	F18	F19	F20	F21	F22	F23	F24	F25	F26	F27
F1	0.000	0.000	0.000	0.000	0.277	0.000	0.000	0.177	0.000	0.000	0.000	0.000	0.806	0.000	0.000	0.000	0.418	0.141	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F2	0.435	0.000	0.404	0.000	0.000	0.185	0.000	0.951	0.414	0.000	0.000	0.000	0.000	0.646	0.327	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F3	0.336	0.226	0.000	0.000	0.000	0.000	0.000	0.233	0.352	0.000	0.000	0.000	0.000	0.000	0.502	0.000	0.502	0.000	0.238	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F4	0.791	0.350	0.000	0.000	0.215	0.550	0.000	0.158	0.480	0.000	0.000	0.000	0.000	0.147	0.485	0.550	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F5	0.221	0.195	0.000	0.000	0.000	0.393	0.270	0.272	0.233	0.000	0.000	0.000	0.000	0.000	0.352	0.102	0.000	0.173	0.185	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.402
F6	0.426	0.000	0.000	0.000	0.000	0.000	0.577	0.271	0.518	0.450	0.000	0.000	0.000	0.000	0.176	0.000	0.710	0.000	0.000	0.000	0.000	0.220	0.000	0.000	0.000	0.000	0.000
F7	0.751	0.320	0.000	0.370	0.000	0.000	0.000	0.460	0.671	0.000	0.000	0.000	0.000	0.000	0.110	0.000	0.000	0.602	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F8	0.928	0.668	0.000	0.404	0.000	1.112	0.132	0.000	0.000	0.000	0.000	0.000	0.000	0.907	0.731	0.000	0.743	0.605	0.598	0.000	0.000	0.150	0.000	0.000	0.000	0.732	0.000
F9	0.770	0.399	0.000	0.000	0.000	0.625	0.000	0.725	0.000	0.340	0.000	0.000	0.000	0.445	0.772	0.000	0.289	0.680	0.482	0.000	0.000	0.000	0.000	0.000	0.000	0.285	0.000
F10	0.410	0.000	0.000	0.000	0.000	0.000	0.000	0.211	0.000	0.000	0.000	0.000	0.000	0.000	0.350	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F11	0.240	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.220	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F12	0.000	0.000	0.000	0.000	0.000	0.189	0.000	0.960	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F13	0.692	0.000	0.000	0.000	0.000	0.910	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.203	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F14	0.851	0.000	0.000	0.000	0.000	0.201	0.000	0.212	0.136	0.000	0.000	0.000	0.000	0.000	0.402	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.620
F15	0.964	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F16	0.620	0.000	0.000	0.161	0.000	0.000	0.510	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.275	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F17	0.231	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.744	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F18	0.650	0.530	0.000	0.580	0.000	0.000	0.343	0.502	0.000	0.000	0.000	0.000	0.000	0.000	0.435	0.204	0.000	0.000	0.483	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.489
F19	0.411	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F20	0.803	0.158	0.000	0.770	0.000	0.000	0.213	0.632	0.790	0.000	0.620	0.000	0.000	0.000	0.569	0.401	0.000	0.857	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F21	0.964	0.000	0.000	0.000	0.000	0.000	0.000	0.272	0.197	0.000	0.000	0.000	0.840	0.000	0.109	0.000	0.000	0.000	0.000	0.000	0.000	0.300	0.000	0.000	0.000	0.000	0.000
F22	0.240	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F23	0.758	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F24	0.596	0.000	0.000	0.000	0.000	0.000	0.000	0.211	0.166	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F25	0.600	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.173	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F26	0.692	0.594	0.000	0.000	0.000	0.000	0.000	0.168	0.184	0.000	0.000	0.000	0.000	0.708	0.000	0.000	0.000	0.000	0.165	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F27	0.820	0.000	0.000	0.000	0.000	0.000	0.000	0.267	0.448	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.411	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

According to the study approach outlined in Chapter 4, the continuation of the third step of the methodology is contingent upon identifying more than 10 unique factors from the literature. With 27 unique factors extracted, the process proceeded with Step 3, with the objective of refining these factors using the ADVIAN® advanced impact analysis technique through the researcher-developed tool. The `advian_analysis.py` script was applied to the matrix in Table 23, generating ADVIAN® classifications and measurements (Figure 37). Only the driving (DRI) and precarious (PRE) classifications were analysed further, as these measures identify those factors with the highest levels of influence and uncertainty.

RESULTS OF ADVIAN ANALYSIS

	FACTORS																										
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27
RDAS	11.967	22.118	15.717	24.513	18.408	22.026	21.605	49.987	38.237	6.3882	3.0263	7.5592	11.875	15.934	6.3421	10.303	6.4145	27.737	2.7039	38.243	17.645	1.5789	4.9868	6.4013	5.0855	16.52	12.803
RDPS	100	22.632	2.6579	15.033	3.2368	26.664	13.454	43.961	31.329	5.1974	4.0789	0	10.829	18.77	43.039	9.7171	17.513	20.118	16.855	0	0	4.4079	0	0	0	6.6908	9.9408
RIAS	11.743	34.918	15.862	30.315	25.904	25.802	39.261	50.085	44.376	6.2532	2.0556	19.65	12.044	16.161	4.2004	12.371	2.1661	35.421	1.7908	56.528	16.539	1.0457	3.3028	9.2515	5.4629	21.219	16.185
RIPS	100	26.398	3.9572	13.918	11.388	39.291	15.677	40.966	23.972	9.5848	5E-11	0	29.907	28.421	52.537	5.1418	40.463	24.71	21.713	0	0	5.4875	0	0	0	13.662	12.72
CRI	34.268	30.361	7.9228	20.541	17.176	31.84	24.809	45.297	32.616	7.7418	1E-05	0	18.979	21.432	14.855	7.9755	9.3619	29.585	6.2357	0	0	2.3955	0	0	0	17.026	14.348
INT	55.871	30.658	9.9098	22.117	18.646	32.546	27.469	45.526	34.174	7.919	1.0278	9.8252	20.975	22.291	28.368	8.7563	21.314	30.065	11.752	28.264	8.2696	3.2666	1.6514	4.6258	2.7315	17.44	14.453
STA	78.982	69.934	93.666	80.922	84.179	68.851	77.593	54.931	68.871	92.431	100	60.699	82.828	79.394	92.221	92.736	95.888	70.889	96.691	13.055	66.922	98.243	93.394	81.497	89.074	83.378	85.755
PRE	20.06	32.56	11.21	24.954	21.093	28.662	31.21	47.631	38.044	6.9578	0.0045	0	15.119	18.611	7.8992	9.9329	4.5032	32.372	3.3417	0	0	1.5827	0	0	0	19.007	15.239
DRI	27.783	49.312	38.217	49.08	46.32	41.936	54.333	52.343	54.683	24.019	14.337	44.329	31.238	35.634	18.911	33.74	14.012	49.942	12.958	75.185	40.668	10.103	18.174	30.416	23.373	41.959	37.232
DRE	81.075	42.876	19.089	33.256	30.712	51.75	34.333	47.339	40.191	29.737	7E-05	0	49.225	47.255	66.882	21.753	60.56	41.713	45.121	0	0	23.143	0	0	0	33.669	33.008
SYSTEM																											
STABILITY	79.742																										

Figure 37: Screenshot of the Excel output file containing the ADVIAN® results for AI factors

Only factors that exceeded the threshold value (two-thirds of the standard deviation above the mean) in the relevant category were retained as they are considered critical. For this study, precarious factors exceeding a threshold of 28.304 and driving factors exceeding 51.745 were considered. The resulting seven factors that complied with these thresholds are highlighted in Table 24, with factor descriptions provided in Table 25. This set of refined factors served as input to the next step of the methodology.

Table 24: ADVIAN® classification of factors for AI adoption in higher education

Factor	Factor Name	Precarious	Driving	Factor	Factor Name	Precarious	Driving
F1	Behavioural intention	20.060	27.783	F15	Attitude	7.899	18.911
F2	Perceived relevance (usefulness)	32.560	49.312	F16	Perceived use for social good	9.933	33.740
F3	Perceived system quality	11.210	38.217	F17	Focused immersion	4.503	14.012
F4	Perceived self-efficacy	24.954	49.080	F18	Social influence	32.372	49.942
F5	Perceived anxiety	21.093	46.320	F19	Habit	3.342	12.958
F6	Hedonic motivation	28.662	41.936	F20	Awareness	0.000	75.185
F7	Facilitating conditions	31.210	54.333	F21	Perceived trust	0.000	40.668
F8	Perceived performance expectancy	47.631	52.343	F22	Perceived intelligence of AI	1.583	10.103
F9	Perceived ease of use	38.044	54.683	F23	Organizational culture	0.000	18.174
F10	Perceived cost value	6.958	24.019	F24	Intrinsic motivation	0.000	30.416
F11	Moral norm	0.005	14.337	F25	User interface design	0.000	23.373
F12	Technological autonomy	0.000	44.329	F26	Perceived satisfaction	19.007	41.959
F13	Social attractiveness	15.119	31.238	F27	Perceived risk	15.239	37.232
F14	Personal innovativeness	18.611	35.634				
Average + 2/3 std dev		**28.304**	**51.745**			**28.304**	**51.745**

Table 25: Refined set of driving and uncertain factors for AI adoption in higher education

Factor Name	Factor Description	Reference
Perceived relevance (usefulness)	The degree to which an individual believes that the target system is applicable or appropriate to his or her job, life or current situation or current need.	Demeke (2023)
Hedonic motivation	The joy, fun or pleasure that is derived from using a technology, without the tool providing any specific benefit.	Venkatesh and Bala (2008)
Facilitating conditions	An individual's perception of the support and resources available to support a behaviour.	Venkatesh and Bala (2008)
Perceived performance expectancy	The degree to which an individual perceives that using a particular system will enhance performance.	Yang, Bashiru Danwana and Yassaanah (2021)

Perceived ease of use	The extent to which a technology is perceived as being difficult to use.	Ashinze *et al.* (2021)
Social influence	The sensed societal influence to engage in or refrain from a certain behaviour.	Yazdanpanah *et al.* (2015)
Awareness	The extent to which individuals understand the technology, including its benefits and drawbacks, and their ability to stay updated with new technological advancements.	Ashinze *et al.* (2021)

Once the most critical factors had been determined, judgements were obtained from experts. These judgements measure the effect that the various states of AI adoption factors have on each other and were gathered from experts who were crowdsourced through the "X" platform. A database was set up to organize and store the data related to this AI adoption experiment with factor names being rephrased based on feedback from a pilot study. The factor renaming ensured that the judgement questions were clear, understandable, and free of ambiguity (see Table 26 for a summary of rephrased factors).

Table 26: Factor rephrasing for AI in higher education application

Factor	Rephrased Factor
Perceived relevance (usefulness)	Expectancy in terms of relevance or usefulness of AI in higher education
Hedonic motivation	Level of joy or pleasure from AI tools in higher education
Facilitating conditions	Expectancy in terms of the amount of support available for AI systems and technologies in higher education
Perceived performance expectancy	Expectancy in terms of the performance of AI systems in higher education
Perceived ease of use	Expectancy in terms of user friendliness of AI in higher education
Social influence	Level of pressure from society regarding adopting AI technology in higher education
Awareness	Level of AI awareness in higher education

On 28 October 2024, the researcher posted a tweet (in accordance with guidelines outlined in Chapter 4 Section 4.2.4), inviting volunteers to participate in the study survey. The hashtags were selected by conducting a detailed review of trending posts on "X" that referenced AI and education. This method ensured the tweet would effectively reach an audience interested in these fields, increasing the likelihood of obtaining responses from knowledgeable participants. Participants who followed the link to the data-gathering tool (available at

https://scenario.biz.ht/welcome_ai.php) encountered a welcome page with a link to the study's letter of information and consent. If a participant opted not to proceed, they were redirected to an "exit" screen while those who agreed to participate were taken to a background information form. The background form assessed participants' eligibility according to the expert criteria outlined in Chapter 4, Section 4.2.4 (Table 11). Eligible participants were directed to the judgement data entry screen, while ineligible participants were provided with a message explaining they did not meet the study's criteria.

Each judgement screen collected participants' assessments on how each independent factor affected a dependent factor in both "high" and "low" states. Participants evaluated a set of seven factors; therefore, participants were each presented with 42 judgement screens. Judgement screens included tooltips that provided additional explanations for each factor, enhancing clarity and precision. On completion, experts' judgements were saved as judgement strings in the RELATIONSHIP table of the database. Finally, participants were directed to a page of thanks that provided the researcher's contact email for any follow-up questions or comments.

Data was extracted from the database for analysis on 11 November 2024. No personal data was collected or stored, the online tool only recorded responses to qualifying questions for participants who met the study's inclusion criteria. Table 27 provides an overview of the expertise of the 45 respondents who met the criteria. Seven participants met two criteria, nine met three, and 10 met four. Eleven participants fulfilled five criteria, six met six of the criteria, and two met all criteria. Beyond the requirement of five years of experience in AI, the most met criterion was having been an invited speaker (82% participants met the criteria). 72% indicated they had published work in AI, further demonstrating their expertise. Additionally, 71% of respondents indicated they contributed to AI policy, while 44% were members of AI committees, and 20% held team leadership roles in AI. A smaller number, 22%, reported being media contacts for AI-related topics.

Table 27: Inclusion criteria for artificial energy experts

Expert ID	5 years' experience	Published in books, journals etc	Invited speaker	Leader of a team	Informs policy	Member of a committee	Media contact	Number of criteria
E1	✓	✓	✓		✓	✓		5
E2	✓	✓	✓	✓				4
E3	✓	✓	✓		✓			4
E4	✓	✓	✓		✓			4
E5	✓	✓						2
E6	✓		✓					2
E7	✓	✓						2
E8	✓	✓						2
E9	✓	✓	✓					3
E10	✓		✓		✓		✓	4
E11	✓		✓	✓				3
E12	✓	✓	✓		✓			4
E13	✓		✓		✓			3
E14	✓	✓	✓		✓			4
E15	✓		✓		✓		✓	4
E16	✓		✓			✓		3
E17	✓						✓	2
E18	✓		✓		✓			3
E19	✓	✓	✓		✓	✓		5
E20	✓	✓	✓		✓	✓		5
E21	✓	✓	✓		✓	✓		5
E22	✓	✓	✓					3
E23	✓	✓	✓		✓	✓	✓	6
E24	✓	✓	✓		✓			4
E25	✓	✓	✓	✓	✓	✓	✓	7
E26	✓	✓	✓	✓	✓	✓	✓	7
E27	✓	✓	✓		✓	✓		5
E28	✓				✓	✓		3
E29	✓	✓	✓		✓	✓		5
E30	✓	✓	✓		✓	✓		5
E31	✓	✓	✓	✓	✓		✓	6
E32	✓	✓	✓	✓	✓	✓		6
E33	✓	✓	✓		✓			4
E34	✓	✓	✓		✓	✓		5
E35	✓	✓			✓		✓	4
E36	✓		✓	✓	✓	✓		5
E37	✓	✓	✓		✓	✓		5
E38	✓		✓				✓	3
E39	✓		✓					2
E40	✓	✓	✓	✓	✓	✓		6
E41	✓	✓	✓	✓	✓	✓		6
E42	✓	✓						2
E43	✓	✓	✓		✓	✓		5
E44	✓	✓	✓		✓	✓	✓	6
E45	✓	✓			✓			3
Total	45	33 (73%)	37 (82%)	9 (20%)	32 (71%)	20 (44%)	10 (22%)	

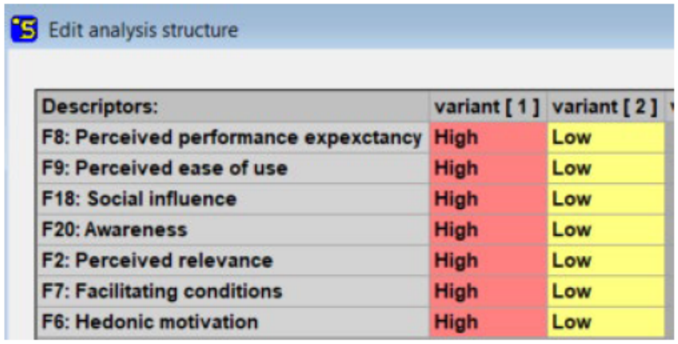
While the recruitment tweet attracted an unknown number of volunteers, 45 respondents met the inclusion criteria. Of these, only 12 completed the survey in full, providing a complete set of factor judgements in the database. This equates to a 73% dropout rate among eligible participants, possibly due to the demanding nature of the judgement questions and the time commitment required to complete the survey. The judgement data from these expert participants that was stored in the database tables was the output from this step and was used to create a final judgement matrix in the next step of the methodology.

The final matrix was created by executing the custom PHP script (`toexcel_ai.php`), available in the GitHub repository (https://github.com/robyn-thompson/AI_Adop_files). The resulting consolidated expert judgement matrix, which was required as input for the final step of the methodology, is shown in Figure 38.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
1	"Cross Impact Balance Matrix"															
2																
3			F8		F9		F18		F20		F20		F7		F6	
4			H	L	H	L	H	L	H	L	H	L	H	L	H	L
5	F8	H	0	0	2	-2	2	-2	2	-2	2	-2	2	-2	1	-1
6		L	0	0	0	0	-1	1	-1	1	0	0	-1	1	-1	1
7	F9	H	1	-1	0	0	1	-1	1	-1	1	-1	1	-1	1	-1
8		L	-1	1	0	0	0	0	0	0	-1	1	0	0	-1	1
9	F18	H	2	-2	2	-2	0	0	2	-2	2	-2	2	-2	1	-1
10		L	-1	1	-1	1	0	0	-1	1	-1	1	-1	1	-1	1
11	F20	H	1	-1	1	-1	2	-2	0	0	1	-1	2	-2	1	-1
12		L	-1	1	-1	1	-1	1	0	0	-1	1	-1	1	0	0
13	F20	H	2	-2	1	-1	2	-2	1	-1	0	0	1	-1	1	-1
14		L	-1	1	0	0	-1	1	-1	1	0	0	-1	1	-1	1
15	F7	H	2	-2	1	-1	1	-1	2	-2	2	-2	0	0	1	-1
16		L	-1	1	0	0	-1	1	-1	1	-1	1	0	0	-1	1
17	F6	H	2	-2	2	-2	1	-1	2	-2	2	-2	1	-1	0	0
18		L	-1	1	-1	1	-1	1	-1	1	-1	1	0	0	0	0

Figure 38: Judgement matrix for AI study (Source: Researcher-developed tool available at: https://scenario.biz.ht/toexcel.php)

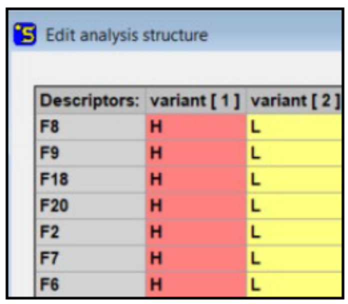
The final judgement matrix was used to create the consistent scenarios for the experiment. This was done by using the ScenarioWizard software tool (Weimer-Jehle 2023a) and implemented according to the tasks outlined in Section 5.1.1. The analysis structure was created (Figure 39 and Figure 40) and the expert judgements (Figure 41) captured according to the final matrix that was created (Figure 38). The scenarios with the highest level of consistency that were constructed by the software are shown in Figure 42 and Figure 43.



Edit analysis structure

Descriptors:	variant [1]	variant [2]
F8: Perceived performance expexctancy	High	Low
F9: Perceived ease of use	High	Low
F18: Social influence	High	Low
F20: Awareness	High	Low
F2: Perceived relevance	High	Low
F7: Facilitating conditions	High	Low
F6: Hedonic motivation	High	Low

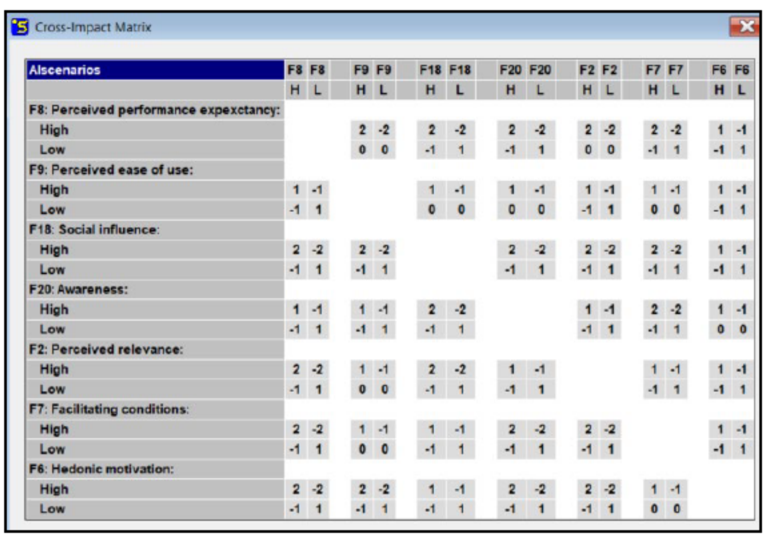
Figure 39: Creating the matrix structure for the AI study with factor names



Edit analysis structure

Descriptors:	variant [1]	variant [2]
F8	H	L
F9	H	L
F18	H	L
F20	H	L
F2	H	L
F7	H	L
F6	H	L

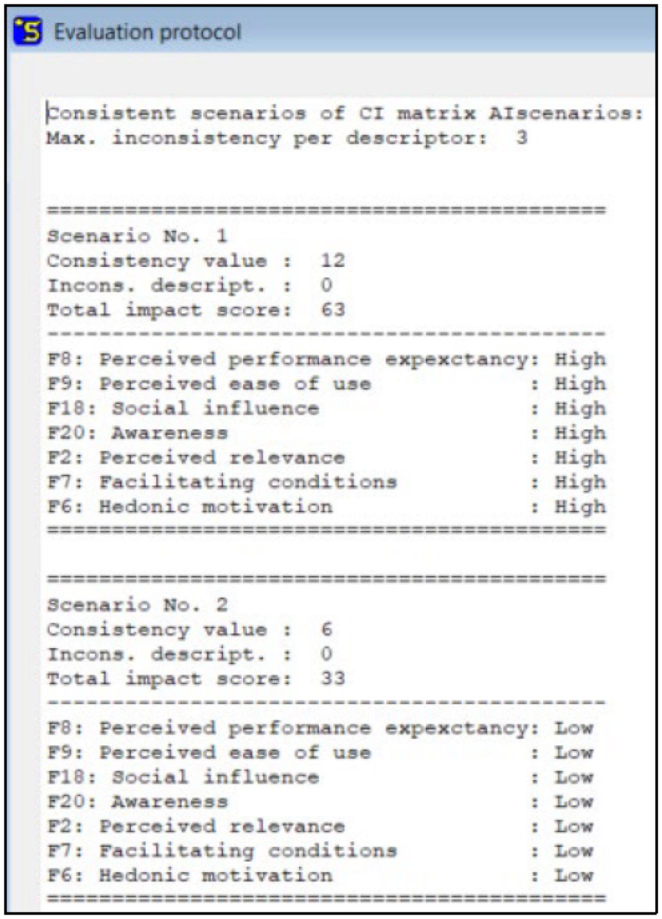
Figure 40: Creating the matrix structure for the AI study with abbreviated factor names=



Cross-Impact Matrix

AIscenarios	F8	F8	F9	F9	F18	F18	F20	F20	F2	F2	F7	F7	F6	F6
	H	L	H	L	H	L	H	L	H	L	H	L	H	L
F8: Perceived performance expexctancy:														
High			2	-2	2	-2	2	-2	2	-2	2	-2	1	-1
Low			0	0	-1	1	-1	1	0	0	-1	1	-1	1
F9: Perceived ease of use:														
High	1	-1			1	-1	1	-1	1	-1	1	-1	1	-1
Low	-1	1			0	0	0	0	-1	1	0	0	-1	1
F18: Social influence:														
High	2	-2	2	-2			2	-2	2	-2	2	-2	1	-1
Low	-1	1	-1	1			-1	1	-1	1	-1	1	-1	1
F20: Awareness:														
High	1	-1	1	-1	2	-2			1	-1	2	-2	1	-1
Low	-1	1	-1	1	-1	1			-1	1	-1	1	0	0
F2: Perceived relevance:														
High	2	-2	1	-1	2	-2	1	-1			1	-1	1	-1
Low	-1	1	0	0	-1	1	-1	1			-1	1	-1	1
F7: Facilitating conditions:														
High	2	-2	1	-1	1	-1	2	-2	2	-2			1	-1
Low	-1	1	0	0	-1	1	-1	1	-1	1			-1	1
F6: Hedonic motivation:														
High	2	-2	2	-2	1	-1	2	-2	2	-2	1	-1		
Low	-1	1	-1	1	-1	1	-1	1	-1	1	0	0		

Figure 41: Final judgement matrix for the AI study



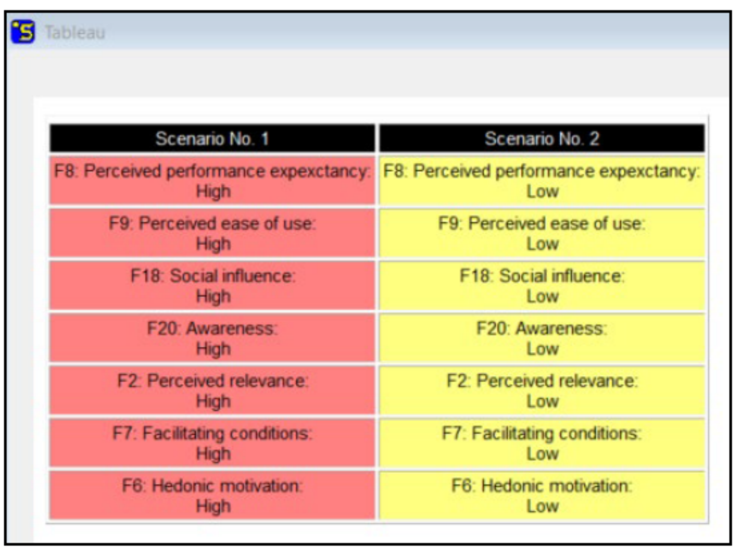
```
Evaluation protocol

Consistent scenarios of CI matrix AIscenarios:
Max. inconsistency per descriptor:  3


============================================
Scenario No. 1
Consistency value :  12
Incons. descript. :  0
Total impact score:  63
--------------------------------------------
F8: Perceived performance expexctancy: High
F9: Perceived ease of use            : High
F18: Social influence                : High
F20: Awareness                       : High
F2: Perceived relevance              : High
F7: Facilitating conditions          : High
F6: Hedonic motivation               : High
============================================

============================================
Scenario No. 2
Consistency value :  6
Incons. descript. :  0
Total impact score:  33
--------------------------------------------
F8: Perceived performance expexctancy: Low
F9: Perceived ease of use            : Low
F18: Social influence                : Low
F20: Awareness                       : Low
F2: Perceived relevance              : Low
F7: Facilitating conditions          : Low
F6: Hedonic motivation               : Low
============================================
```

Figure 42: Fully consistent scenarios generated for the adoption of AI



Tableau

Scenario No. 1	Scenario No. 2
F8: Perceived performance expexctancy: High	F8: Perceived performance expexctancy: Low
F9: Perceived ease of use: High	F9: Perceived ease of use: Low
F18: Social influence: High	F18: Social influence: Low
F20: Awareness: High	F20: Awareness: Low
F2: Perceived relevance: High	F2: Perceived relevance: Low
F7: Facilitating conditions: High	F7: Facilitating conditions: Low
F6: Hedonic motivation: High	F6: Hedonic motivation: Low

Figure 43: Tableau of consistent scenarios for the adoption of AI study

The software generated two fully consistent scenarios, but to capture a range of future possibilities, three to five scenarios would be optimal (Lindgren and Bandhold 2009). To address this, the researcher explored the option of reducing the consistency threshold. Lowering the threshold to two and three produced no additional scenarios, while lowering to four resulted in an additional 13 scenarios, as shown in Figure 44. To remain within the optimal range and to maximize quality, the researcher analysed these additional scenarios for "inconsistent factors", focusing on those with the fewest inconsistencies (Stankov *et al.* 2021b). Scenarios 6 and 8, with only two inconsistent factors each, were retained, while other scenarios with four, five, or six inconsistencies were excluded. This resulted in a final set of four consistent scenarios that consisted of the most critical factors for the adoption of AI in higher education (Table 28).

<table>
<tr><th></th><th>Scenario 1</th><th>Scenario 2</th><th>Scenario 3</th><th>Scenario 4</th><th>Scenario 5</th><th>Scenario 6</th><th>Scenario 7</th><th>Scenario 8</th><th>Scenario 9</th><th>Scenario 10</th><th>Scenario 11</th><th>Scenario 12</th><th>Scenario 13</th><th>Scenario 14</th><th>Scenario 15</th></tr>
<tr><td>Consistency value</td><td>12</td><td>-4</td><td>-4</td><td>-4</td><td>-4</td><td>-4</td><td>-4</td><td>-4</td><td>-4</td><td>-4</td><td>-4</td><td>-4</td><td>-4</td><td>-4</td><td>0</td></tr>
<tr><td>Inconsistent factors</td><td>0</td><td>4</td><td>6</td><td>6</td><td>6</td><td>2</td><td>4</td><td>2</td><td>5</td><td>5</td><td>5</td><td>4</td><td>6</td><td>4</td><td>0</td></tr>
<tr><td>Impact Score</td><td>63</td><td>-4</td><td>-6</td><td>-6</td><td>-7</td><td>-2</td><td>-5</td><td>0</td><td>-7</td><td>-8</td><td>-6</td><td>-5</td><td>-8</td><td>-5</td><td>33</td></tr>
<tr><td></td><td>F8:High</td><td colspan="2">F8:Low</td><td>F8:High</td><td colspan="4">F8:Low</td><td>F8:High</td><td colspan="3">F8:Low</td><td>F8:High</td><td colspan="2">F8:Low</td></tr>
<tr><td></td><td colspan="5">F9:High</td><td>F9:Low</td><td>F9:High</td><td>F9:Low</td><td colspan="3">F9:High</td><td>F9:Low</td><td>F9:High</td><td colspan="2">F9:Low</td></tr>
<tr><td></td><td>F18:High</td><td colspan="9">F18:Low</td><td colspan="2">F18:High</td><td>F18:Low</td><td>F18:High</td><td>F18:Low</td></tr>
<tr><td></td><td>F20:High</td><td>F20:Low</td><td>F20:High</td><td colspan="3">F20:Low</td><td colspan="2">F20:High</td><td>F20:Low</td><td>F20:High</td><td colspan="3">F20:Low</td><td>F20:High</td><td>F20:Low</td></tr>
<tr><td></td><td colspan="2">F2:High</td><td colspan="2">F2:Low</td><td colspan="2">F2:High</td><td colspan="3">F2:Low</td><td colspan="4">F2:High</td><td colspan="2">F2:Low</td></tr>
<tr><td></td><td>F7:High</td><td colspan="3">F7:Low</td><td colspan="5">F7:High</td><td colspan="6">F7:Low</td></tr>
<tr><td></td><td colspan="4">F6:High</td><td colspan="11">F6:Low</td></tr>
</table>

Figure 44: Scenarios generated for adoption of AI study with consistency set to four

Table 28: Table of scenarios generated for the AI in higher education adoption project

Scenario	Best-case scenario	Base-case one scenario	Base-case two scenario	Worst-case scenario
Perceived Performance Expectancy	High	Low	Low	Low
Perceived Ease of Use	High	Low	Low	Low
Social Influence	High	Low	Low	Low
Awareness	High	Low	High	Low
Perceived Relevance	High	High	Low	Low
Facilitating Conditions	High	High	High	Low
Hedonic Motivation	High	Low	Low	Low
	Promotes renewable energy adoption	Moderate renewable energy adoption	Moderate renewable energy adoption	Restricts renewable energy adoption

The four scenarios: 'Best-case' (Optimized Adoption), 'Base-case one' (Relevance-Driven Adoption), 'Base-case two' (Infrastructure-Led Awareness), and ‘Worst-case’ (Systemic Resistance), are based on the extent to which the states of the factors promote or restrict AI adoption. The principle of relatedness allows for the grouping of items based on similarities, contextual relations, and mutual connections (Palmer 1992). Applying this principle to the seven factors in the context of technology acceptance models, unveils three constructs. The first, **perceived value**, includes perceived performance expectancy, perceived ease of use, and perceived relevance. These factors determine whether AI is observed as valuable and worth adopting in higher education based on its effectiveness, relevance, and ease of use. The second, **awareness,** includes awareness, social influence, and hedonic motivation. These factors drive user engagement and interest by shaping knowledge, motivation, and social encouragement. Lastly, **perceived support** includes facilitating conditions and perceived ease of use. These factors determine how practical and feasible AI adoption in higher education is by ensuring users have the necessary resources and support.

The ‘**best-case**’ or **‘optimized adoption’** scenario, which is characterized by high perceived value, awareness, and perceived support, can greatly enhance the adoption of AI in higher education. The ‘**worst-case**’ or ‘**systemic resistance**’ scenario with low high perceived value, awareness, and perceived support, would hinder the adoption of AI in higher education. But both the ‘**best-case**’ and ‘**worst-case’** scenarios are not realistic as they represent extremes in terms of promoting or restricting characteristics. The two ‘**base-case**’ scenarios offer a mixture of high and low states of different constructs. The construct states for both of the **base-cases** are low for perceived value and awareness, while perceived support has a neutral state. This is due to facilitating conditions having a high state, and perceived ease of use having a low state for both base cases. These scenarios with a mixture of states can provide a more realistic view of the future and offer decision makers useful insights into AI adoption issues and where intervention strategies are needed to improve adoption in higher education.

These scenarios help stakeholders visualize potential futures based on the identified factors and their relationships. By using these consistent scenarios, informed discussions and decision-making processes can be facilitated, ensuring that participants can explore and engage with the scenarios in a way that reflects the complexity and interconnectedness of AI adoption in higher education. The scenarios and associated narratives of these two scenario projects meet the study's objective of providing a crowdsourcing method for constructing consistent scenarios based on ADVIAN®, crowdsourcing process, and cross-impact balance analysis to resolve the inherent limitations of CIA and other scenario methods.

5.3 Chapter summary

This chapter demonstrated the methodology outlined in Chapter 4 by applying it to two scenario studies to achieve the final objective of the study: *to validate the methodology through the practical implementation and application to renewable energy adoption and AI adoption in higher education*. The one practical application focuses on the adoption of renewable energy, and the other on the adoption of AI in higher education. Each section began with an overview of the respective research area, providing readers with insight into the importance of enhancing adoption in both fields. By establishing the context for each area, the chapter emphasized the need to improve the adoption processes of these transformative technologies.

The chapter provided a walkthrough of the implementation of each step of the methodology. In **Step 1**, factors empirically tested in the literature were extracted using the PRISMA protocol. For the renewable energy study, 36 factors were identified, while 27 factors were extracted for the AI study. In **Step 2** the relationships between these factors were further explored using SEM path coefficients, and the strongest pairwise relationships were captured in matrices for both applications. These matrices provided the foundation for the factor reduction process in **Step 3**. **Step 3** was required in both implementations as the number of factors identified in each exceeded 10. The researcher-developed ADVIAN® analysis tool was then used to process the matrices and classify the factors as driving (DRI) or precarious (PRE). The factors were then refined to reveal those that were most critical in terms of uncertainty and driving ability.

The subsequent step focused on building a judgement matrix using crowdsourced data. Judgements regarding the strength and direction of influences between factor states were collected from expert participants via an online survey. Links to the survey were shared on the “X” platform, demonstrating the feasibility of using crowdsourcing to recruit participants for scenario-based studies. For the renewable energy adoption study, 14 sets of judgements were obtained, while 12 sets were collected for the AI adoption study. The final judgement matrices for both applications were created using a researcher-developed software tool. In the final step the consistent scenarios were constructed using the CIB technique. Scenarios were generated for each study using the ScenarioWizard software tool and relying on the judgement matrices that were constructed in the previous step. After adjusting the consistency threshold, three scenarios were constructed for the renewable energy adoption study, and four scenarios for the AI adoption in higher education study.

For the renewable energy adoption study, the refined set included **perceived performance expectancy, perceived ease of use, social influence, awareness, perceived cost value, facilitating conditions, and perceived environmental awareness**. For AI adoption in higher education, the refined factors were **perceived performance expectancy, perceived ease of use, social influence, awareness, perceived relevance, facilitating conditions, and hedonic motivation**.

This chapter illustrated the practical application of the methodology and achieves the final objective of the study. It also highlighted how each phase contributed to the successful generation of consistent, well-supported scenarios for both renewable energy and AI adoption.

CHAPTER 6: DISCUSSION OF RESULTS

This chapter discusses the study's key findings in relation to the methodological, theoretical, and practical contributions of the proposed scenario construction framework. Importantly, the methodology adopted for this study diverges from traditional participatory approaches by introducing a novel, time-efficient process that combines systematic secondary data analysis, quantitative factor reduction through ADVIAN®, expert crowdsourcing, and CIB analysis. This integration enabled the generation of robust and internally consistent scenarios while strengthening empirical reliability and procedural transparency. The chapter examines how the combination of the various methods provides a scalable and replicable framework for scenario construction, particularly valuable for complex, interdisciplinary domains where social and technical dimensions intersect. Drawing on the results of the two case studies, the adoption of renewable energy and the adoption of AI in higher education, the chapter evaluates how the methodology addresses the limitations identified in Chapter 2 and how it operationalises the theoretical foundations presented in Chapter 3.

In line with the purpose of this chapter, the following sections discuss the findings in relation to the study's four research objectives, drawing on insights from both case studies. Each section (6.1 to 6.4) discusses how the corresponding objective was achieved, how the findings align with or extend existing literature, and how they advance methodological and theoretical understanding in scenario studies and crowdsourcing-based research. Section 6.5 then provides a critical reflection on the methodology in relation to the limitations identified in the literature, while Section 6.6 synthesises the practical scenario insights generated across the two case studies. Together, these sections demonstrate not only the validity of the proposed methodology, but also its value as a structured and actionable approach for analysing complex and uncertain futures.

6.1 Achievement of Objective 1

Objective 1: *To critically evaluate the theoretical and methodological limitations of existing scenario construction techniques by means of a literature review, establishing the necessity for an integrated approach.*

This objective was achieved through the comprehensive literature review presented in Chapter 2. The review examined the evolution of scenario construction methods and critically assessed four of the dominant approaches: the intuitive logics method (ILM), la prospective (LP), cross-impact analysis (CIA), and cross-impact balance (CIB). Each method was evaluated for its conceptual foundations, practical applications, and limitations. Collectively, this analysis revealed that while existing methods contribute valuable insights, none fully address the combined needs of methodological rigour, systemic coherence, and participatory inclusivity required in contemporary foresight studies (Bradfield *et al.* 2005; Wright, Bradfield and Cairns 2013; Schweizer 2019; Kishita *et al.* 2020; Schirrmeister, Göhring and Warnke 2020; Douglas *et al.* 2021; Kaviani *et al.* 2023). A central finding of this review was that traditional scenario methods often rely heavily on qualitative, expert-driven processes, which, while rich in insight, are limited by subjectivity, scalability challenges, and difficulties in ensuring consistency within scenarios (Musch and von Streit 2017; Gordon and Glenn 2018). Participatory methods, such as workshops and brainstorming sessions, were found to be valuable for stakeholder engagement but often impractical due to resource constraints, time demands, and limited diversity of participants (Phadnis *et al.* 2014; Heinonen, Kuusi and Salminen 2017; Kemp-Benedict, Carlsen and Kartha 2019; Kishita *et al.* 2020). These limitations were amplified during the COVID-19 pandemic, which demonstrated the vulnerability of face-to-face approaches and underscored the need for remote, scalable, and digitally enabled alternatives (Hall, Gaved and Sargent 2021).

The review also highlighted theoretical gaps that underpin the methodological weaknesses of traditional approaches. Specifically, many existing scenario methods insufficiently account for systemic interdependencies (as emphasized by GST), the non-linearity and emergence central to complexity theory, the social construction of knowledge outlined in constructivism, and the need to anticipate disruptive surprises captured by PST. This theoretical fragmentation results in scenario outcomes that may be internally inconsistent, insufficiently dynamic, or overly deterministic.

Furthermore, the chapter established that emerging digital approaches, particularly crowdsourcing, offer a viable solution to several of these methodological challenges. Crowdsourcing provides access to a broad and diverse pool of expert insights, enhances transparency, and reduces logistical barriers inherent to traditional data collection (Raford 2015; Leighton *et al.* 2021; Dortheimer *et al.* 2024). Platforms such as “X” were identified as particularly valuable for expert recruitment, due to their communication-centric nature, global reach, and the ability to engage specialist communities through hashtags and network amplification (Baker, Mitchell and Thomas 2022; Ellington *et al.* 2022).

By synthesizing insights from both the methodological and theoretical criticisms, Chapter 2 successfully demonstrated the need for an integrated scenario construction framework that combines the strengths of existing methods while mitigating their limitations. This directly laid the groundwork for the development of the novel, multi-step methodology presented in Chapter 4.

6.2 Achievement of Objective 2

Objective 2: *To identify and critically structure the key factors and their interdependencies from a set of factors derived from of a structured literature review, as a foundational analytical step informing scenario construction.*

This objective was achieved by means of the systematic factor identification and reduction process described in Chapter 4. Building on the foundation established in Objective 1, this stage sought to transform the theoretical points of criticism of scenario methods into a structured, empirically grounded procedure for identifying key drivers of change. The process began with a comprehensive literature-based data collection phase using the PRISMA framework, which ensured the systematic and unbiased identification of factors across peer-reviewed, empirical studies (Moher *et al.* 2015; Page *et al.* 2021). This approach replaced the reliance on subjective expert elicitation traditionally used in scenario planning with an evidence-based process that enhances transparency, reproducibility, and content validity (Kishita *et al.* 2020).

The initial outcome of this phase was a broad set of empirically supported factors relevant to the selected domains: 36 for the renewable energy adoption study (from 81 papers) and 27 for the AI adoption study in higher education (from 66 papers). In both domains, the highest number of factors evaluated in any single study was nine, with medians of six and five factors, respectively. This far exceeds the typical range in scenario construction exercises, which often include fewer than 15 variables due to cognitive and logistical constraints (Bradfield *et al.* 2005). By capturing a larger and more diverse set of factors, the current study extends traditional approaches, enabling a more comprehensive exploration of system complexity and providing a robust foundation for subsequent factor reduction and scenario development.

A further distinction of the current study is its broad theoretical coverage. Most previous studies focused on factors derived from single theoretical frameworks, such as the unified theory of acceptance and use (Lau *et al.* 2020), the theory of planned behaviour, the theory of reasoned action, behavioural finance and institutional theory, and the technology-organizational-environmental model (Maqbool 2018), with few examining combinations of these perspectives.

In contrast, the current study systematically extracted factors across all these models, integrating multiple theoretical lenses to capture a more complete representation of the factors influencing system behaviour. The larger and more diverse factor sets allowed a comprehensive and nuanced exploration of system complexity before reduction through structured analytical methods, representing a significant methodological and theoretical advancement over previous studies.

SEM was employed as a statistical alternative to qualitative causal mapping to assess the interdependencies among factors. SEM enabled the empirical estimation of relationships among variables, offering a more objective and data-driven representation of system structure. This marked a methodological advancement over traditional participatory mapping techniques, which often depend on group consensus and are limited by subjectivity and potential groupthink (Phadnis *et al.* 2014; Kayser and Shala 2020; Schweizer and Lazurko 2020). The use of SEM thus strengthened construct validity and supported the generation of replicable models grounded in observable data.

Following SEM, factor reduction was carried out using the ADVIAN® method, which systematically identifies the most important factors for scenario construction, those that are both highly impactful and highly uncertain. This approach requires no participant involvement, eliminating subjectivity, the need for consensus, and the potential biases associated with expert-driven reduction. By automating the analysis, ADVIAN® provides a time-efficient process, with the researcher-developed application further ensuring accuracy and speed in evaluating and prioritizing factors. The results of the two applications demonstrate the method's practical effectiveness. For the renewable energy adoption study, seven factors were identified as most important: perceived performance expectancy, perceived ease of use, social influence, awareness, perceived cost value, facilitating conditions, and perceived environmental awareness. For the AI adoption in higher education study, seven factors were unveiled: perceived performance expectancy, perceived ease of use, social influence, awareness, perceived relevance, facilitating conditions, and hedonic motivation. These concise, representative sets of key drivers provide a robust foundation for subsequent crowdsourcing and scenario generation stages, illustrating the method's ability to distil larger, complex factor sets into critical inputs for scenario construction.

Through this integrated approach, the study successfully achieved Objective 2, producing empirically grounded, systematically reduced factor sets with mapped interdependencies. The combination of secondary data, SEM, and ADVIAN® represents a scalable, transparent, and efficient methodology for identifying critical factors in complex socio-technical systems, advancing beyond the limitations of prior scenario studies.

6.3 Achievement of Objective 3

Objective 3: *To develop a theoretically grounded methodology for constructing consistent scenarios.*

This objective was achieved through the design and integration of a multi-step methodology that combines empirical data, expert insights, and structured analytical techniques to generate internally consistent scenarios. The methodology is grounded in the theoretical foundations established in Chapter 3, including GST, complexity theory, constructivism, and PST. Each theoretical lens directly informed specific elements of the methodology: GST guided factor identification and the understanding of interdependencies (Von Bertalanffy 1968); complexity theory informed the consideration of non-linearity, emergence, and feedback loops (Holland 1995; Prigogine and Stengers 2018); constructivism underpinned the crowdsourcing process, ensuring inclusivity and social co-construction of knowledge (Guba and Lincoln 1994; Schwandt 1994); and PST sensitized the methodology to plausible surprises and disruptions (Derbyshire 2017).

The methodology is structured into **six steps**, each informed by a literature-based rationale and prior research:

1. **Identification of impact factors** from secondary data. This step builds on the findings of Bradfield *et al.* (2005), Douglas *et al.* (2021), and Kishita *et al.* (2020), who note that traditional workshop-based factor elicitation is resource-intensive and prone to subjectivity. By relying on systematically gathered secondary data, the methodology ensures an empirically grounded starting set of factors while avoiding the limitations of time-consuming primary collection. Identifying factors for secondary data also allows for the identification of a larger cohort of factors.

2. **The creation of the factor matrix using SEM**, provides a statistically validated model of factor interdependencies. This approach enables the simultaneous identification of factors and their relationships, saving time and ensuring construct validity without requiring primary data collection from experts.

3. **The determination of critical factors using ADVIAN®** systematically identifies the most impactful and uncertain factors. This method eliminates subjectivity, consensus bias, and participant dependence, which are common challenges in traditional expert-driven reduction methods (Linss and Fried 2009; Musch and von Streit 2017; Kemp-Benedict, Carlsen and Kartha 2019; Kayser and Shala 2020). The researcher-developed application further ensures speed, accuracy, and scalability, allowing for the inclusion of larger factor sets than is feasible with conventional methods.

4. **The elicitation of expert judgements through crowdsourcing** leverages the “X” platform following established recommendations for online expert engagement (Wasilewski *et al.* 2019; MacDermott *et al.* 2020). This approach aligns with constructivist principles by enabling broad

participation, inclusivity, and socially co-constructed insights while being time-efficient and logistically feasible. An online researcher-developed tool was developed to identify expert participants and gather factor state judgements from these experts. For the renewable energy adoption application, 31 experts were successfully recruited on the platform within 21 days, of whom 14 completed the survey, reflecting a 55% dropout rate. Similarly, for the AI adoption in higher education application, 45 experts were recruited within 14 days, with 12 completing the survey, resulting in a 73% dropout rate. These dropouts are consistent with McConnell, Finetto and Heise (2024) and Esch, Mylonopoulos and Theoharakis (2025), who report that participant recruitment through “X” frequently exhibits dropout rates ranging from 2% to 75%, confirming that high attrition is a common characteristic of crowdsourced expert engagement.

Despite the researcher’s limited online presence, the ability to recruit qualified participants and gather judgement data within two to three weeks underscores the efficacy and scalability of crowdsourcing as a recruitment mechanism. In contrast, academic literature on expert-based methodologies consistently emphasizes that the process of identifying, recruiting, and obtaining judgements from experts is typically lengthy, spanning 8 to 20 weeks (Linstone and Turoff 1975; Okoli and Pawlowski 2004; Hsu and Sandford 2007). This extended timeframe is largely attributed to the recruitment bottleneck, where the identification and securing of high-calibre participants often require 4 to 12 weeks, followed by additional delays associated with scheduling and the iterative nature of participatory techniques such as the Delphi method. By comparison, the use of crowdsourcing in this study achieved rapid expert engagement and data collection within 14 to 21 days, offering a substantially more time-efficient and logistically flexible alternative to traditional recruitment processes, without compromising methodological rigour or inclusivity.

5. **The creation of the judgement matrix for CIB analysis**, guided by Weimer-Jehle (2006), involved structuring the interdependencies and expert judgements into a formal computational format. To streamline this process, a researcher-developed application was designed to extract judgement strings directly from the database storing the crowdsourced expert input and automatically consolidate them into a single, coherent matrix of judgements. This automation ensured accuracy, consistency, and efficiency in data handling, eliminating the need for manual transcription or aggregation, which are prone to human error and time delays. The resulting matrix served as a foundation for the subsequent CIB computation, enabling the systematic evaluation of factor interdependencies and ensuring methodological transparency and replicability.

6. **The construction of internally consistent scenarios using CIB analysis**. CIB is a structured, rule-based method that systematically assesses the logical compatibility of qualitative judgements among interdependent factors (Weimer-Jehle 2006). This step was operationalized through the validated open-source software tool *ScenarioWizard*, which automates the consistency checks and identifies configurations of factor states that are logically coherent and plausible. CIB analysis ensures that the resulting scenarios are internally consistent, with each factor's state supporting rather than contradicting the others, and that they are aligned with the theoretical foundations of this study, particularly complexity theory and GST.

    In the renewable energy adoption study, the CIB analysis yielded three consistent scenarios: a *best-case*, *worst-case*, and *base-case* scenario, each illustrating alternative evolutions under different conditions. In the AI in higher education study, four consistent scenarios emerged: a *best-case*, *worst-case*, and two varying base-case scenarios. These scenarios serve as a precursor for further elaboration and strategic interpretation, forming structured foundations for subsequent planning, policy formulation, and participatory refinement. The resulting scenarios are elaborated on in the discussion of Objective 4 in Section 6.4.

The novel methodology addresses several limitations of traditional scenario construction approaches. By combining secondary data with SEM and ADVIAN®, the approach reduces the reliance on subjective workshops, consensus-based decisions, and small expert panels. Crowdsourcing further enhances scalability and access to diverse expert insights while maintaining methodological rigour, as highlighted in recent literature on online expert engagement. Additionally, the use of CIB analysis ensures the internal consistency of the scenarios produced, systematically reconciling interdependencies among factors and providing a structured, analytically robust foundation for scenario generation.

The practical effectiveness of the methodology is demonstrated through its application to two domains, which is discussed with reference to the fourth objective.

6.4 Achievement of Objective 4

Objective 4: *To validate the methodology through the practical implementation and application to renewable energy adoption and AI adoption in higher education.*

This final objective was achieved by applying the newly developed scenario construction methodology to two distinct contexts: the adoption of renewable energy technologies; and the adoption of AI in higher education. These dual applications served as validation exercises, demonstrating the adaptability, robustness, and replicability of the proposed framework across different domains. Each implementation followed the six-step methodological process, from factor identification to the construction of consistent scenarios, thereby providing an end-to-end evaluation of methodological performance. The following sections discuss the findings and methodological validation outcomes for each of the two applications.

6.4.1 Scenarios for the adoption of renewable energy

The scenarios developed in this implementation, comprising of **best-case**, **worst-case**, and **base-case** scenarios, demonstrates distinct configurations of **perceived value**, **awareness**, and **perceived support**, which collectively influence the adoption of renewable energy technologies. These findings align with and extend existing literature on technology acceptance, energy transitions, and scenario analysis. The following sections compare each scenario configuration with key theoretical and empirical studies in the field.

The **best-case scenario**, representing a convergence of **high perceived value, awareness, and support**, reflects optimal conditions for the widespread adoption of renewable energy technologies. This scenario is supported by Rogers, Singhal and Quinlan's (2014) diffusion of innovations theory, where perceived relative advantage, a construct closely aligned with perceived value, is a primary predictor of technology adoption. In the context of renewable energy, the study by Claudy, Peterson and O'Driscoll (2013) found that individuals who perceive renewable energy as economically advantageous and environmentally beneficial are more likely to adopt such technologies.

High awareness also plays a critical role. Empirical research by Zografakis, Menegaki and Tsagarakis (2008) demonstrates that environmental knowledge significantly increases willingness to invest in renewable energy, both as a cognitive precursor shaping perceptions and motivation. Moreover, broader meta-analytic evidence confirms that awareness of environmental problems and familiarity with renewable options significantly influence adoption behaviours in both developed and developing countries .

High perceived support, including both policy and community-level backing, is equally essential. The multidimensional framework of social acceptance, comprising socio-political support (e.g., favourable policies and incentives), community acceptance (e.g., local engagement), and market acceptance (e.g., investor confidence), was originally conceptualized by Wüstenhagen, Wolsink and Bürer (2007) and remains highly influential in contemporary research. Recent studies in geothermal and energy storage contexts reaffirm this model, demonstrating that high socio-political and community backing is critical to project success. Building on this, more recent empirical research by Palm and Eriksson (2018) underscores that public trust in institutions and confidence in long-term policy stability significantly enable household and commercial investment in renewable energy systems. Further evidence from Chen *et al.* (2025) shows that strengthening communication and establishing transparent mechanisms are among the highest priorities for improving social acceptance. Studies from Europe reaffirm that procedural fairness, process transparency, and early local engagement are pivotal for fostering community support, particularly in wind and community energy projects (Peterson, Stephens and Wilson 2015).

In terms of broader outcomes, this scenario aligns with global policy frameworks that link renewable energy adoption to the achievement of Sustainable Development Goals (SDGs), particularly SDG 7 (Affordable and Clean Energy) and SDG 13 (Climate Action) (Olhoff and Christensen 2020; Gielen *et al.* 2021). Although the scenario presents an idealistic configuration, it serves as a normative vision that guides strategic planning and policy development.

The **worst-case scenario,** characterized by **low levels across all three impact factors (perceived value, awareness, and support)**, represents a stagnation context that significantly hinders renewable energy adoption. While this scenario may be considered implausible in its absolute form, it effectively illustrates how systemic inertia and negative perceptions can reinforce each other to impede progress. **Low perceived value** has been identified as a persistent barrier in multiple studies. Recent evidence shows that high upfront capital costs continue to deter adoption, especially when users do not see immediate economic returns , such as solar installations in South Africa (Smarte Anekwe *et al.* 2024). Research on battery storage acceptance in Australia similarly finds that concerns about cost and technical performance are strongly linked to lower acceptance levels (McCarthy and Liu 2024). A 2023 study on homeowners reveals that while both environmental and financial benefits shape decision making, financial returns often have a dominant effect (Halim *et al.* 2024). A broader meta-analysis confirms that perceived benefits, particularly economic ones, strongly predict PV adoption, outweighing demographic factors (Schulte *et al.* 2022). In the EV sector, an Indian study also found that price-value perceptions significantly affect purchase intentions (Hasan *et al.* 2024).

Low perceived support, particularly due to inadequate policy frameworks and unstable incentives, remains a critical systemic barrier. Institutional lock-ins, inconsistent subsidies, and regulatory uncertainty continue to impede clean energy investments from both public and private actors, a pattern originally noted by Sovacool and Griffiths (2020). This analysis is strongly reinforced by a 2025 global scoping review, which found that almost half of the surveyed studies cited policy instability and fragmented regulations as key obstacles to renewable energy deployment (Obuseh *et al.* 2025). Moreover, a 2025 empirical study from Nigeria reveals that economic policy, uncertainty, and weak institutional quality consistently suppress renewable energy transitions (Iormom *et al.* 2025). Similarly, in South Africa, policy gaps, bureaucratic inertia, and regulatory fragmentation have been shown to stall renewable procurement and infrastructure deployment (Todd and McCauley 2021). Internationally, projects across the Americas and Europe are frequently delayed or derailed due to outdated permitting processes and uneven incentive structures (PhiCap 2025). Returning to the institutional perspective, the foundational insights of Meadowcroft (2009) on political resistance and institutional inertia are validated by ongoing fossil fuel lobbying, regulatory capture, and entrenched incumbents, barriers documented in recent global policy reviews and news analyses.

While this scenario does not reflect current global trajectories, it serves a cautionary purpose similar to that of ‘fragmented world’ or ‘business-as-usual’ scenarios commonly used by the IPCC or Shell Global. These narratives help identify conditions under which sustainability transitions could fail, thereby reinforcing the importance of coordinated multi-stakeholder action.

The **base-case scenario** presents a hybrid configuration: **high awareness coupled with low perceived value and low support,** which closely mirrors empirical findings in transitional contexts. This scenario illustrates that awareness, while necessary, is insufficient on its own to drive adoption. **Low perceived value** despite **high awareness** often arises in regions where effective environmental education succeeds, yet economic or infrastructural hurdles persist. Poortinga *et al.* (2019) highlighted that while climate awareness is widespread, perceived cost and convenience barriers frequently prevent pro-environmental behaviour. Van den Broek and Walker (2019) confirm this pattern among young adults, finding that monetary incentives, not environmental awareness, drive energy-saving choices. Similarly, the experiment in the United Kingdom by Scarpa and Willis (2010) showed that awareness of renewable benefits does not guarantee uptake unless financial savings are clearly perceived. Further, Shen and Wang (2022) demonstrate in China that consumer-perceived costs significantly weaken the path from environmental awareness to green behaviour, reflecting a persistent value-action gap.

The role of **perceived support** is equally significant. Palm and Eriksson (2018) found that homeowners in Sweden were notably less likely to invest in solar photovoltaic systems when they felt unsupported by local authorities or utility providers; lack of regulatory clarity, unreliable subsidy schemes, and complex installation procedures fostered a perception of systemic indifference, deterring investment despite high public awareness. From a theoretical lens, this scenario aligns with Geels' multi-level perspective (MLP) on socio-technical transitions, where misalignment between landscape pressures (e.g., climate urgency), regime responses (e.g., institutional resistance), and niche innovations (e.g., renewable technologies) leads to delayed or stalled transitions (Geels 2002).

Overall, the base-case scenario illustrates the complexity and unevenness of real-world transitions. It supports the notion that increasing awareness must be matched by structural incentives and efforts to increase the perceived personal and societal value of renewable energy.

In summary, the scenario typology produced in this study confirms and extends current literature by demonstrating how varying configurations of **perceived value**, **awareness**, and **support** affect the likelihood of renewable energy adoption. The best-case scenario is aligned with high-adoption frameworks that emphasize system-wide convergence, while the worst-case scenario highlights the consequences of institutional and perceptual breakdown. The base-case scenario, representing a mixed state, is perhaps most reflective of ongoing transitions and underscores the need for integrated strategies that address both perceptual and systemic dimensions. Collectively, these findings contribute to a more nuanced understanding of how socio-cognitive and institutional factors interact to influence the pace and direction of sustainable energy transitions.

6.4.2 Scenarios for the adoption of artificial intelligence in higher education

The scenarios derived from this study, consisting of **best-case, worst-case,** and two **base-case** scenarios, demonstrates how varying combinations of **perceived value**, **awareness**, **perceived support**, **facilitating conditions**, and **perceived ease of use** influence the potential adoption of AI in higher education institutions. These findings align with and extend current theoretical and empirical literature on technology acceptance, educational innovation, and organizational change. The discussion below situates each scenario within the broader academic discourse and identifies implications for practice and policy.

The **best-case scenario,** characterized by high **perceived value**, **awareness**, and **perceived support**, represents an ideal context in which AI adoption in higher education can flourish. This configuration reflects the core constructs of the technology acceptance model (TAM) (Davis 1989), the unified theory of acceptance and use of technology (UTAUT)(Venkatesh *et al.* 2003), and subsequent models that emphasize the role of value perception and awareness in shaping behavioural intention. Studies such as Zawacki-Richter *et al.* (2019) and Sajja *et al.* (2024) have emphasized that **perceived value**, in terms of teaching enhancement, administrative efficiency, and personalized learning is a key driver for AI integration in education. Zawacki-Richter *et al.* (2019) highlight that AI-enabled platforms significantly boost teacher support and administrative workflows, freeing educators to focus on pedagogy. Sajja *et al.* (2024) present an AI-enabled intelligent assistant (AIIA) system that demonstrably improves adaptive learning and reduces teacher workload. When educators and institutional leaders recognize these concrete benefits for learning outcomes and performance, the likelihood of adoption increases markedly.

Similarly, **awareness** plays a crucial enabling role. Ferikoğlu and Akgün (2022) find that a lack of faculty awareness about AI's capabilities and constraints often impedes adoption. For example, a case study in Northern Cyprus reveals that practical AI knowledge and positive beliefs significantly predict actual classroom use (Güneyli *et al.* 2024). Higher awareness enables better-informed decisions and more strategic implementation. **High perceived support**, in terms of institutional commitment, leadership endorsement, and resource availability, is also critical. Recent work by Viberg *et al.* (2024) across six countries connects teacher self-efficacy and understanding of AI with greater trust and willingness to integrate AI tools. Without strong leadership backing and material support, confidence in feasibility—and thus adoption—is undermined.

Although this ***best-case* scenario** is aspirational, providing a valuable normative benchmark aligned with digital transformation goals, it may still be overly optimistic in many real-world institutional settings.

The **worst-case scenario** is defined by low levels of **perceived value**, **awareness**, and **support**, and reflects a context in which AI adoption is significantly hindered. This scenario aligns with known resistance factors and inertia documented in the literature on innovation in higher education. **Low perceived value** of AI in education often originates from doubts about its relevance, reliability, and pedagogical benefits. Selwyn (2024), synthesizing recent debates, notes that many educators remain sceptical of AI tools, viewing them as potential threats to professional autonomy and academic judgement unless they clearly add educational value. When AI is not perceived to enhance teaching, research, or learning significantly, resistance is common.

Lack of awareness further hinders adoption. Shata and Hartley (2025) found that many educators are either uninformed about AI's possibilities or misunderstand its role, leading to fear, uncertainty, or indifference. These factors limit engagement and reinforce negative attitudes. **Inadequate institutional support**, including visible commitment, leadership endorsement, and access to resources, is also a well-documented barrier. Recent meta-review work by Bond *et al.* (2024) across 66 studies on AI in education highlights that without clear infrastructure, professional development, and strategic guidance, faculty are unlikely to move beyond isolated experiments. Contextual survey-based research further confirms that most institutions provide limited training, unclear policies, and minimal pedagogical frameworks for AI: lacking these, meaningful adoption stalls (Sutedjo, Liu and Chowdhury 2025).

Like “best-case” strategic foresight scenarios, this ***worst-case*** outlook is unrealistic in its extremity but serves as a valuable caution, highlighting the risk conditions that can be mitigated through proactive institutional action.

The first **base-case** scenario features **low perceived value**, **low awareness**, and **conflicted support** and illustrates an environment where adoption remains limited despite some infrastructural readiness. **Low perceived value** of AI in education may occur even when relevance is recognized if performance expectancy and ease of use remain low. According to Davis’s technology acceptance model (TAM), perceived usefulness, a close proxy for performance expectancy, is central to the formation of adoption intentions (Davis 1989). When educators fail to perceive clear functional benefits or find AI tools difficult to use, even those who acknowledge their potential relevance may resist adoption. This has been confirmed by recent studies such as Smutny and Schreiberova (2020), who show that relevance alone is insufficient to drive meaningful engagement without accompanying perceptions of utility and usability.

Limited awareness similarly constrains adoption. In many institutions, low levels of general AI awareness are compounded by minimal peer influence and a lack of hedonic motivation. Rogers, Singhal and Quinlan (2014) identify awareness as the crucial first stage in the diffusion of innovation, essential for catalysing broader engagement. However, as Holstein *et al.* (2019) note, when AI tools are not embedded in institutional discourse and educators lack opportunities to explore or discuss them in supportive communities, awareness fails to translate into informed decision making or behavioural change. Institutional **support** in this scenario is **conflicted**. While many universities may provide basic infrastructure such as platforms and devices, referred to as facilitating conditions, this is often not matched by adequate pedagogical support, clear training pathways, or user-oriented design. As Ifenthaler and Yau (2020) point out, the presence of infrastructure alone does not ensure adoption if educators do not feel empowered or competent to use the tools. The result is a situation in which AI integration remains technically possible but practically difficult.

Taken together, this mixed configuration of **low perceived value, low awareness, and conflicted support** represents a constrained but realistic base-case scenario. It signals an institutional climate where adoption may occur sporadically or experimentally but is unlikely to scale without targeted interventions that improve usability, promote awareness, and embed AI in professional development frameworks.

The second **base-case** presents **high awareness**, but **low perceived value**, **low social influence**, and **conflicted support**, highlighting a disconnect between knowledge and commitment. **Low perceived value** of AI in education can also stem from a more entrenched configuration where educators rate performance expectancy, ease of use, and relevance as uniformly low. In such cases, AI tools are not only seen as difficult to use or unreliable, but also as lacking alignment with academic tasks or disciplinary needs. Dwivedi *et al.* (2021) emphasize that when educators do not see a clear connection between AI and improved learning or research outcomes in their specific context, adoption is unlikely, regardless of the level of institutional investment.

High levels of awareness, on their own, do not guarantee adoption. In this scenario, individual awareness is relatively strong, but social influence and hedonic motivation remain low. Ferikoğlu and Akgün (2022) argue that awareness must be accompanied by social reinforcement and emotional engagement to be effective. Without peer support or intrinsic interest, informed educators may still remain disengaged, reinforcing a passive or sceptical stance toward AI. **Perceived support** in this scenario remains **conflicted**. Institutions may provide enabling infrastructure, such as learning platforms and AI-enhanced tools, but these are often not accompanied by effective implementation support or usability-focused design. Bond *et al.* (2024) stress that faculty need more than access;

they require targeted training, clarity around expectations, and opportunities to explore AI use in their teaching practice. When support feels abstract or disconnected from real teaching needs, adoption tends to stall.

While this base-case does not reflect a worst-case breakdown, it highlights a stalled adoption pathway: a context where knowledge of AI exists but is not matched by confidence, motivation, or practical engagement. As such, it offers a realistic foresight scenario that underscores the need for integrated institutional strategies, where communication, training, and relevance are addressed collectively to move toward more effective and sustainable AI integration.

Together, these scenario analyses align with and contribute to the literature on AI adoption and digital transformation in higher education. The **best-case scenario** reflects ideal conditions where perceptions and institutional enablers converge to support change. The **worst-case scenario** illustrates how widespread disengagement and lack of support can stall progress. The **base-case scenarios**, which feature a mix of enabling and constraining factors, are the most reflective of current institutional realities. They underscore that technical infrastructure and policy frameworks must be matched with perceived relevance, usability, and clear institutional advocacy to achieve meaningful adoption of AI. These insights offer practical value for higher education leaders, policymakers, and educational technology developers by identifying leverage points for intervention. Improving perceived value and ease of use, increasing faculty awareness, and enhancing visible support mechanisms can significantly improve adoption outcomes and help institutions realize the benefits of AI-enhanced education.

While the study does not develop full narrative scenarios, the structured outputs generated through the methodology provide valuable insights for decision-makers. The analysis of factor configurations and interdependencies enables the identification of key drivers and critical conditions that shape possible future outcomes. Across both case studies, the results indicate that perceived value, awareness, and institutional support are consistently influential factors. These drivers represent key leverage points that can be targeted by policymakers and organisations seeking to influence system outcomes.

The identification of best-case, worst-case, and intermediate scenario configurations provides a structured understanding of how different combinations of factors may influence future developments. This allows decision-makers to assess potential risks and opportunities without requiring fully developed narrative scenarios. In practical terms, the findings suggest that:

- Interventions aimed at increasing awareness and perceived value can significantly influence adoption outcomes
- Institutional and policy support mechanisms play a critical role in enabling positive system transitions
- Understanding interdependencies between factors is essential for effective strategic planning

These insights demonstrate that the methodology can support evidence-informed decision-making by identifying critical drivers, highlighting system sensitivities, and providing a structured basis for scenario-based analysis.

6.5 Critical Reflection and Insights

The application of the proposed methodology across the two case studies provides an opportunity to critically evaluate its performance in relation to the limitations identified in the literature (Chapter 2), as summarised in Table 6, as well as to reflect on its theoretical contribution. Chapter 2 highlighted several key challenges in existing scenario construction methods, including subjectivity in factor identification, time-intensive data collection processes, limited diversity of expert participation, difficulty in modelling interdependencies, and a lack of theoretical coherence. The findings from this study demonstrate that the proposed methodology addresses these limitations to a considerable extent, while also revealing new considerations.

In relation to subjectivity, the integration of SEM-derived path coefficients with ADVIAN® analysis provides a more empirically grounded and transparent approach to factor identification and refinement. This represents a clear improvement over traditional methods that rely primarily on expert judgement. However, this approach remains dependent on the availability and quality of existing empirical studies. With respect to time intensity, the replacement of workshop-based processes with a semi-automated, tool-supported approach significantly improves efficiency. The use of an online tool enables faster data collection and analysis, although it introduces new challenges related to participant engagement in non-facilitated environments. The limitation of restricted expert participation is addressed through the use of crowdsourcing, which enables broader and more diverse input. While this enhances inclusivity, it also introduces variability in participant expertise, requiring careful screening and validation mechanisms. The challenge of modelling complex interdependencies is effectively addressed through the integration of ADVIAN® and CIB analysis. The results demonstrate that the methodology is capable of capturing and analysing interdependent relationships across relatively large factor sets. However, the necessary reduction of factors introduces a trade-off between comprehensiveness and analytical manageability. In addition, the identification of inconsistent factor configurations during scenario construction, and the resulting development of an additional scenario, highlights the adaptability of the methodology. This is considered an application-specific extension rather than a formalised step, as it is dependent on the characteristics of the context in which the methodology is applied.

Finally, the issue of theoretical fragmentation, described in the literature as “methodological chaos,” is addressed through the integration of GST, complexity theory, constructivism, and PST into a unified and operational framework. The application of the methodology demonstrates how these theoretical perspectives can be translated into practice, providing a more coherent foundation for scenario construction. Compared to traditional approaches such as ILM, LP, and CIA, which tend to rely on either qualitative narratives or isolated analytical techniques, the proposed methodology offers a more integrated, systematic, and theoretically grounded approach. The empirical application shows that this integration enables both analytical rigour and practical scalability.

Despite these contributions, several limitations remain. These include dependence on existing data sources, challenges associated with crowdsourced participation, the changing landscape of social media platforms and the absence of probabilistic modelling in CIB analysis. As such, the scenarios generated should be interpreted as plausible and internally consistent configurations rather than predictive forecasts. Based on these insights, future research could explore the integration of additional data sources, refinement of participant validation mechanisms, and the incorporation of probabilistic or simulation-based techniques to complement consistency-based analysis.

Overall, this critical reflection demonstrates that the proposed methodology not only addresses key limitations identified in the literature but also advances the theoretical and methodological foundations of scenario construction, while highlighting important considerations for its practical application.

6.6 Scenario Insights

This study applied the proposed methodology to two case studies: renewable energy adoption and AI adoption in higher education. These domains were selected to demonstrate the applicability of the methodology across contexts characterised by complexity and uncertainty. In the renewable energy case study, 36 factors were identified and analysed, while 27 factors were considered in the AI in higher education case. In both applications, the methodology enabled the identification of key drivers, the analysis of interdependencies, and the generation of multiple internally consistent scenarios. Across both application domains, a consistent set of influential drivers emerged, including perceived value, awareness, social influence, and enabling conditions. These factors represent priority areas for targeted intervention, where strategic action is most likely to influence system outcomes. Furthermore, the identification of internally consistent factor combinations provides insight into plausible configurations of future states, enabling stakeholders to anticipate potential risks, trade-offs, and opportunities.

The findings also demonstrate that system behaviour is highly sensitive to changes in a small number of interdependent factors, reinforcing the importance of analysing relationships rather than isolated variables in strategic planning. Collectively, these insights support more informed and proactive decision-making by providing a structured understanding of how key drivers interact to shape possible future developments, even in the absence of fully articulated narrative scenarios.

Although the methodology does not produce fully developed narrative scenarios, the outputs generated provide structured and practically relevant scenario insights. By identifying the most critical and uncertain factors and mapping their interdependencies, the analysis highlights key leverage points that may shape future system behaviour.

6.7 Chapter Summary

Chapter 6 synthesized the key findings of the study by discussing the results in relation to the four research objectives and reflecting on their broader methodological, theoretical, and practical significance. The chapter has shown that the proposed methodology responds to several of the central limitations identified in the scenario construction literature, particularly those relating to subjectivity, inconsistency, limited scalability, and insufficient theoretical coherence.

Methodologically, the study introduces a novel, theoretically grounded scenario-construction methodology that replaces time-intensive participatory workshops with a semi-automated, data-driven, and interpretively inclusive process. The methodology integrates multiple, complementary techniques: systematic secondary data collection via the PRISMA framework, ADVIAN® analysis for empirical factor reduction, expert crowdsourcing through the “X” platform for participatory input, and CIB analysis for the generation of internally consistent scenarios. Grounded in GST, complexity theory, constructivism, and PST, the methodology addresses limitations identified in existing scenario methods, including subjectivity, reproducibility, scalability, and limited inclusivity. The integrated approach ensures transparency, efficiency, and analytical rigour, enabling the exploration of larger factor sets, systematic evaluation of interdependencies, and the generation of scenarios that are both plausible and strategically relevant.

Empirically, the methodology was validated through application in two distinct domains: renewable energy adoption and AI adoption in higher education. The analysis revealed that perceived value, awareness, and perceived support consistently emerged as the most influential drivers of adoption. In the renewable energy study, three consistent scenarios: best-case, worst-case, and base-case, illustrated the effects of alignment or misalignment of the various constructs. In the AI study, four scenarios: best-case, worst-case, and two base-case variations, demonstrated the significance of factors in the domain. Compared with prior research, which typically considers a narrow set of factors (often fewer than 10), this study identified 36 factors for renewable energy and 27 for AI adoption in higher education, drawn from multiple theoretical models, including TAM, UTAUT, theory of planned behaviour, theory of reasoned action, behavioural finance, institutional theory, and technology–organization–environment frameworks, thereby providing a broader, more nuanced foundation for scenario construction.

Theoretically, the study confirms the value of combining GST, complexity theory, constructivism, and PST to construct scenarios that are structurally rigorous, dynamically sensitive, socially relevant, and imaginatively challenging. The scenarios serve as learning instruments, enhancing understanding of systemic interdependencies, stakeholder dynamics, and potential disruptions, while guiding context-specific interventions.

Practically, the research demonstrates the efficiency and scalability of crowdsourced expert input using “X,” significantly reducing the time and logistical burden of traditional participatory methods. The study also highlights challenges such as dropout rates, confirming prior reports of variability in online expert participation. The integration of automated tools for factor reduction (ADVIAN®), judgement gathering and matrix creation further enhances methodological efficiency and accuracy, enabling rapid yet reliable scenario development.

The chapter has also critically reflected on the strengths and remaining limitations of the proposed approach. Although the methodology addresses many of the shortcomings of traditional methods, important challenges remain, including dependence on existing data sources, variability in crowdsourced participation, the changing social media environment, and the static nature of consistency-based modelling. At the same time, the scenario insights presented in Section 6.6 demonstrate that, even without fully developed narrative scenarios, the structured outputs of the methodology provide meaningful and actionable guidance for decision-makers by identifying key leverage points, system sensitivities, and plausible future configurations.

In conclusion, Chapter 6 illustrates that the study has successfully achieved its objectives: it critically evaluated existing scenario methods (Objective 1), identified key factors and their interdependencies (Objective 2), developed a theoretically grounded methodology (Objective 3), and validated this methodology through practical application (Objective 4). By combining rigorous theory, robust methodology, and practical validation, the study advances both the science and practice of scenario construction, providing a replicable framework for researchers, policymakers, and planners to anticipate and navigate complex, evolving futures. Moreover, the proposed methodology is not only theoretically grounded and methodologically robust, but also practically relevant. By combining analytical rigour with structured scenario insights, the study advances both the theory and practice of scenario construction and provides a useful foundation for policymakers, planners, and researchers seeking to engage with complex and uncertain futures.

CHAPTER 7: CONCLUSION, LIMITATIONS AND FURTHER RESEARCH

This chapter provides a comprehensive synthesis of the research, reflecting on the key findings and their significance for both theory and practice. It revisits the research question and critically assesses the extent to which each objective was achieved. In addition, the chapter presents the key methodological, theoretical, and practical contributions of the study, highlighting how the proposed approach advances existing scenario construction research. The chapter concludes by outlining the study's limitations and offering recommendations for future research, informed by the insights and outcomes generated throughout the investigation.

7.1 Answering the Research Question

The study's overarching aim was to develop and evaluate a novel methodology for scenario construction that leverages ADVIAN® for factor refinement, crowdsourcing for diverse expert judgement, and CIB analysis to ensure internal consistency, thereby producing robust, timely, and credible scenarios. This research sought to address long-standing challenges in scenario construction, such as prolonged development timelines, bias, limited scenario diversity, and difficulty ensuring consistency, within a field that remains in a state of theoretical flux and methodological fragmentation.

To guide the investigation, the primary research question was defined as follows: "***How can a theoretically grounded methodology combining computational impact analysis and the collective intelligence of human experts overcome the key limitations of rigour, scalability, and consistency in traditional scenario construction?"*** Given the complexity of this research question, the study was structured around four specific objectives:

1. *To critically evaluate the theoretical and methodological limitations of existing scenario construction techniques by means of a literature review, establishing the necessity for an integrated approach;*
2. *To identify and critically structure the key factors and their interdependencies from a set of factors derived from of a structured literature review, as a foundational analytical step informing scenario construction;*
3. *To develop a theoretically grounded methodology for constructing consistent scenarios; and*
4. *To validate the methodology through the practical implementation and application to renewable energy adoption and AI adoption in higher education.*

7.2 Achieving the Aim and Objectives

The overarching aim of this study was to develop a theoretically grounded, methodologically rigorous, and practically validated framework for constructing consistent and plausible scenarios. Through the design, application, and evaluation of a novel multi-step methodology, the study has successfully met this aim by integrating four complementary theoretical perspectives: GST, complexity theory, constructivism, and PST, with empirically robust methods for factor identification, reduction, and scenario generation. While the first objective was achieved in Chapter 2, the method for achieving Objective 2 was described in Chapter 4, while the methodology that achieves Objective 3 was presented in Chapter 4 Section 4.2. The achievement of the final objective was demonstrated through two experimental implementations in Chapter 5.

Objective one, which was *to critically evaluate the theoretical and methodological limitations of existing scenario construction techniques by means of a literature review, establishing the necessity for an integrated approach,* was achieved in Chapter 2 through a comprehensive literature review. It highlighted gaps in existing methods, including reliance on subjective workshops, limited scalability, insufficient systemic integration, and inadequate consideration of emergent, unpredictable system behaviour. The review also identified the potential of digital and crowdsourced approaches to overcome these challenges.

The second objective, which was *to identify and critically structure the key factors and their interdependencies from a set of factors derived from of a structured literature review, as a foundational analytical step informing scenario construction*, was detailed in the first three steps of the methodology. The study extracted a broad set of empirically supported factors from multiple theoretical models and domains, exceeding the typical factor ranges in prior studies. Relationships between these factors were identified SEM path coefficients and subsequently reduced to the most impactful and uncertain drivers using the ADVIAN® advanced impact analysis method, ensuring analytical rigour and objectivity without the need for participant intervention.

The third objective was *to develop a theoretically grounded methodology for constructing consistent scenarios*. A six-step methodology was formulated, combining secondary data collection, factor reduction, crowdsourced expert judgements, and CIB analysis. The approach addresses limitations of traditional methods by providing a time-efficient, reproducible, and scalable framework that generates internally consistent scenarios while retaining interpretive and participatory insights.

The final objective was *to validate the methodology through the practical implementation and application to renewable energy adoption and AI adoption in higher education.* The application of the methodology to these two distinct domains demonstrated its flexibility and effectiveness. The renewable energy study produced three scenarios while the AI study produced four scenarios. The resulting scenarios offered nuanced insights into key drivers of adoption, systemic interdependencies, and potential interventions, confirming the methodology's practical utility and empirical validity.

Overall, the study has not only achieved its stated aim but has also demonstrated that scenario construction can be approached in a more structured, scalable, and theoretically grounded manner. The integration of ADVIAN®, crowdsourcing, and CIB analysis provides a coherent framework for addressing key limitations identified in the literature, including subjectivity, inefficiency, and limited inclusivity. The following section consolidates the contributions of the study in relation to knowledge, theory, methodology, and practice.

7.3 Research Contributions

The primary contribution of this study is the development of a six-step, theoretically grounded methodology for constructing internally consistent scenarios. This framework integrates the study's theoretical foundations and analytical techniques into a coherent and replicable process. Given its importance, the methodology is presented again in this chapter (Figure 45) to provide a clear overview of the study's core contribution. In addition, the theoretical framework underpinning the study is reproduced in Figure 46 to highlight the conceptual foundations of the proposed methodology. Together, these figures illustrate the integration of theory and method that forms the core contribution of this research.

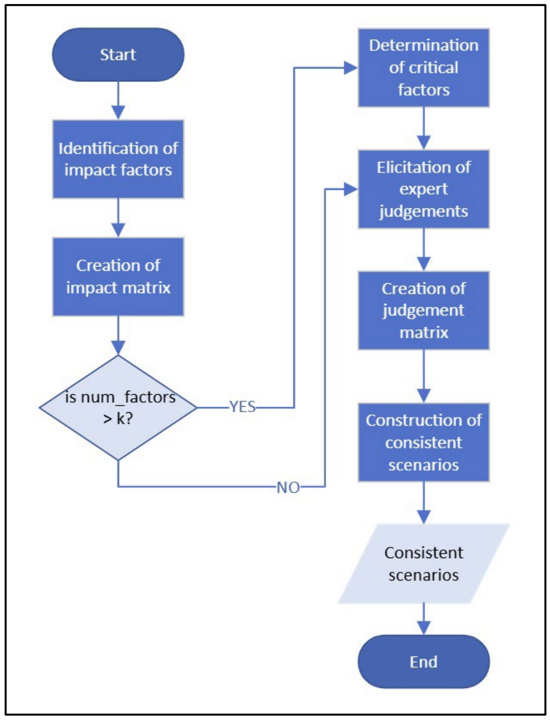


Figure 45: Six-step scenario construction methodology (reproduced from Figure 5)

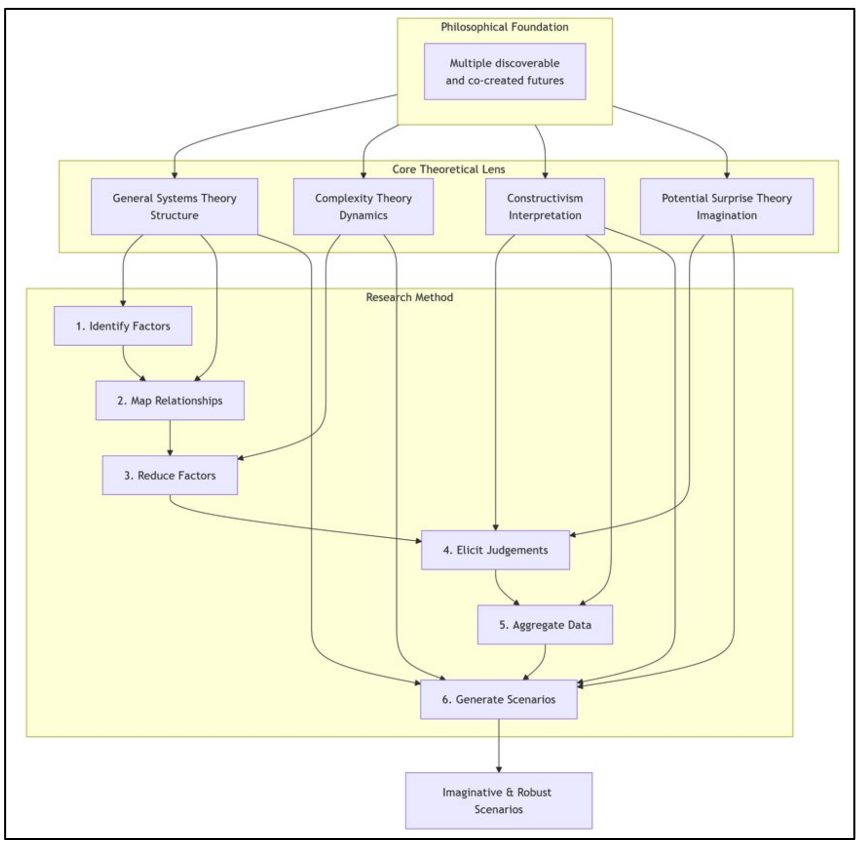


Figure 46: Theoretical Framework (reproduced from Figure 2)

This research contributes to knowledge by demonstrating that scenario construction can be both analytically rigorous and scalable through the integration of data-driven and participatory techniques. A key contribution lies in showing that factor identification and interdependency analysis can be grounded in empirical evidence, rather than relying solely on subjective expert judgement. The use of SEM-derived path coefficients, combined with ADVIAN® analysis, provides a structured and transparent mechanism for identifying critical system drivers. In addition, the study demonstrates that larger and more complex factor sets can be effectively incorporated into scenario construction. The successful application of the methodology to domains involving 36 and 27 factors represents a significant advancement over conventional approaches, which typically rely on smaller and more constrained factor sets.

This study contributes to theory by addressing the lack of a coherent theoretical foundation in scenario construction methods. The proposed methodology is grounded in an integrated framework combining GST, complexity theory, constructivism, and PST. While prior literature has acknowledged these perspectives individually, their systematic operationalisation within a single methodological framework represents a key advancement. Compared to existing scenario approaches, which are often either narrative-driven or quantitatively rigid, the proposed methodology provides a balanced framework that incorporates: systemic structure (GST) through explicit modelling of interdependencies; dynamic behaviour (complexity theory) through sensitivity to non-linearity and emergence; social construction (constructivism) through participatory input via crowdsourcing; and imaginative exploration (PST) through the development of diverse and plausible scenarios. This integration extends existing literature by demonstrating how these theoretical perspectives can be practically implemented, rather than remaining at a purely conceptual level.

The central methodological contribution of this study is the development of a six-step framework for scenario construction, as illustrated in Figure 12. This framework provides a structured and linear process that integrates factor identification, factor reduction, expert judgement elicitation, and scenario generation into a unified workflow. This methodology advances existing approaches by: replacing time-intensive workshops with a semi-automated and scalable process; introducing ADVIAN®-based factor reduction grounded in empirical relationships; incorporating crowdsourcing as a mechanism for expert engagement, enhancing inclusivity; and using CIB analysis to ensure internal consistency, avoiding reliance on probabilistic assumptions. In comparison to existing scenario construction methods such as ILM, LP, CIA, and CIB in isolation, the proposed methodology offers a more integrated and systematic approach. It overcomes limitations related to subjectivity, lack of transparency, and methodological fragmentation identified in the literature.

From a practical perspective, this study provides a replicable and accessible framework for scenario construction that can be applied across multiple domains. The methodology enables organisations and policymakers to: construct scenarios more efficiently; incorporate diverse expert perspectives; analyse complex interdependencies within systems; and generate internally consistent and actionable scenario outputs. In addition, the findings of this study have important implications for practice. The integration of data-driven techniques, such as SEM-based analysis and ADVIAN®, enhances the transparency and robustness of scenario inputs, supporting more informed and defensible decision-making. The use of crowdsourcing demonstrates a scalable and inclusive approach to expert engagement, enabling broader participation beyond traditional methods. The findings from the case studies further provide actionable insights, particularly highlighting the importance of perceived value, awareness, and institutional support as key drivers of adoption in both renewable energy and AI contexts. These insights offer practical guidance for policymakers, institutional leaders, and practitioners seeking to design effective interventions and strategies in complex and uncertain environments.

Although full narrative scenarios were not developed, the structured outputs of the methodology provide actionable insights for policymakers and practitioners. By identifying key drivers and analysing interdependencies, the study highlights critical leverage points that can inform strategic decision-making and policy development.

The application of the methodology to renewable energy adoption and AI adoption in higher education also provides empirical validation of its robustness and applicability. Across both domains, the study demonstrates that: scenario outcomes are highly sensitive to interdependent factor configurations; key drivers of adoption are consistent across contexts; and the methodology is capable of generating multiple internally consistent scenarios, including best-case, worst-case, and base-case configurations. These findings reinforce the importance of modelling interdependencies and provide practical insights for decision-makers operating in complex and uncertain environments.

The contributions of this study should also be considered in relation to the limitations identified in existing scenario construction methods, as summarised in Table 6. The proposed methodology addresses key shortcomings, including subjectivity, time-intensive processes, limited participant diversity, and inadequate modelling of interdependencies, through the integration of data-driven techniques, crowdsourcing, and consistency-based analysis. While these limitations are mitigated to a considerable extent, some challenges remain, particularly in relation to expert validation, data dependency and the absence of probabilistic modelling, as discussed in Chapter 6, Section 6.5.

7.4 Research Limitations

While this study offers methodological, theoretical, and practical contributions, several limitations should be acknowledged to provide context for interpreting the findings.

The expert judgements collected through crowdsourcing were not independently validated. The methodology relied on participants' self-assessed expertise, and there was no mechanism to confirm the accuracy or consistency of their responses. Consequently, while the approach captures diverse perspectives efficiently, the lack of validation may introduce uncertainty regarding the robustness of individual opinions. This limitation is inherent in many expert elicitation methods; however, given the relatively small number of participants who completed all stages of the data collection process, the potential influence of individual responses is amplified. In addition, the recruitment strategy, while effective, could be further refined through more targeted use of hashtags and platform-specific mechanisms to better reach domain-specific experts.

Although crowdsourcing offers scalability and access to a wide pool of experts, it may not fully address contextual nuances or domain-specific constraints. Experts' responses reflect their personal experiences and understanding, which might not always capture local, organizational, or sector-specific dynamics critical to scenario planning.

The study relied on secondary data for factor identification, which brings advantages in terms of empirical validity and reliability. However, this approach may lead to the omission of less common or emerging factors, as these are less likely to appear in published literature. While the method ensures that identified factors are well-supported, it may overlook subtle but potentially influential variables.

In modelling factor interdependencies, the use of the maximum path coefficient from SEM to represent relationship strength could skew the results, particularly if extreme values or outliers are selected. This simplification was necessary for operationalizing the methodology, but it may overemphasize certain relationships while underrepresenting others, potentially affecting the prioritization of factors in scenario construction.

From a methodological perspective, CIB analysis addresses a limitation of ADVIAN® by ensuring the internal consistency of scenarios, while ADVIAN® addresses CIB's limitations of not being able to evaluate complex systems and not considering the uncertainty of an environment. What has not been addressed by the methodology and remains an open challenge is that neither method allows for dynamic modelling and changes that may occur with factors over time.

A further limitation relates to the structural complexity of the proposed methodology. As identified in the literature on the LP method (Chapter 2, Section 2.5.2), the use of multiple modelling tools may increase methodological complexity and potentially reduce process replicability. This consideration is also relevant to the present study, given the integration of multiple analytical techniques across the six-step framework. While each stage of the methodology is clearly defined and theoretically grounded, the cumulative process introduces a level of procedural complexity that may pose challenges for replication, particularly in contexts with limited technical expertise or access to the required tools. However, unlike approaches where the interaction between tools is opaque or dependent on expert facilitation, the methodology developed in this study emphasises standardisation, transparency, and sequential structure. Several stages incorporate data-driven and automated processes, which reduce reliance on subjective judgement and enhance consistency. As such, although a trade-off exists between analytical depth and ease of replication, the structured integration of techniques mitigates, but does not entirely eliminate, concerns regarding replicability.

The selection of the "X" platform as the primary mechanism for crowdsourcing expert participation also presents limitations. While its use was justified on the basis of accessibility, scalability, and its ability to facilitate rapid engagement with a geographically dispersed expert community, social media platforms are subject to ongoing structural, political, and user-driven changes. Since the data collection for this study, shifts in platform governance, user trust, and engagement patterns have contributed to the fragmentation of expert communities across alternative platforms such as BlueSky and Mastodon (Tkacz and Gehl 2025). This evolving landscape introduces a degree of platform dependency within the methodology, whereby the effectiveness of expert recruitment and participation may vary depending on the accessibility, credibility, and user base of a given platform at a particular point in time (Peña-Fernández, Larrondo-Ureta and Morales-i-Gras 2025). As a result, reliance on a single platform may limit the consistency and replicability of the crowdsourcing process in future applications, particularly if relevant expert communities migrate or become less active. While the methodology demonstrates the value of crowdsourcing as a scalable and inclusive approach to expert engagement, this limitation highlights the need for greater flexibility in the selection of digital platforms.

Taken together, these limitations suggest that while the methodology provides a robust, scalable, and theoretically grounded approach, caution is warranted when generalizing findings, and further research can refine validation, contextualization, and factor inclusion processes.

7.5 Future Work

Building on the findings and methodological innovations of this study, several avenues for future research are proposed to enhance the robustness, applicability, and inclusivity of the scenario construction framework.

Future research could incorporate citizen science methodologies to address the identified limitations of unvalidated expert opinions and the potential neglect of contextual issues. Engaging local stakeholders, such as community members, practitioners, or end-users in the research process can provide valuable insights into context-specific challenges, which can validate expert assessments. Citizen science initiatives have been shown to enhance data quality through redundancy and cross-validation, where multiple participants independently contribute to the same data points, thereby increasing confidence in the reliability of the information collected (Baker *et al.* 2021). Additionally, involving local participants ensures that contextual nuances and domain-specific constraints are captured, which may be overlooked by geographically dispersed expert crowds (See 2019). By integrating citizen science approaches, future studies can improve the validity, reliability, and contextual relevance of scenario construction processes, leading to more robust and applicable outcomes.

This study utilized SEM path coefficients to quantify relationship strengths within the ADVIAN® framework. To bolster the reliability of these findings, future research could validate them by directly sourcing relationship assessments from experts, for instance, through structured crowdsourcing. Furthermore, expanding the initial factor identification itself could be valuable; employing social media crowdsourcing to gather a wider range of factors from a diverse population might better capture highly uncertain and novel elements, thereby strengthening the foundation of the analysis.

A further direction for future research involves refining the aggregation method for the path coefficients used in the impact matrix. The present study's reliance on the maximum reported value, while providing a clear, high-impact snapshot, carries the risk of skewing results if that maximum constitutes a statistical outlier rather than a central tendency. Subsequent studies could therefore investigate and compare more robust measures of central tendency, such as the mean, median, or a trimmed mean, to aggregate the path coefficients. Employing such methods would mitigate the influence of extreme values and potentially offer a more stable and representative estimate of the true relationship strength between factors, thereby enhancing the validity and reliability of the ADVIAN® analysis.

Future work may also focus on improving the accessibility and usability of the methodology. The development of integrated toolsets or simplified workflows could reduce procedural complexity and support wider adoption across different contexts, particularly where technical expertise or resources are limited.

In addition, the study highlights the need for further research into the role of digital platforms in supporting crowdsourced expert engagement. Given the evolving nature of social media environments, including changes in platform governance and the fragmentation of expert communities across platforms such as BlueSky and Mastodon, future research should examine how platform selection influences recruitment effectiveness, participation quality, and data reliability. In particular, multi-platform or platform-agnostic approaches may enhance the resilience and adaptability of the methodology, enabling engagement with dispersed expert communities across different digital environments.

By exploring these avenues, future research can build on the foundation laid by this study, further advancing the methodologies for time-sensitive and consistent scenario construction while broadening the applications of innovative data collection and analysis techniques.

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