

Adaptive self-regulating guidelines for the use of Generative Artificial Intelligence in Business customer experience

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ADAPTIVE SELF-REGULATING GUIDELINES FOR THE USE OF GENERATIVE ARTIFICIAL INTELLIGENCE IN BUSINESS CUSTOMER EXPERIENCE

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ABSTRACT

This research interrogates the Generative Artificial Intelligence moral dilemma in South African business customer experiences. Hereto, businesses contend with striking the right balance between capitalising on the competitive gains of GenAI while averting the inherent risks. Moreover, to exacerbate this dichotomy, businesses have to confront the lag in regulation amidst the fast-paced GenAI developments capable of autonomous updates in real time. To grapple with the GenAI regulation lag and moral dilemma holistically, the research explores the role of adaptive self-regulation. Adaptive self-regulation by businesses was recommended as systemic government-led policy development requires much of the state's resources and takes time to implement, oversee and manage change. To this end, a qualitative research design was adopted to garner in-depth business GenAI regulation insights through the lived experiences of the participants. This corresponded with the interpretivist philosophical underpinnings of the research. Data was collected from technology experts who are involved in the sphere of technology in South Africa. These experts also work with technology, and their job titles and experiences are described in the participant characteristics table. Hereon, these are referred to as technology professionals in South Africa (n=21). Collectively, they had between 5 and 30 years of experience. To enrich the study, an exploratory design was used to cross-examine the implications of the perspectives of the research participants. The findings were scientifically analysed using ATLAS.Ti and the themes were in congruence with the research objectives. These included the benefits of GenAI, the gaps of GenAI and the enabling factors of self-regulating GenAI.

To this end, the insights drawn from the research participants met the objectives of the research. From the perspectives of the research participants, the GenAI benefits are ubiquitous. They recognised speed, saving time, automation, customisation, elimination of mundane repetitive tasks, large data analysis and more. At the same time, they noted with concern the ethical and moral inherent gaps, such as a lack of human touch (warmth and empathy), hallucinations, security threats, algorithmic biases and others. The research participants were also concerned about the businesses' position on the safety of customers' personal information. These concerns illuminate the relevance of adaptive self-regulatory guidelines. The findings recognised that the guidelines should enhance transparency, safety, and diversity and limit the proliferation of social injustices. Even more concerning is that in the literature review findings, most businesses' GenAI policies have remained outdated on a static webpage and are not as current as the GenAI technology. This research gap points toward the contribution of this research in advancing agile and adaptive GenAI governance. Similarly, another research gap highlighted by the research participants was the limited knowledge on how to adaptively self-regulate GenAI. Thus, this research contributes to the academic body of literature by exploring the steps toward developing adaptive self-regulation.

This exploration was undergirded by the theoretical underpinning of Bandura's Social Cognitive Theory (SCT) of self-regulation. There was convergence between the findings in theory and practice. These findings show the significance of human oversight, self-monitoring of performance, exercising judgement, and self-reaction and self-efficacy. Research participants also highlighted the role of proactive thinking as opposed to reacting to gaps. This included benchmarking, evaluations, testing, data masking, secure prompt engineering and several other proactive regulatory measures. The role of a multidisciplinary approach was also identified as a limitation by the participants. Thus, they recognised the impact of a human-centred approach that encompasses all facets and disciplines. Similarly, South Africa's National AI Policy advocates for a human-centred approach to the development of these technologies. Hence, this holistic approach of aligning theory with the research findings culminated in the development of 10 steps for the development of adaptive self-regulation guidelines.

KEYWORDS: Adaptive Guidelines, GenAI, Dilemma, Business Customer Experience, Self-Regulation

Declaration

I declare that the Dissertation entitled, The Adaptive Self-Regulation of Generative Artificial Intelligence in Business Customer Experience, which I hereby submit for the degree, Master of Commerce in Integrative Thinking at Rhodes University, is my work. I also declare that this dissertation has not previously been submitted by me for a degree at this or any other tertiary institution and that all the sources that I have used or quoted have been indicated and acknowledged by means of complete references.



Rufaro Joylyn Kanganga

Name Surname (*signed*)

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Only God.

I wish to thank my Heavenly Father, my Lord and Saviour, the Lord Jesus, for the provision, the guidance, strength of the Holy Spirit in the commencement and completion of my thesis. I went through a lot, and my faith anchored me from start to finish.

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“My victory and honour come from God alone. He is my refuge, a rock where no enemy can reach me. Psalm 62:7”

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INDEX OF KEY RESEARCH DEFINITIONS

<u>TERM</u>	<u>DESCRIPTIONS</u>
Artificial Intelligence (AI)	Computational technology that simulates human intelligence, for example, robots performing human tasks.
Generative Artificial Intelligence	Generative Artificial Intelligence is a subcategory of AI where computational technology uses prompts to generate video, text and other content.
Adaptative self-regulation	According to (Oxford, 2024) Adaptive refers to the process of altering something to adapt to changing conditions. The phrase ‘<i>adaptive self-regulation</i>’ in this research context refers to the process of businesses continuously adjusting or altering systems, policies, behaviours, processes, or strategies to respond to arising threats or gaps from the use of GenAI business customer experience (Wrosch & Scheier, 2020).
Guidelines	Guidelines refer to specific information, guides or steps on how a task or something should be done (Cambridge, 2024).
Integrative thinking	Integrative thinking is a constructive approach to opposing tensions or ideas where creative solutions are generated by combining these opposing ideas (Lattemann & Fritz, 2014).
Business Customer Experience	Customer experience refers to a set of emotions that are evoked in a customer as a result of their interaction with a business (Wereda & Ggrzybowska, 2016). These interactions take place in various capacities, including virtually, in person, through third-party representatives and more, and this interaction is vital for a business to maintain its competitive advantage (Lemon & Verhoef, 2016).

“We’re only at the beginning of what AI can accomplish. Whatever limitations it has today will be gone before we know it” – Bill Gates

1 Introduction and Research Overview

1.1 Background and context of the study

Artificial Intelligence (AI) is a computer’s ability to simulate human intelligence or intellectual capability, for example, decision making, learning or inference (Stone, 2024). Notably, it was first described by John McCarthy in 1955 as “the engineering and the science of intelligent making of machines” (Tehseen et al., 2021). On the other hand, Generative Artificial Intelligence (GenAI) is a subset of Artificial Intelligence that can autonomously generate content when prompted (Sai et al., 2024). GenAI uses prompts, including text, images, audio, or video, to create content without human input (Naqbi et al., 2024).

Therefore, the difference between AI and GenAI is that AI simulates human intelligence (Huang & Rust, 2018; Makore, 2024). While GenAI is a category of Artificial Intelligence that leverages computational systems to autonomously generate novel content, including but not limited to images, faces, voices, and music (Caporusso, 2023). The origins of this technology was recognised in cybernetics theory by Norbert Wiener in the 1950s. Wiener also noted that machines can learn patterns of behaviour and self-reproduce, which is similar to the foundational principle of GenAI (Wiener, 2019). Therefore, cybernetics has also been described as the progenitor of theories such as Artificial Intelligence Theory (Mistry & Goswami, 2024; Wiener, 2019). To this end, GenAI systems generate new content autonomously by learning patterns and relationships within large datasets, as exemplified by advanced language models like Generative Pretrained Transformer 4 (GPT-4) (Feuerriegel et al., 2024).

Given the broad nature of some of the many use cases of GenAI, this research paper has narrowed the focus down to business customer experiences. In this context, business customer experience refers to a variety of feelings, thoughts and sensations that are created or evoked by a business in a customer (Wereda & Ggrzybowska, 2016).

These transformative GenAI novelties have resulted in a business moral dilemma to society in general. Their use also results in unintended, adverse ethical issues such as biases, incorrect results, security breaches, and more (Akhtar, 2024). Hence, this research confronts this

business moral dilemma where the benefits are competing against the ethical concerns and other ethical shortcomings of GenAI (Golda et al., 2024). Additionally, Ferrara (2024) explained that GenAI offers competitive advantages, but it is also susceptible to biases. This raises critical concerns regarding its impact on marginalised groups and accentuates the need for vigilant monitoring and mitigation strategies to address these gaps.

Given the complexities of this moral dilemma, businesses still adopt GenAI, as it confers significant transformational benefits in yielding returns, enhanced productivity, efficiency, automation, speed, and applicability (Yikilmaz & Halis, 2023). To exacerbate these gaps, businesses are confronted with the regulation of GenAI that is lagging behind the fast-paced development of these technologies. It is alarming that the exponential upgrading of GenAI models in real-time outpaces the development of adaptive self-regulatory measures to mitigate associated risks (Popomaronis, 2024).

To this end, the research explores ways these gaps can be mitigated through adaptive self-regulation guidelines. This is particularly critical, especially in the adoption of GenAI models in business customer experience, due to its multifaceted consequences and potential harmful effects to customers, such as personal data misuse (Daqar & Smoudy, 2019; Kshetri et al., 2024). Notwithstanding, the mounting complexity of GenAI-generated content in customer experiences underscores the need for continuous adaptive self-regulation.

Adaptive self-regulation in this research refers to the adaptive or continuous business process of adjusting their customer systems, policies, behaviours, processes, or strategies to respond to arising threats or gaps from the use of GenAI in their business (Wrosch & Scheier, 2020). Such an agile approach to GenAI self-regulation in business is vital, and research in this field provides knowledge to comprehend and mitigate the risks, and harness the potential of GenAI (Banh & Strobel, 2023; Marie & Mathews, 2021). More so, it is also imperative to study the gap between harnessing the full potential and benefits of GenAI while simultaneously mitigating the risks of its deployment in customer experiences (Ferraro et al., 2024; Velasco et al., 2024).

Given the abovementioned research gaps, this study critically interrogates the GenAI business moral dilemma. Equally, the research examines the role of adaptive self-regulating guidelines in confronting the research gaps (Min, 2023; Newstead et al., 2023; Rastogi et al., 2022; Salazar et al., 2024; Zhou et al., 2023).

1.2 Problem statement and research questions

Given the abovementioned background into the complexities that businesses face when adopting GenAI, the research problem statement is;

“How can businesses avert the regulation lag and the GenAI through adaptive self-regulation guidelines?”

In view of the above, the research adopted an integrative thinking technique for problem-solving to cross-examine the research problem. Integrative thinking is defined as the continuous agile task of recognising that opposing tensions are not merely resolved by selecting one option versus another, but rather it is an ongoing process of fine-tuning resolutions. Integrative thinking grapples with opposing trade-offs long enough to have an optimum novel solution that transcends duality and solves. This technique uncovers novel and effective solutions that might have otherwise gone unnoticed (Martin & Austen, 1999). Contextually, this research interrogates the opposing tensions of the GenAI dilemma and identifies novel key steps towards achieving adaptive self-regulating guidelines (Marie & Mathews, 2021; Strümke et al., 2022).

1.3 Purpose of the Study and Objectives

The purpose of the research is to develop key steps toward achieving adaptive self-regulating guidelines. These guidelines will guide the deployment of GenAI in business customer experiences in South African businesses. To this end, the research has three objectives:

- (i) To identify key steps for developing adaptive self-regulation guidelines for GenAI use in business customer experience, informed by Albert Bandura’s Social Cognitive Theory of Self-Regulation.
- (ii) To determine the role, use, and benefits of GenAI in business customer experience.
- (iii) To explore the ethical and operational gaps, such as biases encountered in GenAI that present a business moral dilemma in customer experience.

1.4 Theoretical and managerial practical contribution of the research

1.4.1 The practical use of GenAI in businesses

GenAI has various practical uses across different facets of business operations and management (McKnight et al., 2024). One such practical use is in decision-making enhancements to augment GenAI business customer experiences (Ferraro et al., 2024).

Decision-makers and policymakers to leverage this need a clear understanding of the inner workings of algorithms and the role that data sets play in algorithms (Jawarkar, 2022).

However, the use of such GenAI models entirely without guardrails in place can lead to several unintended harms in decision-making, including data bias (Ferrara, 2024a). Data bias relates to the bias resulting from an AI system that learns a bias from historical information, algorithms and datasets (Min, 2023). Therefore, some considerations need to be made in the use of algorithmic decision-making GenAI systems in business customer experience to guard against risks such as privacy breaches, inaccuracies, and incomplete decisions (Breidbach, 2024).

Additionally, other practical uses in business are in providing customers with customised goods, services and products. However, this has been criticised for possible privacy infringements. Furthermore, biases have been realised in such tools towards certain ethnic groups (Georgievskaya et al., 2023).

Notwithstanding the risks, more practical uses are in the data analysis of customer data. Although concerns have been raised about the potential misuse of personal data, biases and other ethical risks, big data can now be analysed at a much faster and cost-effective pace (Scarpi & Pantano, 2024). Henceforth, policymakers are making complex decisions toward protecting the privacy of customers and how to avoid biases that negatively impact minority groups, and more (Christodorescu et al., 2024).

Notwithstanding, GenAI has become so advanced that it can create images and other visuals from prompts. For example, DALL-E, GenAI systems are now also capable of composing music and even assisting lawyers to review legal documents. However, these capabilities in the wrong hands can lead to other ethical implications, such as copyright issues or identity theft (Shashkina, 2023).

Lastly, for the financial sector, some practical uses of GenAI models are in financial risk evaluation, which are critical for fraud detection and risk management (Saivasan & Lokhande, 2023). Furthermore, data from GenAI models for financial markets is useful in predicting market performance (Che et al., 2024).

Although the practical uses are transformative, there are emergent gaps that cannot be ignored, such as deepfakes, hallucinations and inadequate regulation of GenAI (Saivasan & Lokhande, 2023).

1.4.2 Theoretical contribution

The key contribution of this research is threefold. Firstly, this research engages a topic that contributes new knowledge toward GenAI in business customer experiences. Specifically, the research contributes theoretically by developing insights into the benefits and shortcomings of GenAI. Furthermore, the research provides a nuanced understanding of this dichotomy through the lens of South African Technology professionals.

The second contribution is towards the understanding of the role of adaptive self-regulation of GenAI models. This is due to the regulation and governance gap caused by the current state of technology advancements trends (Kanbach et al., 2023). GenAI business models are being proliferated beyond the pace of their self-regulation (Chouinard, 2024). Therein lies a gap or opportunity to contribute theory that addresses this gap. Therefore, in line with the exploratory nature of the research, the role of agile and adaptive behaviour toward GenAI self-regulation is explored. An in-depth analysis of the intricacies of GenAI governance, locally and internationally, is also acknowledged.

The third theoretical contribution is toward the advancement of knowledge and understanding of the development of GenAI adaptive self-regulatory guidelines. There is a gap in understanding how South African businesses can develop governance guidelines that leverage these technologies while adaptively self-regulating. Before 2024 there were no policies that were for South Africans. In 2024, the National AI policy was launched.

Lastly, this research paper focuses on developing key steps toward responsible GenAI use through adaptive self-regulating guidelines. Melise et al., (2024) notes that although there is already a significant amount of literature on the subject, there is still ample opportunity for further growth and investigation, particularly in light of developing new GenAI models.

1.4.3 Managerial significance

The managerial significance of the research is toward informing governance practise by providing steps for the development of adaptive GenAI self-regulation guidelines. Companies such as Meta, Amazon, IBM, Accenture and Google have already adopted self-regulating guidelines. Recently, Amazon has also enforced strict prohibitions for evaluating all their GenAI tools through human oversight to avoid human violations, biases or prejudice and circumvent any risks arising (Amazon, 2024). Similarly, Google has a human-centred AI approach. Google has seven principles for AI applications that include the need for GenAI to be socially beneficial, reinforced against biases and tested for safety (Google, 2023). Accenture

also has an AI policy protecting data privacy, benefiting markets and clients and ensuring transparency through a checklist (Porter et al., 2024).

Given the above patterns of GenAI self-regulation in large tech companies, it is evident that business firms are already actively self-regulating their own GenAI (Halperin & Daley, 2024). Therefore, in South Africa, this too can potentially be replicated.

Managers are also facing challenges that most regulatory guidelines are static and not adapting to the ever-changing GenAI landscape. Potentially, managers are also improving their sales support through GenAI. For example, in addressing queries, after-sales support, processing orders and other tasks, however, there have been gaps that have occurred, such as data security and sometimes customer dissatisfaction (Ferraro et al., 2024).

The research also contributes toward informing management on aligning with GenAI statutory requirements internally. For example, the South African government recently launched the National AI Policy, and they were open towards receiving contributions from researchers (South Africa's National AI Policy Framework, 2024).

1.5 Overview of methodological approach

The research paradigm of this research study is interpretivist philosophy (Pervin & Mokhtar, 2022). Interpretivism research is underpinned by the formation of new ideas with a richer understanding. In this case, the focus is on creating a new understanding of the self-regulation of GenAI in the wake of a moral dilemma. The research design is exploratory. The major focus of this exploratory study is to discover new knowledge, insights or ideas to help build adaptive self-regulating guidelines (Singh, 2021). The research is cross-sectional, whereby data is collected in a single period from a sample drawn out of a population (Thomas, 2020). The study interviews experts who are working in the Sphere of technology in South Africa and understand GenAI. An expert in this case refers to professionals in the field of technology who have at least 10 years of experience (Mergel et al., 2019) and a minimum of 1 year of experience in GenAI technology, specifically business customer services as some of the technologies are still relatively new (Hadi et al., 2023). Because there is a specific requirement that needs to be satisfied, a non-probability method using a purposive sampling technique was used in this research (Siva et al., 2019). The saturation is assessed using the methodology recommended by Guest et al., (2020). Saturation signifies the point in data analysis where new interviews provide insignificant new and relevant information regarding the study objectives (Guest et al., 2020). This saturation analysis relies on three key factors: the base size, the run length, and the calculation of new information. The new information threshold measures the proportion of

incoming new information. A value of 5% or less is considered acceptable, indicating a satisfactory level of new information, while a value of 0% indicates no new information (Guest et al., 2020). The research thematic analysis was conducted using ATLAS. Ti following is a step-by-step process. The study is transferable to similar settings as well as confirmability and dependability (Nowell et al., 2017). This research is considered to be of low risk because it satisfies the following criteria for a low level of risk: the participants are not minors but are adults making use of GenAI tools; the research data collected is non-sensitive information; the data is gathered anonymously (Ficker, 2017).

1.6 Delimitation, Scope and Assumptions

This study's scope focuses on the use of GenAI and the self-regulation of such models in business customer experiences. A major delimitation is that the sole perspectives of the customers independently are an area of research that may be explored for another research study. One of the main assumptions in the study is that participants who are experts in technology have both used the GenAI as professionals but also as customers.

Another assumption of this study is that GenAI businesses are aware of the GenAI benefits and that, inherently, there are innate gaps, such as the ethical and moral risks (McKnight et al., 2024). Hence, the scope of this study focuses on understanding the trade-offs between businesses leveraging personalised GenAI solutions while facing the effects of any unintended harms (Singh et al., 2024).

This research has specific delimitations; the research focuses exclusively on GenAI in business customer experience and not AI in the broader context. The study's geographical scope is limited to South Africa, which may not be representative of global trends. The study's timeframe is 2 years, which may not capture long-term effects or changes in the GenAI self-regulation arena. By acknowledging these delimitations, this research aims to provide a detailed understanding of the complex issues surrounding the self-regulation of GenAI (Shukla, 2023).

1.7 Research Structure

The research study adheres to a chronological order to ensure clarity and coherence. The study commences with an Introduction (Chapter 1), providing a comprehensive background, research problem statement, objectives, significance, and scope. This introductory chapter sets the stage for the entire study, outlining the justification, purpose, and potential contributions of the

research. Additionally, Chapter 1 clarifies the scope and introduces the research context, research design and methodology. This foundational chapter serves as a roadmap for the remainder of the study. Subsequent chapters build upon this introduction, progressing logically through the research process.

The next chapter is the Literature Review (Chapter 2), which critically evaluates existing knowledge and theories relevant to the research topic, identifying gaps and areas for investigation. The Literature Review is an interrogation of existing knowledge and theories pertinent to the research problem. This is achieved through a systematic and methodological analysis of relevant studies. This chapter evaluates the strengths and limitations of existing research. Furthermore, it clarifies key concepts and definitions, and highlights inconsistencies and unresolved issues.

The chapter discusses the applicability of Albert Bandura's Cognitive Theory of Self-Regulation as the theoretical framework grounding the research. By conducting this thorough review, Chapter 2 establishes a foundation for the research. It demonstrates the research's originality and contribution to the existing body of knowledge.

Chapter 3 focuses on the Methodology, providing a comprehensive overview of the research design and methodological approach. This chapter describes the research paradigm, the data collection and analysis methods and the use of qualitative methods for this research. Notably, the chapter provides a justification of the chosen approach, considering factors such as ontological and epistemological assumptions.

Research Findings (Chapter 4) describes how the methodological approach outlined in Chapter 3 was operationalised. This includes detailing procedures undertaken to collect, analyse, and interpret data. This chapter also presents findings, shedding light on the research problem. Specifically, it illustrates the outcomes of the data collection, describes analysis procedures, and presents findings aligned with research questions and objectives.

Chapter 5 discusses the results, but importantly, this is where the findings are mapped with the theoretical frameworks to develop the guidelines. The chapter also provides the identified steps for achieving adaptive self-regulating guidelines and recommendations.

The final chapter (Chapter 6) provides actionable recommendations for guidelines for enforcing the self-regulation of GenAI. This account informs practise and future research. Chapter 6 also acknowledges the research limitations and concludes with a summary of the

research contributions and implications. Ultimately, this chapter presents a clear and compelling conclusion, influencing theory, policy, and practise in the field of GenAI self-regulation.

1.8 Key Definitions for the Readers

1.8.1 Adaptive self-regulation guidelines

According to the Oxford Dictionary adaptive refers to the process of altering something to adapt to changing conditions (Oxford, 2024). The phrase '*adaptive self-regulation*' in this research context refers to the process of businesses continuously adjusting or altering systems, policies, behaviours, processes, or strategies to respond to arising threats or gaps from the use of GenAI business customer experience (Wrosch & Scheier, 2020).

Guidelines refer to specific information, guides or steps on how a task or something should be done (Cambridge, 2024).

1.8.2 Integrative thinking

Integrative thinking is a constructive approach to opposing tensions or ideas, where creative solutions are generated by combining these opposing ideas (Lattemann & Fritz, 2014).

1.8.3 GenAI in Business Customer Experience

Customer experience refers to a set of emotions that are evoked in a customer as a result of their interaction with a business (Wereda & Ggrzybowska, 2016). These interactions take place in various capacities, including virtually, in person, through third-party representatives and more, and this interaction is vital for a business to maintain its competitive advantage (Lemon & Verhoef, 2016). To ensure precision and avoid ambiguity in this research, the term "*business customer experience*" shall be used to specifically focus on the experiences of business customers with GenAI.

Therefore, in this research, GenAI in business customer experience refers to the use of GenAI to create or generate new content or data that enhances business customer experiences.

2 Literature review & Philosophical perspectives

2.1 Introduction

The rapid integration of GenAI has sparked interest and debate among scholars, policymakers and researchers. While GenAI has augmented business customer experiences and heralded in unprecedented levels of opportunities, it has been met with some concerns. The innate complexities of GenAI technologies have resulted in unintended harms and are fast becoming ubiquitous. As businesses continue to grapple with the fast pace of GenAI development versus adaptive self-regulation, standards, guidelines and research play a critical role.

As GenAI is renowned for its innovation, creativity, speed, convenience and efficiency, more businesses are investing. With this push, GenAI continues to gain popularity. However, this has been overshadowed by businesses having to make decisions on how to circumvent the complex side effects. This raises critical questions and debates on the readiness of businesses for this technology. Notwithstanding the growing interest around GenAI, research on adaptive self-regulation measures is required.

Despite the growth in the research on GenAI, there remain gaps in ways to adaptively mitigate the moral consequences of these technologies in business customer experience. Hence, this chapter critically evaluates GenAI capabilities in the wake of the risks involved. Furthermore, it examines literature on this moral dilemma and how businesses can adopt GenAI in a manner that is safe, transparent and beneficial to all.

Therefore, this chapter explores the current state of knowledge on GenAI. It articulates the GenAI business moral dilemma, customer experiences and self-regulation (Melise et al., 2024). The theoretical underpinning of this research is Albert Bandura's Social Cognitive Theory (SCT) of self-regulation. The chapter also outlines the research gaps, thereby showing the contribution of the research to the academic body of literature. The chapter also reviews literature on how other emergent technologies have been regulated. Thus, building a foundation for the development of adaptive self-regulation guidelines for GenAI. This is essential for readers to better understand and appreciate that GenAI technologies are ubiquitous and unavoidable, but they can be regulated (Kumar Kar et al., 2023).

The chapter also provides context for the business moral dilemma with supporting literature. Henceforth, the South African context of GenAI in business customer experiences is explored. The former is crucial for understanding why South African businesses are adopting GenAI for business customer experience, and the role that self-regulation plays (Gupta et al., 2024). Lastly, the chapter explores the theory that grounds the research and literature on the pivotal concepts within the research, for example, extant research on developing guidelines.

2.2 Overview of Artificial Intelligence and Generative Artificial Intelligence

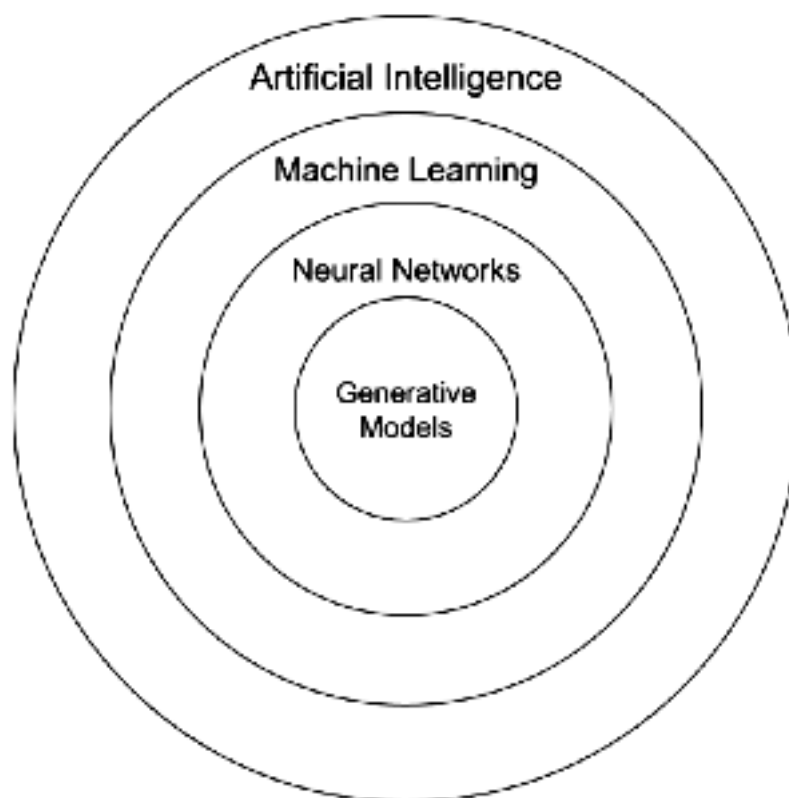


Figure 1: Overview of the difference between GenAI and AI | Source (Tayade et al., 2024)

The term Artificial Intelligence (AI) is a broad term that encapsulates computing systems that execute tasks that are akin to human cognitive skills (Patel & Ragolane, 2024). Alternatively, AI refers to the intelligence of computers used to complete tasks where previously human intelligence was required. Earlier Artificial Intelligence research in the 1950s focused on understanding the development of machines or computers with human cognitive skills, intelligence or capabilities (Storey et al., 2025). One of the early scholars was Wiener who coined 'cybernetics' theory and noted that machines can learn patterns of behaviour and self-reproduce. This is similar to the foundational principle of GenAI (Wiener, 2019). Therefore, cybernetics has been described as one of the early progenitors of theories such as Artificial

Intelligence Theory (Mistry & Goswami, 2024; Wiener, 2019). However, recently, AI has evolved to include various other systems such as GenAI.

GenAI is a type of Artificial Intelligence system that is capable of autonomously generating novel content, such as text or images, based on the data it is trained on (Mariani & Dwivedi, 2024). Therefore, GenAI focuses on autonomous output generation based on prompts (for example, Copilot), whereas AI focuses on other functions, such as determining actions (for example, self-driven cars) (Toner, 2023). Ultimately, GenAI encompasses some AI features and is a subset of AI, as shown in the diagram below (Tayade et al., 2024).

2.3 GenAI in Business Customer Experience

Contextually, GenAI models are adopted to augment business customer experiences (Daqar & Smoudy, 2019). More so, these GenAI models are also deployed in education, banking, architecture, construction, mining and more to enhance customer experiences. Therefore, understanding GenAI's applications lays the groundwork for exploring its impact on business customer experiences.

The concept of customer experience emerged in the 1960s and gained prominence in the 1970s. By the mid-1990s, business customer experience reached its "Golden Age" (Ullah, 2023). GenAI-enabled business customer experiences encompass two dimensions: hedonic (memorable, entertaining, and novel) and recognition (feeling valued, respected, and safe) aspects (Ameen et al., 2021). The research of business customer experience and GenAI is still in its formative stages since GenAI technologies are still fairly new; for example, ChatGPT only came out in 2022, and Meta AI was just released in 2024 (Melise et al., 2024).

A Zendesk research revealed that 52% of customers immediately shift from their business to a competitor when they are dissatisfied, and this has raised their desire to invest in GenAI (Law, 2024). Hence, GenAI in business customer experience is burgeoning in e-commerce, for example, chatbots have been modelled to respond to customers' questions in real-time (Moura et al., 2021). The next section explores the various examples of GenAI business customer experiences for clarity and understanding of its integration and role in various businesses.

2.3.1 Examples of GenAI business customer experience cases

There are several use cases of GenAI in business customer experience; therefore, this section is not exhaustive. This section is important because it further underscores the need for adaptive self-regulation and the everyday use case it is encountered.

2.3.1.1 GenAI business customer experience in business and management operations

Every day, businesses are adopting GenAI to enhance business customer experiences (Ullah, 2023). Intelligent GenAI business customer experience models assemble highly sophisticated customer experience features such as the ability to locate stores, send reminders, set up appointments and more (Eldman & Abraham, 2022). Moreover, business managers can leverage GenAI models to better serve their customers through streamlined operations and processes and more (İşgüzar et al., 2024). In sales operations, Einstein GPT, a GenAI model, provides real-time support to employees, thereby boosting their productivity. This innovative solution caters to the needs of business-to-business (B2B) clients, setting a new standard for customer engagement; however, this must be self-monitored to mitigate any privacy risks (Ooi et al., 2023).

2.3.1.2 GenAI customer experiences in the medical fraternity

In the area of health, GenAI models enhance their customers' experiences, for instance, in predicting and allocating adequate medical resources. For example, in India, GenAI models predicted the number of healthcare workers needed in the COVID-19 pandemic. Here, judgement is also critical to discern where there are miscalculations (Torres-Rahman & Nelson, 2023). More so, GenAI models in psychological care, GenAI models are set to enhance their customers' therapeutic paradigms through personalised care. Furthermore, by enhancing the accessibility of mental health services, surmounting barriers such as distance or socioeconomic constraints (Haber et al., 2024). Patients also reap the benefits of augmented customer experiences through the use of GenAI models. For example, in the real-time monitoring of their recovery progress by using a wearable GenAI device, also be used to monitor whether a patient is abiding by their medicine regimen, which raises concerns about the privacy of such sensitive patient records (Chatterjee et al., 2024).

2.3.1.3 GenAI in Climate Change

GenAI models used in climate change are generating visuals of future landscape scenarios that incorporate diverse nature-based solutions (Richards et al., 2024). In terms of disaster preparedness, GenAI models provide real-time data analysis in emergencies, real-time access to information, warnings of disasters, and scenario simulations, but this also requires judgement and self-reaction procedures in place for an appropriate course of action (Ellencweig et al., 2023).

2.3.1.4 GenAI in Education

In the sphere of education, tools such as Grammarly or Turnitin extensively assist students in their writing, research and learning (Latifi, 2024). Additionally, GenAI models have a profoundly positive impact on learning outcomes, for instance, in augmented language learning; however, self-monitoring by schools is necessary in preventing inaccurate knowledge transfer (Mason, 2024). One research study involving 364 students showed that students tend to believe that GenAI integration can stimulate educational creativity and enhance employability prospects (Tală et al., 2024). Furthermore, another research study in the design of the education of nurses revealed that the GenAI, ChatGPT system significantly enhanced learners' critical thinking abilities (Ching-Yi et al., 2024). The utilisation of GenAI model features saves time, for example, a meeting/lesson can automatically be transcribed and shared; however, caution and judgement are needed to proofread and check accuracy (Göçen & Asan, 2023).

2.4 Artificial Intelligence Ethical concerns, the GenAI business moral dilemma and critical review

2.4.1 Ethical concerns

Drawing from the abovementioned integration of GenAI across various use cases of society, business ethical concerns tend to arise. Ethics in this context refers to the discipline of conducting morally acceptable actions (Kirova et al., 2023). These ethics include balancing safety and innovation, considering privacy risks, inaccuracy, algorithmic bias, job displacements and other cases that require businesses to self-monitor (Pressman et al., 2024). Furthermore, the mining and use of consumer data in these models raises concerns on informed consent, infrastructure exploitation and data security (Tehseen et al., 2021).

Thus, organisations face ethical decisions on responsible GenAI development and deployment that ensure equitable outcomes (İşgüzar et al., 2024). Hence, the relationship between businesses and customers can be fractured by breached trust from the lack of transparency and the misuse of customer data (Olusegun, 2024). Some of these ethical decisions linked to the development of ethical GenAI include the development of transparent, responsible, inclusive, secure and explainable models (Tehseen et al., 2021). Furthermore, GenAI continues to raise significant ethical concerns, in line with the surveillance of personal data and potential exploitation (Zuboff, 2017).

KPMG has had debates on some of these ethical concerns of AI technologies (Kirova et al., 2023). The company recommended that having structures is critical to add value to communities while optimising the use of these technologies. Therefore, the development of guidelines for the adaptive self-regulation of GenAI in businesses' customer experience is one of the structures, crucial for optimising responsible, fair and transparent deployment (Shittu et al., 2024). Other long-standing debates are around the ethical use of this 'artificial' intelligence to substitute or, in some cases, replace human capabilities in multiple fields (Tehseen et al., 2021).

To this end, the next section further critically reviews some ethical concerns and moral issues through the lens of the research's GenAI moral dilemma.

2.4.2 The GenAI Moral Dilemma and Critical Review

In the adoption of GenAI, there is a business moral dilemma handoff opposing outcomes. This means that on the one hand, the adoption of GenAI yields many benefits to businesses, but on the other hand, there are unintended harms (Mariani & Dwivedi, 2024). For instance, businesses such as Tesco, Starbucks, and Qantas are harnessing GenAI technology to gather customer details and analyse their data, but also succumb to unintended gaps like privacy security threats, which require monitoring (Hua et al., 2024; Ramos Salazar et al., 2024; Salazar et al., 2024). More so, GenAI capabilities are enabling businesses to disseminate disproportionate amounts of aggregated data about customers. However, some of these capabilities involve commercialising consumer data, "surveillance capitalism", hence customers and businesses need to exercise discretion and judgement in what they share (Capraro et al., 2023).

In banking effective business customer experience can be crucial in driving trust through data analytics-aided personalised services, which can offer accurate recommendations (Akolkar, 2024). However, one researcher concluded that there is still a need to have a human agent monitoring because of the high risk of social engineering attacks (Dana & Zwiendelaar, 2023).

Therefore, the power of cutting-edge GenAI technology empowers enterprises to refine their business customer experience (Oanh, 2024). A notable example is CarMax, which is leveraging GenAI to generate concise text summaries for its car research pages. These summaries are also optimised for high search engine rankings (Capgemini, 2023). However, biases can occur as

the range of propositions presented by the GenAI technology may be narrow, requiring businesses to self-monitor the results (Lecocq et al., 2024).

Moreover, GenAI is beneficial in data-driven decision-making by making accurate, faster decisions, also solving complex human problems (Seda et al., 2024). These GenAI models can also solve critical problems with minimal human input, for example, in some medical diagnoses (Gokul, 2023). Notwithstanding these benefits, there lie the concerns about privacy and fewer jobs requiring human input (Melise et al., 2024). Also, another concern is that GenAI makes autonomous yet the opaque decision-making processes of GenAI make it difficult to hold developers or users accountable for any harm caused (Badet, 2021; Ferrara, 2024b; Zhang et al., 2024).

Business customer experiences are set to become more immersive through the adoption of hyper-realistic experiences, instant videoconferencing, gamification and more (Yaici, 2024). For example, chatbots have been modelled to be able to assist customers with their purchases, respond to customers' questions in real-time, and more (Moura et al., 2021). However, this realistic attribute of GenAI can be misused in cases such as deepfakes. Deepfakes are GenAI-synthetically simulated images or videos purporting to be an actual person (Whittaker et al., 2021). These deepfakes can be used to commit crimes or even to tamper with evidence where a crime was committed. Customers are also susceptible to being scammed or vulnerable to financial fraud (Kaushik et al., 2024). For example, in the United Kingdom (UK) in 2019, an AI-generated voice impersonating an executive tricked a UK-based energy firm into transferring \$243,000 (Ferrara, 2024b). This highlights the risks of GenAI applications adoption without adequate self-monitoring and sound judgement of reality versus virtual reality when transacting.

Moreover, the GenAI customer service industry is becoming one of the fastest-growing sectors valued at USD 308 million in 2022, and is poised to expand in value to over USD 2,897.57 million by 2032 (Precedence Research, 2023). It is even estimated by the Bank of America that GenAI should contribute up to US\$15 billion to the global economy by 2030 (Bodini, 2024). GenAI is tailored to revolutionise, improve and transform the workforce by automating routine and mundane, tedious tasks, allowing employees to focus on the customers (Cooke, 2024). The former has been widely debated as it has begun to create job losses (Gokul, 2023). Despite these debates, businesses still favour GenAI as it fosters the creation of new ideas faster, providing innovative processes for customers (Yikilmaz & Halis, 2023). However, over-

reliance on these systems is not sustainable as they can also face challenges. It is not uncommon for systems such as GenAI to have downtime, crash, have a bug or virus, underperform, or not be able to cope timely with prompts, new updates or version releases, leaving businesses at risk (Akolkar, 2024).

Additionally, the integration of GenAI in learning environments presents a dual-edged sword, offering potential benefits while also risking the promotion of superficial understanding. For example, literacy levels can be distorted (Yan et al., 2024). In contrast, the reliance of academic GenAI tools poses a risk of plagiarism and transparency issues, which can threaten to erode their learning development (Zhai et al., 2024).

To this end, the GenAI benefits versus the risks creates a complex moral dilemma. This dilemma requires more than self-regulation but adaptive habits such as self-monitoring, judgement and self-efficacy to mitigate the negative consequences while amplifying the positive outcomes (Iyer, 2024).

The next section depicts the role that Albert Bandura's Social Cognitive Theory of Self-Regulation plays in contributing toward averting the abovementioned ethical concerns and moral dilemma. This theory further explores the role of self-monitoring, judgement, self-reaction and self-efficacy in self-regulation (Bandura, 1991).

2.5 Social Cognitive Theory as a Theoretical Lens

Albert Bandura's Social Cognitive Theory (SCT) of Self-Regulation is premised upon self-regulation through self-monitoring, self-judgement, self-efficacy and self-reactive capabilities (Bandura, 1991). The theory provides a valuable framework for understanding and promoting the self-regulation of GenAI by businesses. Control of an environment is imperative as highlighted in cybernetic theory which focuses on human-machine communication and control of systems (Wiener, 2019). Interestingly, both theories focus on the causal processes involved in maintaining control of an environment. Bandura describes a triadic causation where a human's self-belief (self-efficacy) shapes a perception of whether they can control their environment, which influences their subsequent choices.

Consciously, a business environment is shaped through the dynamic interaction of personal beliefs (self-efficacy), behaviour, and environmental influences (Bandura, 1991). In organisational contexts, the responsiveness of the environment to managerial decisions—such as the implementation of security protocols—plays a critical role in reinforcing perceived self-

efficacy. In SCT, forethought or predetermination of future events influences self-regulation (Bandura, 1991). In this context, the GenAI's models are pre-engineered based on a business's data, influencing future performance. Therefore, in the context of GenAI, adaptive self-regulation refers to the active and voluntary role played by businesses in establishing procedures, standards, practises or measures elected by a business to regulate their models (Bodini, 2024). These measures ensure an agile and proactive role in regulations, mitigating the risks and gaps that are inherent in the use of such technologies in business customer experience. The next section describes in more detail the parallels that can be drawn from this theory and the GenAI models' self-regulation.

2.5.1 Social Cognitive Theory of self-regulation applied to GenAI models

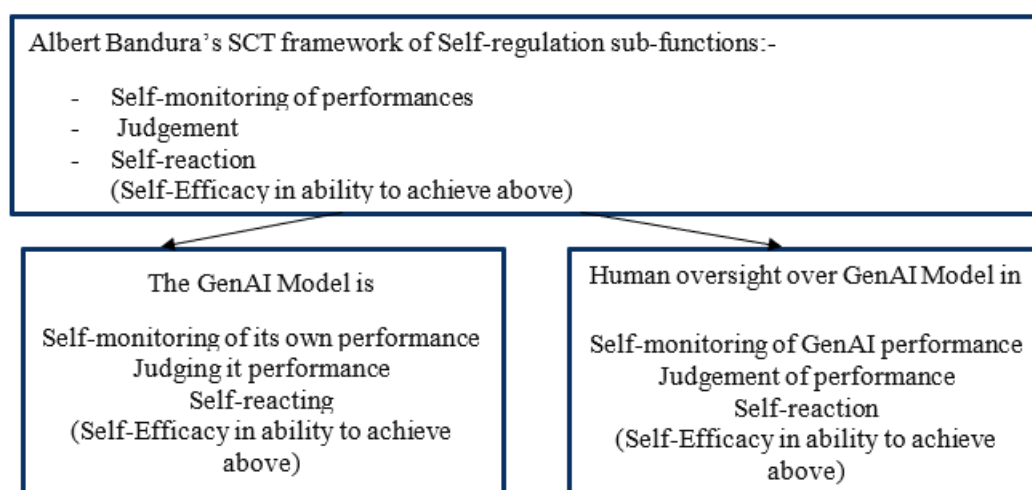


Figure 2 Albert Bandura SCT Model aligned to the GenAI Self-regulation

According to Scott et al., (2024) Albert Bandura's SCT framework of self-regulation focuses on cognition. In this case, GenAI models simulate the cognitive skills and intelligence of humans. Thus, these GenAI models, as they simulate human intelligence, have some form of cognitive skills, where they have been trained to plan their actions and experiences (Scott et al., 2024). An example of how this can be done is, for instance, reducing algorithmic bias by carefully selecting machine learning algorithms that inherently exhibit reduced susceptibility to bias. This process takes place through the identification of models with architectures designed to uphold ethical GenAI values (Chadha, 2024). The possibility of GenAI also contributing to automating self-regulation updates suggests that the models simulate cognition capable of self-regulation. The former was first conceptualised by Norbert Wiener in a study of cybernetics where he recognises the role of human and machine interactions through

communication and control. He also recognised the ability of machines to simulate learning and propagate behaviour and self-regulate through feedback and control loops much like a human (Wiener, 2019). However, the role of human oversight cannot be underscored, as some users opt to switch to humans (Liu et al., 2024). This dual approach was a common theme in the literature review, where human oversight was important to mitigate gaps such as social engineering attacks. This can strengthen the role of the adaptive self-regulation guidelines where both human judgement and GenAI machine learning are integrative. Thus, creating a more holistic and robust GenAI self-regulation structure to cater to their business customer experiences.

Furthermore, the Social Cognitive Theory (SCT) of self-regulation is rooted in psychology and is applicable across interdisciplinary fields, including Information Science (Middleton et al., 2018). In this case, as previously indicated, this theory has been applied to the science behind the cognition of self-regulation of GenAI models themselves and the person/people who are in oversight of these models (Carillo, 2010).

The subfunctions behind Albert Bandura's SCT of self-regulation framework are self-monitoring, judgement, self-reaction in self-regulation and self-efficacy (Stajkovic & Stajkovic, 2019). Contextually, the role of self-monitoring of the GenAI model is enacted where a model is trained to capture performance logs that monitor its performance, and a human oversight is also self-monitoring the performance of these models. After this, both agents exercise judgement on performances, applying self-reactive measures, and the effectiveness of their responses depends on their self-efficacy.

This theory is relevant as a self-regulation behaviour theory because it encapsulates the intrinsic processes of self-regulation (Bandura, 1991).

Social Cognitive Theory (SCT) acknowledges that individuals are shaped by their social environment while concurrently influencing it (Stajkovic & Stajkovic, 2019). In this case, the GenAI model's training dataset, as well as the human oversight, is influenced by the environment. For example, in South Africa, the models have training from a South African customer base perspective as opposed to a Western perspective. The acquisition of knowledge and skills in SCT occurs through two primary mechanisms: enactive mastery experience, involving direct, hands-on experience, and mastery modelling, which facilitates observational learning from role models (Gong et al., 2009). Contextually, GenAI models' oversight

knowledge is a result of direct hands-on experience and years of observation and interaction with the model.

Furthermore, the theory explains how an individual can change the course or outcome of events by forming decisions through the evaluation of performances; and in this case, where a GenAI is used for business customer experience is biased the course or outcomes of events triggering this event are changed in the retraining of the GenAI model. This self-reaction through exercising judgement of the performance logs to identify the bias is what constitutes self-regulation, including the ability to be effective, identified as self-efficacy. Thus, Albert Bandura in his theory understands that not only is self-regulation critical, but it should be effective or self-efficient.

Henceforth, self-regulation entails guiding the GenAI model used in business customer experiences and its system administrator (human oversight) by training the model on what to circumvent based on environmental influences and ensuring the model makes decisions that do not cause harm to the customers, upholding moral conduct (Bandura, 1977).

For further clarity, the operational theory grounding the research, Albert Bandura's SCT framework, emphasises key components of self-regulation of GenAI systems: self-monitoring, self-judgement and self-reaction (Bandura, 1986). Self-monitoring involves tracking performance and progress, while self-judgement entails evaluating performance against predefined standards. Self-reaction involves responding to self-evaluation of performances with adjustments or reinforcement, and self-efficacy refers to the belief and effectiveness in one's ability to achieve goals. These components interact reciprocally, influencing one another to facilitate self-regulation (Bandura, 1991).

SCT highlights the significance of control over thoughts, emotions, motivation and actions (Bandura, 1986). This subfunction describes how the process of self-regulation is actively cultivating adaptive cognitive and behavioural patterns in response to environmental stimuli, thereby facilitating the attainment of intended GenAI customer experiences.

Effective self-regulation entails a cyclical process wherein performers continually assess their environmental context and systematically evaluate outcomes (Locke & Latham, 1990). In this case, a self-regulated GenAI model and its human oversight shall continually assess their environment and develop strategies for optimum GenAI business customer experiences. For

example, where Black Friday sales occur annually, the GenAI facing the customer needs to skillfully implement sales.

Albert Bandura's Social Cognitive self-regulation framework includes self-monitoring, judgement, and self-reaction (Bandura, 1991). The aforementioned are contextually defined sequentially as;

(a) **Self-monitoring** of GenAI performances

Self-monitoring involves continuous evaluation of GenAI systems to ensure optimal performance. The aforementioned is executed through the evaluation and tracking of GenAI model performance, detecting errors and addressing technical or ethical issues to maintain quality. Customer feedback loops, encouraging GenAI business customer feedback, refine GenAI applications. This ongoing assessment facilitates improvement.

(b) **Judgement** of GenAI performances

Judgement in Bandura's theory is a critical component of SCT, where exploring the above-identified performances requires judgement. This process involves cognitive processes where GenAI business stakeholders evaluate (make a judgement call) on the GenAI's business customer experience performances, limitations and potential biases. This evaluative process involves setting standards, metrics or baselines for GenAI performance, accuracy and ethics, ensuring alignment with organisational goals (Bandura, 1991). By recognising responsibility for GenAI's impact on customers, stakeholders and society, developers and businesses promote mindful development and deployment.

(c) **Self-Reaction** and Adjustment of GenAI performances

Based on the judgement of the quality of performance of the GenAI models and the business customer experiences. Self-reaction involves emotional responses to GenAI successes or failures, influencing a corrective measure if required. Reflecting on GenAI's performance in customer experience informs future development strategies. Adjustments based on self-evaluation and monitoring ensure continuous improvement (Bandura, 2006). This reflective process enhances accountability.

(d) **Self-Efficacy** in GenAI performances

Self-efficacy, defined as the personal belief in effectively and successfully achieving the above three tasks and warrants particular attention (Bandura, 1986). This subfunction significantly requires learning and skill development, underscoring the importance of confidence in achieving goals in terms of optimising GenAI business customer experiences (Middleton et al., 2018).

Self-efficacy plays a vital role in determining the efficiency and effectiveness of GenAI systems' self-regulation, as developers' confidence in their ability to effectively integrate and manage GenAI fosters successful implementation. Businesses' perception of their capability to leverage GenAI enhances strategic decision-making (Bandura, 1991). Overcoming GenAI-related challenges strengthens developers' and businesses' self-efficacy, promoting resilience.

Altogether, given the above contextual definitions in practise, self-regulation in SCT is an integrative theory encompassing various self-regulatory subfactors including; 'self-monitoring' GenAI business customer model performances, assessing those monitored findings to form a clear 'judgement' on the corrective measures and thereafter acting on those corrective measures through 'self-reactive' interventions such as updating their GenAI business customer experiences frequently to eliminate any new biases.

Human behaviour is primarily driven and governed by the continuous process of self-regulation, which operates through an integrated mechanism comprising self-monitoring, judgement, self-efficacy, and self-reaction (Bandura, 1991). This self-regulatory process enables monitoring behaviour self-efficacy, underlying subfunctions, and their consequences, while also assessing their actions regarding personal standards and environmental contexts. Consequently, individuals experience affective responses to their behaviour, which in turn influences their future actions, thereby facilitating adaptive decision-making and behavioural control (Bandura, 1991).

Importantly, not only is this approach holistic, but it closes the current gap of GenAI models not regulating as quickly as technological advancements. This is supported by a continuous cyclical process of self-monitoring, judgement and self-reaction, which can be supported by GenAI change management and governance (Gandhi et al., 2025).

2.5.2 Limitations of Social Cognitive Theory

While Bandura's Social Cognitive Theory (SCT) of self-regulation has been widely applied and proven useful in understanding human self-regulatory behaviour, it has a few limitations, for instance the theory does not take into consideration other biological factors, chemical imbalances or learning disorders in a person that can affect their cognitive processes where self-regulation occurs (Bandura, 1977). Additionally, SCT was developed primarily within Western cultural contexts, which may mean that its experimental environment was predominantly Western (Rothbaum et al., 2000). This Western-centric bias may result in a lack

of consideration for cultural differences in environment, values, beliefs, and practises that influence human behaviour in South African businesses about the business moral dilemma at hand.

2.5.3 The Need for self-regulation in GenAI

Bandura's SCT of self-regulation sets the groundwork for an imperative understanding of self-regulation specifically for GenAI. The need for this self-regulation is affecting many businesses worldwide, not only in South Africa. Globally, in the United States, in 2023, seven prominent tech companies committed to eight voluntary commitments with the White House to self-regulate and develop these technologies in a safe and trustworthy manner (Heikkiläarchive, 2024). These companies, including Meta, Google, Microsoft and Meta AI, have since been joined by several other top companies like IBM, which also later signed the commitment (Mitchell, 2023; Wadhwani, 2023). The commitment involves opening up their algorithms to security checks and outside testing of systems before release, among other stringent measures (Diamond, 2023). The aforementioned portrays the relevance of Bandura's theory as self-monitoring, judgement, and reaction play a significant role in achieving transparent algorithms.

India is also recognising the need to self-regulate and has asked their tech developer to regulate GenAI models by adding labels to the output to warn customers that the output can be inaccurate. Such transparency contributes to the safe and trustworthy use of GenAI business customer experience (Budiki, 2024). This approach enhances self-regulation by businesses without the overreliance on governing authorities. Similarly, in Singapore, businesses are encouraged to consult with their AI regulation model framework and to tailor-make their self-regulation methods that are ideal for their business (Boggs, 2024).

Countries in the BRICS, as of 2024, excluding China, which has Artificial Intelligence legislation, have also adopted a self-regulatory approach to avoid hindering any development. Furthermore, this self-regulatory approach is poised to serve a supporting role in attracting investment (Bolotskikh, Dorokhova, et al., 2024). In Russia, businesses committed to self-regulation and pledged to abide by an AI Code of Ethics that was also supported by the Declaration on Responsible Development and Use of GenAI. Russian businesses are committed to minimising risks by alerting customers of any liabilities that may arise (Bolotskikh, Abanitov, et al., 2024).

Through the adoption of GenAI self-regulatory measures, businesses can demonstrate their commitment to responsible GenAI development and safe customer experiences, as this approach is self-led and self-sustaining. Guidance on the best approach to take toward self-regulation of GenAI is still growing globally and requires much consultation and monitoring of progress, challenges and success (Shukla, 2023). This is because of the complexities and varying designs of these models adopted to exist in various organisational, geographical, political and cultural settings, but self-regulation seems to be a more pragmatic and manageable approach (Shukla, 2023). While self-regulation remains a viable strategy, developer-led self-regulatory measures can significantly contribute to the responsible development of GenAI, alleviating the regulatory burden on governments (Budiki, 2024).

However, the long-term effectiveness of self-regulation is an area of research that also needs to be closely monitored as GenAI in business customer experience continues to expand and broaden its capabilities.

2.5.4 Artificial Intelligence Application of theory and practise in the self-regulation of GenAI

Self-led measures exist in terms of self-regulation of GenAI in business customer experiences, and the following section explores some of the common or frequently recurring measures identified from Bandura's theory and the academic body of literature.

(i) Self-regulation Software

Software such as LangSmith is deployed by developers on their GenAI business customer experience tools. LangSmith accelerates AI application development by streamlining evaluations, helping developers overcome the paradox of choice. LangSmith consists of two core components: the Dataset, which provides input data for evaluation, and the Evaluator, a function that scores AI performance based on the dataset. By utilising LangSmith, developers can rapidly compare AI models and prompts, balance accuracy, latency, and cost (LangSmith, 2024). Furthermore, LangSmith is a comprehensive platform for testing, debugging, and evaluating Large Language Model (LLM) applications (Tuychiev, 2024).

(ii) Governance

The establishment of robust self-led GenAI governance initiatives could avert risks and unintended consequences, necessitating effective governance to ensure societal benefits (Budiki, 2024; Heikkiläarchive, 2024; Marie & Mathews, 2021; Wadhwani, 2023). However,

like any change, there is resistance and the implementation of GenAI governance. These challenges include opaque algorithms and unpredictable outcomes, which hinder controllability and accountability. To address these issues, governance plays a crucial role where businesses are expected to incorporate transparency and explainability (Fui-Hoon Nah et al., 2023). In terms of governance, self-efficacy on the part of the GenAI model administrator in line with Albert Bandura's Social cognitive theory framework is imperative as they have to be effective in recognising incidents (Bandura, 1995).

(iii) *Policy making*

The Organisation for Economic Cooperation and Development (OECD) also recognises the critical role of self-regulation of technology. The organisation is actively participating in policy-making initiatives, providing recommendations around Artificial Intelligence. For example, one of the recommendations was for agile and adaptive regulatory environments, including self-monitored GenAI deployment using experimentation in a controlled ecosystem (OECD, 2019).

(iv) *Monitoring and Evaluation*

Furthermore, monitoring and evaluation of Large Language Models (LLMs) used in GenAI business customer experiences is crucial because of the delicacy of the nature of the use cases. GenAI models can misinterpret a diagnosis and delay treatments, which becomes a matter of life and death (Meskó & Topol, 2023). Self-monitoring is also a subfunction of self-regulation in Albert Bandura's Social Cognitive theory of self-regulation framework (Bandura, 1991).

(v) *Reporting*

Periodic reporting is another indirect method of self-regulation whereby businesses of GenAI models report concerning the performance, suspected malicious cyber activities, and any other observations. This can also be enforced in policies (Christodorescu et al., 2024). Reporting is another form of actively self-monitoring the performance of the GenAI business customer performances which is contributes to self-regulation according to Bandura's SCT (Bandura, 1991).

(vi) *Human-centred approach to self-regulation*

Hua et al., (2024) recommended that technology developments should adopt a human-centeredness approach to self-regulation. This approach prioritises safety, privacy, security

and more to mitigate the risks that may arise (Hua et al., 2024). This means that the oversight of humans should always be considered, and technologies should ideally not be fully autonomous. The abovementioned is further corroborated by Wakunuma & Eke, (2024) who elucidated the importance of implementing policies, and regulation measures in the development and deployment of GenAI technologies.

2.6 Contextualising GenAI self-regulation in South Africa

In South Africa, research concluded by the South African GenAI Roadmap 2024 revealed that 45% of businesses have adopted the use of GenAI; 45% are evaluating ways to implement GenAI; whereas the other 10% do not yet have plans to implement GenAI (Woolley, 2024).

Given the gaps in adaptive self-regulation, this research focuses on the business moral dilemma of the GenAI South African landscape. The adoption of GenAI in business customer experience has potential liabilities of gaps such as cybersecurity attacks and more. Hence, self-regulation is imperative (Makore, 2024).

Another study investigated the opportunities and gaps of GenAI by small to medium enterprises in South Africa. The findings revealed that these businesses yielded several benefits, but also gaps, such as a lack of expertise and security concerns (Muzuva et al., 2024).

Lastly, for countries such as South Africa, although the nation aligns with global trends, other social repercussions may also need to be considered, for example, unemployment may potentially increase as some jobs become automated. For example, sales agents for customer experiences can be substituted for GenAI bots (Gumede, 2024).

Therefore, the GenAI business moral dilemma in South Africa is grappling with not only ethical issues but also social issues that need proper governance or regulation.

Given the above, it is relevant to comprehend (a) how GenAI is being regulated by businesses in South Africa and (b) key steps required for adaptive self-regulation.

In August 2024, South Africa released its National AI Policy Framework. The National AI Policy Framework emphasises fairness, accountability, transparency, and inclusivity. Key pillars include robust data governance, infrastructure enhancement, and research investments. The framework fosters trust, mitigates risks, and promotes human-centric AI solutions aligned with South African values. South Africa's Department of Communications and Digital Technologies unveiled its National Artificial Intelligence Policy Framework in August 2024

(Broadcast Media Africa, 2024; Ormond, 2024; Pretorius & Ongeso, 2024). This groundbreaking framework initiates the development of a comprehensive National AI policy aiming to foster a vibrant AI ecosystem benefiting society, economy and development. It addresses ethical, social and economic implications, ensuring broad sharing of benefits and effective risk management. Stakeholder feedback was sought to inform policy development, and Artificial Intelligence supplemented by formal stakeholder engagements and email submissions (Broadcast Media Africa, 2024; Ormond, 2024; Pretorius & Ongeso, 2024). The policy aims to improve the quality of life and societal progress, and position South Africa as an AI innovation leader (South Africa's National AI Policy Framework, 2024).

2.6.1 Review of literature on other self-regulation measures

Drawing from the objectives of the research, which are to identify the key steps for developing guidelines, it is imperative to critically review how other regulations, including guidelines, were developed.

In the South African business customer experience landscape, GenAI self-regulation is still relatively new, but the overarching piece of new legislation that has recently been promulgated in 2024 is South Africa's National AI Policy (Funa & Gabay, 2025; South Africa's National AI Policy Framework, 2024). Hence, there is a knowledge gap for guidelines specifically for businesses and customer experience in South Africa.

Many other countries have attempted to self-regulate or to develop legislatures, policies, frameworks, or guidelines for AI, including GenAI. In Europe, guidelines for the orientation of Artificial Intelligence Governance were developed. Research experts in Europe were consulted to draw up what has been termed '*Ethics Guidelines for a Trustworthy AI*'. The guidelines are structured according to three levels or tiers; the top tier addresses ethics premised upon human rights, in the second tier are the key requirements for assessing and AI systems and their lifecycle, lastly, the base lists recommendations for operationalising requirements in the first tier from which each system has been developed.

Nations in the BRICS (including Brazil, Russia, India, China, South Africa, United Arab Emirates (UAE) and others) have also been developing guidelines (Bolotskikh, Dorokhova, et al., 2024). For example, in China, they developed the '*2017 National AI Strategy*' (Bolotskikh, Dorokhova, et al., 2024). Another example is in the United Arab Emirates, where technology is largely governed by the government, and they aim to become the global

leader in AI by 2031, focusing also on GenAI growth. The UAE developed ‘*The National Strategy for Artificial Intelligence 2031*. On the other hand, legislation is still in development in India, but guidelines have been established. The papers below were reviewed to identify how guidelines are developed for GenAI. Henceforth, to achieve transparency and eliminate researcher bias, some research papers on developing guidelines were reviewed, and a matrix was developed. The following table also shows the theories that were adopted as well as the steps that were followed. In the Chapter 5 section of developing guidelines, these steps will be juxtaposed with the steps that were followed in this research study, bridging the gap between theoretical frameworks and developing adaptive self-regulatory guidelines.

Table 1 A table showing literature on how other regulatory measures were developed

Author(s)	Research Methodology	Steps followed to develop guidelines or regulations	Focus	Did they refer to any other theory	Name of other theory, if any	Type
(Olusegun, 2024)	Secondary Data Collection Primary Data Collection through interviews with Experts Thematic Analysis Content Analysis Fairness, Accountability and Transparency (FAT) framework assessment.	Scope & Purpose of Guidelines Ethical Risk Assessment Development of Guidelines Training and Awareness Monitor and Update Accountability	Guidelines for AI in Digital Marketing	Yes	FAT Framework	Guidelines
(Gopalakrishna et al., 2013)	Secondary Data Collection Primary Data collection through interviews with Experts for development of initial research and from experts Quote Extraction and Initial Matrix Thematic Categorisation Summary and Development of Draft Guidelines	Scope & Purpose Stakeholders Clarity and Presentation Dissemination and Communication Editorial Independence	Guidelines for guideline developers	No	No	Guidelines
(Bobrova & Perego, 2025)	Synthesising initial guidelines from experts, academic research and others Heuristic Evaluation to assess and evaluate initial guidelines Validation and refinement of guidelines with professionals	Development of initial draft guidelines Quote Extraction and Matrix Thematic Categorisation and subgrouping Opinions, contradictions and choice Summarising each topic and forming guidelines	User-Centric Design Guidelines for W3 Applications	No	No	Guidelines

Author(s)	Research Methodology	Steps followed to develop guidelines or regulations	Focus	Did they refer to any other theory	Name of other theory, if any	Type
(Wang et al., 2025)	Secondary Data Collection Primary Data collection through interviews with Experts Summary and Data Analysis	Current situation Analysis Guideline Development	Managerial Guidelines	Yes	Theory of Sports Management	Guidelines
(Shittu et al., 2024) ...continued	Literature Review Stakeholder Engagement Contextual Analysis Development of Draft Guidelines Consultation and Feedback Pilot Testing Monitoring and Evaluation Implementation Strategies	Establishing a foundational framework based on core ethical principles such as transparency, accountability, fairness, privacy, and respect for human rights (tailored to Nigeria) Stakeholder engagement Develop Guidelines Implementation, Support adoption of guidelines Training to educate stakeholders on compliance requirements Implementation Monitoring and Evaluation Regular Reviews	Ethical guidelines for AI and digital transformation in Nigeria	Yes	Various	Guidelines
(Janse van Rensburg, 2020, p. 2)	Awareness of problem Knowledge (Primary and Secondary Data Collection) Suggestion Evaluation Development	Reasoning and Reflection Requirements Design and Scheduling Guidance and Scaffolding Monitoring and Management Assessment	IT Higher Education	Yes	Critical Social Theory / IT Theory	Guidelines
(Falavigna et al., 2025)	Primary Data Collection through meetings Development of Guidelines	-	Guidelines for Health Centres	Yes	Guidelines International Network	Guidelines
National Policy Development (2025)	Problems raised by Electorates Political Manifesto Processing through Medium Term Strategic Framework Developing Policies and Laws Implementation	Policy Formulation Policy Adoption Policy Evaluation Policy Implementation	Framework for the development of South African Policies	Yes	Theory of Change	Framework

2.6.2 Rationale behind the self-regulation of GenAI

Adaptive self-regulation initiated by businesses emerges as a pragmatic alternative to national regulation. State-led oversight can often become constrained. This is due to several reasons, including significant fiscal burdens and suffering from limited enforcement capacity due to the influx of businesses adopting GenAI (Marwala, 2024). However, self-regulation leverages the agility and domain-specific expertise of industry actors to establish and maintain ethical standards and best the self-regulation of GenAI is essential to harness its benefits while minimising its risks. The unregulated deployment of GenAI in society and business has raised significant concerns, as exemplified by Italy's 2023 ban on ChatGPT due to privacy concerns (Meskó & Topol, 2023). This incident highlights the imperative need for self-regulation in GenAI technologies. Although GenAI has the potential to yield benefits, such as reducing healthcare costs (Palaniappan et al., 2024), its unregulated use poses significant risks, including the misuse of personal information. Moreover, GenAI presents various risks, as outlined in the table below, underscoring the necessity of implementing effective regulatory measures to mitigate these risks and ensure the responsible development and deployment of GenAI technologies. By establishing a regulatory framework, we can maximise the benefits of GenAI while minimising its risks and ensuring public trust. The following table summarises some of the risks of unregulated GenAI systems to further support the contribution of this research study.

Table 2 Risks of GenAI if not regulated (Source Adapted from (de Almeida et al., 2021; Kirwan, 2024; Palaniappan et al., 2024)

Category of GenAI Risk	Description	The effect of the risks if not regulated
Unintended Harms	Unregulated GenAI tools conceal unintended harms that may prejudice an organisation. These include harms that result from the machine itself and are unavoidable, for example Biases that result from the machine learning the wrong information, hallucinations, false positives and false negatives and others that result from distorted information inputs and outputs in the machines.	Societal prejudices, for example, GenAI systems that are biased, can further promote societal discriminations such as gender biases, racial biases and more. For example, Amazon's hiring system once learned to hire male candidates over female candidates unintentionally.
Privacy infringements	An exposed GenAI system can perpetuate privacy breaches. Therefore, since GenAI systems require data to function, sometimes there is a risk that the data is compromised through, for example, the commodification of personal data.	Loss of privacy and compromised safety.
Social Engineering Attacks	Unregulated systems could fall into the wrong hands. For example, GenAI systems are being used to create social engineering attacks and to scam people.	Loss of income and other high-risk crimes.

Category of GenAI Risk	Description	The effect of the risks if not regulated
Social Injustices	GenAI systems are costly, and the concentration of their adoption can become concentrated in only a few companies.	The gaps between higher-income businesses and lower-income businesses are enlarged.
Safety	If safety measures are unregulated in terms of GenAI, there is a risk of accidents and other dangerous events. Safety should be uncompromised in the adoption of high-risk use cases such as GenAI, for example, in Aviation (Kirwan, 2024), it was concluded that regulation is vital in the design, training.	Physical and mental harm is being done to ordinary citizens.

Ultimately, the self-regulation of GenAI is imperative, as highlighted by the abovementioned illustrations, because GenAI cannot go unregulated, especially in the hands of customers.

Moreover, the adoption of self-regulatory reforms has also been cited as vital in society to address gaps in security, trust, transparency and more (Lazo & Ebardo, 2023).

Effective self-regulation of emerging technologies requires a multifaceted approach. Drawing lessons from past experiences, regulators must first understand the problems and causal pathways associated with emerging technologies. Next, they should focus on shaping industry behaviour through targeted regulations. To achieve this, regulatory organisations need to strengthen their technological capacities and, more importantly, invest in human capital by developing top-quality personnel with specialised skills and expertise. By adopting this strategic approach, regulators can successfully address the challenges posed by technological innovation, as emphasised by (Coglianese, 2021).

Given the pervasive and profound impact of GenAI on various businesses and societal domains, rigorous and uncompromising regulation of these tools must become a paramount priority. The far-reaching influence of GenAI necessitates a careful and deliberate approach to regulation, ensuring that its benefits are maximised while mitigating potential risks and negative consequences. Effective self-regulation requires collaboration among stakeholders, including policymakers, industry leaders, and experts, to establish clear guidelines and frameworks that promote responsible development and deployment of GenAI technologies (Özer, 2024).

2.6.3 The GenAI Moral Dilemma Research Gap and Research Contribution

McKinsey and Company recently reported that businesses have been grappling with the disparity between the rapid advancements in GenAI and the slower pace of self-regulation.

This gap raises serious concerns and also suggests that there is a lack of knowledge or a research gap on the challenges of balancing the deployment of safe, transparent and ethical

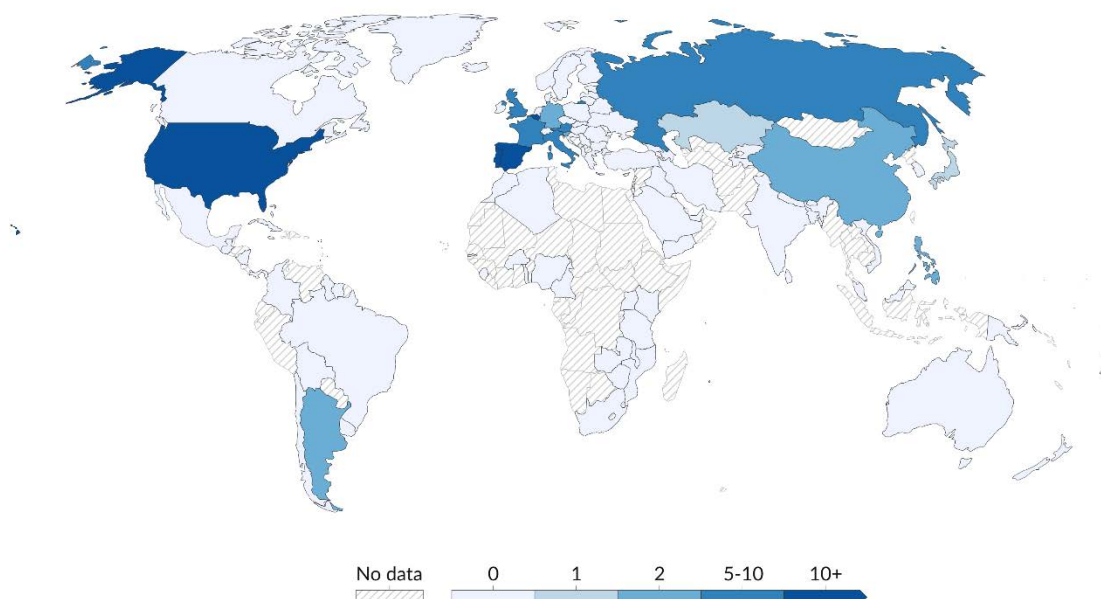
models while keeping up with self-regulation (Luget et al., 2023). Hence, GenAI is evolving rapidly, and businesses need to move at the same pace, if not ahead of the rapid advances of GenAI, in terms of self-regulation of these models (Storey et al., 2025). Another research study highlighted that the traditional regulation methods fall short of adaptability, and a resilient-based approach to regulation that incorporates adaptability and rapid responses is required (Bodini, 2024).

Most self-regulation measures are not adaptive. For example, the self-regulation commitments by tech firms with the White House were signed in 2023, and yet, since then, many new developments have taken place. This disparity between the pace of technological innovation and the adaptability of self-regulation poses a significant risk and challenge. Bridging this gap is essential to ensure that self-regulatory guidelines remain adaptive and current.

To address the GenAI dilemma in business customer experience, this research adopts an integrative thinking approach grounded in Albert Bandura's Social Cognitive Theoretical framework and explores the role of adaptive self-regulating guidelines. The following section, therefore, explores the need for self-regulation as a means to address the research problem.

Cumulative AI-related bills passed into law since 2016, as of 2023

Bills passed into law by national legislative bodies (e.g., congress, parliament) with the keyword "artificial intelligence" (translated to the respective languages) in the title or body of the bill.



Data source: AI Index (2024)

Figure 3 Cumulative AI-related bills passed into law. AI Index, "AI Index Report" [original data] Source AI (AI Index, 2025) in (Bodini, 2024).

Furthermore, the Figure above shows a 2024 AI Index 2024 report on the legislation that has been enacted between 2016 and 2023 by national bodies, such as congresses and parliaments, includes references to "Artificial Intelligence" (translated into various languages) within the titles or content of the bills. This data originates from the [AI Index, \(2025\)](#) with minor processing by Our World in Data. The report for 2025 is still in progress, as many more countries have since enacted their legislations, including South Africa.

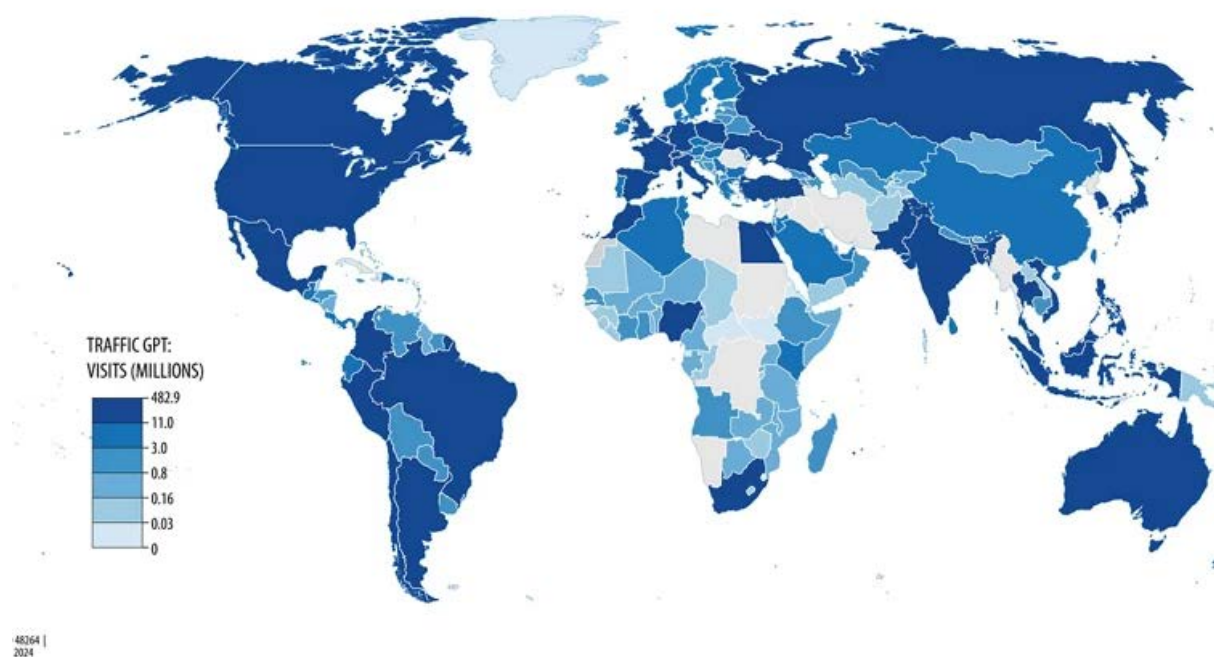


Figure 4 Generative AI, particularly ChatGPT, has demonstrated a global reach, with usage recorded. Source: World Bank Official Boundaries: (Qiang Zhenwei et al., 2024; World Bank, 2024). Data source: Semrush and the authors' calculation.

The two images show that there was a lot more usage of GenAI compared to the legislation or regulation of GenAI around the world. Hence, the emergence of new bills has not been as rapid as the exponential deployment of GenAI across the world (World Bank, 2024).

Another research paper encapsulated the findings from a workshop co-organised by Google, the University of Wisconsin-Madison and Stanford University. Some of the findings obtained from the workshop also highlighted the misalignment and gap between the pace at which GenAI technology is developing and policymaking. It was emphasised that there are gaps that have arisen from mismatches between the demands of regulation and the technical capabilities of GenAI, which should be proactively addressed (Christodorescu et al., 2024). Importantly,

another study focusing on what the priorities are for the regulation of GenAI in the United Kingdom highlighted that the regulation should intrinsically be scalable and adaptive, further emphasising the gap and need for adaptive regulation measures (Eben et al., 2023).

2.7 Conclusion

This chapter explores extant literature relevant to the core dimensions of the study. It cross-examines the multifaceted applications of GenAI, the moral dilemma and its regulation. The chapter provides an in-depth analysis of the dichotomy that formed the basis of the business moral dilemma. Therefore, a broad understanding of the current benefits, gaps of the adoption of GenAI in business customer experience was provided.

Furthermore, the chapter also draws insights from how other regulatory measures, including guidelines, have been developed. Importantly, the research gap was identified, showing the contribution to the study and contributing to the academic body of literature in the area of these gaps. Thus, the foundations were laid to better understand the areas of further research and recommendations.

Additionally, the theoretical foundation underpinning this research is explored. Bandura's Social Cognitive Theory (SCT) has a specific focus on the mechanisms of self-regulation. In his theory, Bandura (1991) recognises that self-regulation operates through three interrelated subfunctions: self-monitoring, judgment of one's behaviour against personal and social standards, and affective self-reaction.

In conclusion, this chapter's findings form the basis for the development of the steps toward achieving adaptive self-regulation guidelines. The next chapter delineates the methodologies adopted to gather empirical evidence to further contribute to the development of these guidelines.

3 Methodology

3.1 Introduction

The systematic methodological approach of the research study is encompassed in this chapter. Specifically, the steps that have been taken to complete the study and address the research problem (Swarooprani, 2022). Through clearly articulating the methodology, there is a demonstration of the rigour and transparency of this study. Also, providing enough detail for readers to understand the research processes undertaken by the researcher.

A summary of the research methodology adopted for this study is in the research onion below.

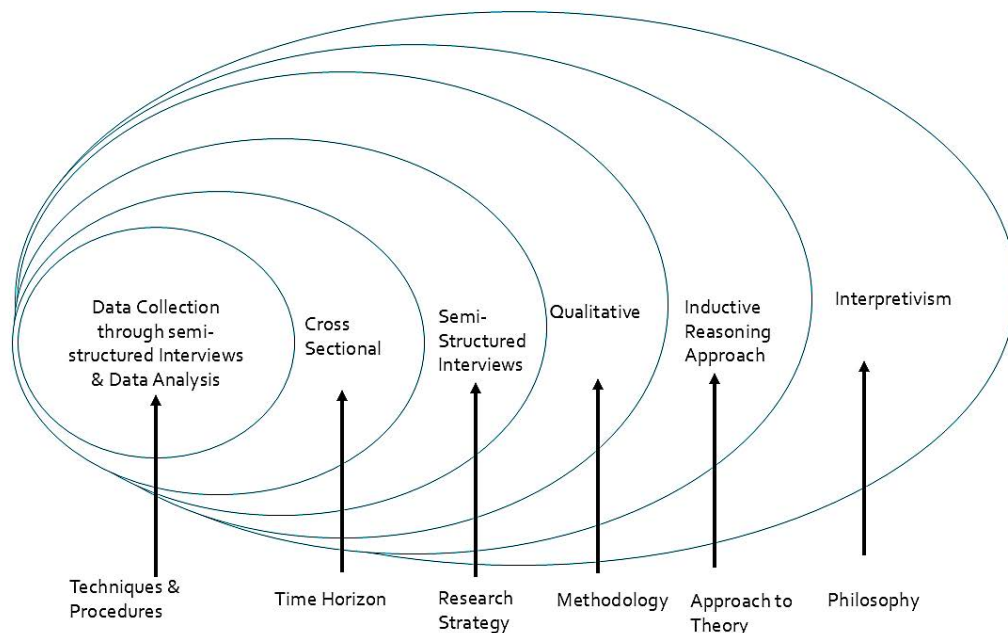


Figure 5 Saunders Research Onion adopted for this study

3.2 Research Design and Philosophical Approach

A research design is a comprehensive plan for a research study (Saunders, 2016). Additionally, the design of the research methods, procedures, and techniques used to collect and analyse data is described hereafter. Various types of research designs exist, including experimental, case study, ethnographic, grounded theory, and mixed-methods designs, each with its strengths and limitations (Saunders, 2016).

This study is exploratory and is further supported by incorporating elements of integrative thinking. Furthermore, to resolve the GenAI business moral dilemma, the major focus of this

exploratory study was to discover new knowledge, insights to guide the identification of key steps for adaptive self-regulating guidelines (Singh, 2021). This is in line with integrative thinking, where a holistic approach is taken to consider opposing ideas to form new solutions without eliminating any of the opposing ideas.

Given the above, one-on-one semi-structured interviews were organised for data collection. This allows for thorough, in-depth probing and understanding of the research problem, fully engaging participants' thoughts and opinions to enrich the research findings (Kuphanga, 2024).

3.2.1 Research Philosophy: Interpretivism

The research's philosophy is interpretivism. This is described as a social phenomenon, comprehended "through the lens or perspective of the research participants and not of the researcher" (Rehman & Alharthi, 2016, p. 55). In this particular research, the social phenomenon is the business moral dilemma of GenAI in business customers through the lens of Technology experts. The questions themselves were designed to factor in the opinions, as opposed to providing what seemed to be the correct answer. For example, the first question;

"Research Question 1: In your view, what are the current benefits of using GenAI in business customer experiences in South Africa? Explain".

Given the abovementioned style of semi-structured interview questions, the opinions that were gathered were not those of the researcher but of the research participants.

Moreover, interpretivism philosophy was an appropriate choice for this study because it is a paradigm that developed as a critique of positivism in social sciences, recognising humans' unique capacity for complex meaning-making (Saunders, 2016). In this particular context, subjective experiences result from the different experiences and knowledge that the participants have with GenAI in business customer experience.

Furthermore, the paradigm's core principles include subjective reality and contextual understanding in exploring social phenomena. Therefore, interpretivism provides a robust framework for social sciences research, acknowledging the complex relationship between culture, history and an individual's subjective perception (Junjie & Yingxin, 2022). Interpretivism seeks to elaborate more on individuals' experiences, perspectives and social contexts, acknowledging the intricacies of human behaviour (Saunders, 2016). Contextually,

in this research, the reality and truth behind GenAI business customer experiences are created through the dynamic interactions with GenAI models.

The purpose of the interpretivism approach in this context was to allow for the formation of new ideas and formulate a new, richer understanding of the GenAI moral dilemma and adaptive self-regulation. Interpretive research excels at providing rich, contextual insights, acknowledging the intricacies of individual situations. Furthermore, one of the major strengths of interpretivism is contextual insights into complex social phenomena, prioritising participant voices (Pervin & Mokhtar, 2022). However, if not applied correctly, this philosophy has been criticised for concerns around complex data analysis (Nowell et al., 2017). Additionally, its findings face criticisms regarding validity, reliability and generalisability (Leitch et al., 2010; Pulla & Carter, 2018). To address these concerns, rigorous methodology, data triangulation and transparent research processes were applied.

Lastly, interpretivists gather qualitative data from their research participants over some time and analyse the data inductively, where patterns are discovered in the data and the themes are used to generate a theory and in this context, guidelines (Rehman & Alharthi, 2016). Inductive reasoning is the process whereby general conclusions are drawn from specific observations, lived experiences or from data (El-Badawy, 2022). In this context, the research participants provide their own opinions based on their observations of GenAI.

3.3 Sampling Strategy and Saturation

Sampling denotes the systematic process of selecting a representative subset, and the sample serves as a proxy for the population in South Africa, facilitating inferences about the larger group (Nanjundeswaraswamy & Divakara, 2021; Vasileiou et al., 2018).

The rationale behind contextualising the research in South Africa is that at the time of the inception of the research, there were gaps in terms of AI regulations in this country. Furthermore, businesses also require legislative guidance on how to adaptively self-regulate themselves to safeguard themselves and for equitable returns and benefits. To this end, the South African policy makers in government followed a holistic consultative process that also garnered feedback from the research community (South Africa's National AI Policy Framework, 2024). Notwithstanding their efforts, it was clear that the country needs such knowledge and research. The National AI Strategy was only launched recently in August 2024.

The sampling of this research comprises business professionals in South Africa with a technological background and some knowledge of GenAI. This criterion is because the research primarily focuses on identifying key steps for self-regulating a type of technology (GenAI). Because there is a specific requirement that needs to be satisfied, a non-probability method using a purposive sampling technique is adopted in this research (Siva et al., 2019).

Purposive sampling method involves actively creating a selection criterion for choosing sampling units that is based on specific research objectives (Creswell & Clark, 2017). Purposive sampling is suitable for exploratory research, qualitative studies, pilot projects and context-specific investigations, and this technique gathers targeted insights, often when probability sampling is impractical (Singh & Masuku, 2014).

Correspondingly, sample size refers to the number of observations extracted from a population (Creswell & Clark, 2017). The advantages of sampling are faster data collection and lower costs but if sampling is not An expert in this case refers to professionals in the field of technology who have about 10 years of experience in technology and a minimum of 1 year of experience in GenAI technology specifically business customer services as some of the technologies are still relatively new (Hadi et al., 2023).

Saturation is a fundamental principle in qualitative research, indicating that additional data collection yields diminishing returns. This concept optimises research efficiency by signalling when no new insights emerge or indicates that no new data can be explored (Naeem et al., 2024). Saturation is also influenced by several factors, including the research participant's available resources, time, and availability of these technology experts, as well as the prospective participants' experience in technology, specifically GenAI (Fugard & Potts, 2015; Guest et al., 2020; Hennink & Kaiser, 2021; M. Mason, 2010). In this case, the sample is homogenous, meaning that they have the same attributes of being South African company technology professionals. The acquired sample size is expected to be sufficient, based on the guidelines of Mason's meta-study for data saturation in qualitative studies where even 20 samples are sufficient (Chitac, 2022). A value of 5% or less is considered acceptable, indicating a satisfactory level of new information, while a value of 0% indicates no new information (Guest et al., 2020). For thematic research analysis, similar to this research study, 12-20 participants are considered an adequate sample (Ahmed, 2025). An analysis of this approach was conducted to further validate the adequacy of the sample. To this end, research papers were consulted and reviewed. One study empirically assessed papers from 4 databases

to determine a range whereby sample sizes for saturation in qualitative research are reached, and the research paper concluded that saturation can be reached between 9 and 17 research participants (Hennink & Kaiser, 2021). Furthermore, according to Guest et al., (2020) Saturation can be reached even at a median of 12 participants. Notwithstanding, another study also concluded that saturation can take place with a minimum of 5 research participants in grounded studies (Thompson, 2004) in Moti, 2013). The abovementioned literature is contingent upon the interplay of various factors such as the nature of the research, the research objectives, methodological approach, sample characteristics, and this was considered (Guest et al., 2020; Hennink & Kaiser, 2021; Saunders, 2016).

3.3.1 Research Time Frame

Data was collected at a single point in time, thus making the research a cross-sectional type of research (Setia, 2016; Thomas, 2020). The data was collected using online communication platforms such as Zoom and in-person engagements with experts in GenAI.

3.4 Data Collection

The research data collection protocol followed a structured approach. This commenced with acquiring consent, followed by providing an overview of the research context, problem and objectives. Once participants were ready to proceed, discussions around the research problems ensued (guided by the attached questionnaire). It is noteworthy that participants could ask to stop at any given time. To enhance the quality of the interviews, both online and in-person interviews were conducted following the same protocol. Thereafter transcribed verbatim

By using semi-structured interview questions, the research study was enriched with contextual data, a deeper understanding of participants' perspectives and experiences. Open-ended questions helped to establish trust and rapport with participants, increase response rates, and provide a more accurate representation of participants' views.

The questions gave the participants the freedom to share diverse and unpredictable responses, which led to more insights and revelations. This, in turn, prompted further inquiry and additional follow-up questions for a more in-depth and nuanced understanding of the topic (Hyman & Sierra, 2016). This style of interviewing also broadened the understanding of the GenAI business moral dilemma, revealing new aspects of adaptive self-regulation that were not considered previously (Ferrario & Stantcheva, 2022).

Ethics approval was granted (letter in the appendix). The research is considered low-risk as it involves adult participants, non-sensitive information, and anonymous data collection (Ficker, 2017). All the participants also consented to the research, and they read through the consent form. For transparency, all the participants consented to the research in writing and verbally. Virtual interviewees automatically retained a digital copy; a few in-person interviewees did not keep a copy after consent.

3.5 Data Analysis

ATLAS.ti was adopted for data analysis purposes (Ferrario & Stantcheva, 2022). ATLAS.ti, is a software for qualitative analysis created for the analysis of large unstructured data such as textual data, video data, or even audio data. ATLAS.ti was ideal for coding, exploring hidden meanings in the transcripts. Furthermore, the software enabled the raising of analytical questions, distillation and sorting of data, to facilitate comparisons between different segments of data (Ñañez-Silva et al., 2024).

This data analysis process for the qualitative methods, such as coding, theme identification, and narrative analysis, was used to interpret responses (Bryman, 2016). This approach allows for flexibility and depth in data analysis.

The analysis followed a step-by-step process ATLAS.ti adapted from Naeem et al., (2023). The thematic analysis was conducted using the following steps; (i) transcription and identification of quotes (ii) selection of key words, (iii) coding (iv) themes (Naeem et al., 2023).

This method retains the connection between individual perspectives and other aspects of their transcription, familiarisation with the interviews, and then identifies quotes, coding, and developing themes.

3.6 Trustworthiness

Trustworthiness is described as the methods through which research is conducted. This ensures confidence in the study findings, addresses validity, reliability and academic rigour (Ahmed, 2024; Stahl & King, 2020). Trustworthiness encompasses four primary aspects: credibility, transferability, dependability and confirmability, which then offers invaluable insights by tackling validity and reliability concerns and innovative ideas previously overlooked or underestimated.

Credibility asks the question of the level of congruence and harmony of the findings or whether they are representative of participants' experiences and perspectives. The researcher shall achieve credibility through prolonged interactions or engagements with the research participants, persistently observing the participants (Stahl & King, 2020). Credibility was achieved by ensuring that a consistent line of semi-structured questions was asked (attached in the Addenda). Trustworthiness through credibility was achieved through triangulation (Bans-Akutey & Tiimub, 2021). Through conducting both online interviews and in-person interviews, triangulation in this research was attained. The study also ensures transferability to similar settings, as well as confirmability and dependability (Nowell et al., 2017).

Recordings were facilitated specifically through the researcher's personal laptop or mobile cellular devices equipped with high-quality recording applications. For online interviews, Zoom call interviews were recorded on the Zoom platform (Archibald et al., 2019). This approach ensured accurate capture of participants' responses, allowing for detailed transcription and analysis. Transcription and familiarisation of the interviews were done simultaneously as the research interview recordings were being played back repeatedly.

3.7 Limitations

It is important to recognise methodological limitations, as all research studies have limitations. These can include sample sizes, lack of available data, cultural bias and more factors depending on the kind of research (Labaree, 2025).

The methodological limitations of the study were that the participants were 21, from one geographical area, which was South Africa. Additional participation would have yielded diminishing marginal returns (Labaree, 2025). Notwithstanding, there is no limit to the transferability due to the context being South African, a bulk of the findings in terms of recommendations can be transferred internationally. Their exposure can be limited, but technology is fast bridging this gap, and it is possible they have familiarity with first-world standards and procedures, as some participants worked for global companies which had offices in first-world countries. Furthermore, qualitative studies are known for small sample sizes.

3.8 Summary

In conclusion, the research adopted a rigorous qualitative research design grounded in interpretivist philosophy. The data will be collected through semi-structured interviews at a cross-sectional point in time.

The data will be analysed using thematic analysis as the main analytical technique, which is guided by Naeem's six-step process for thematic analysis (Naeem et al., 2023). Guided by this framework, the data analysis will entail key steps including transcription, familiarisation, followed by coding, development of themes and lastly interpretation. A data analysis software, ATLAS. Ti will facilitate the management and analysis of the data.

The methodological approach further advance trustworthiness through extensive involvement with the design and collection process. Furthermore, data triangulation, ensured the adequacy and relevance of the sample (Guetterman, 2015). The purposive sampling strategy eliminated any threat to validity, minimising biases and increasing the transferability of the findings (Nyimbili & Nyimbili, 2024). The research methodology also ensured transferability to similar settings, confirmability, and dependability by providing brief accounts of all steps taken to collect the data (Nowell et al., 2017).

4 Findings & Data Analysis

4.1 Introduction the research findings

This chapter primarily focuses on the research findings and the data analysis. To ensure conciseness in the chapter, the findings have been scientifically organised according to the research themes identified during the data analysis.

The theoretical framework underpinning the research is Albert Bandura's Social Cognitive Theory of self-regulation. This theoretical framework provided a systematic approach for the selection of keywords, which then informed the selection of codes, themes and lastly the development of a conceptual model. This theory defines the subfunctions of Bandura's SCT of self-regulation, as self-monitoring, self-judgement, self-reaction and self-efficacy, contribute toward self-regulation.

The thematic analysis revealed various trends, for example, most participants thought that self-regulation should not only occur after the effect but before the deployment of the GenAI model. This can be through prompt engineering, secure by design features, and adequate data training. Given the above, the purpose of this chapter is to provide a detailed account of the findings in order to address the research problem. The research question being addressed is reiterated below;

“How can businesses avert the regulation lag caused by the GenAI moral dilemma through adaptive self-regulation guidelines?”.

For a more coherent understanding and easier navigation of the findings, the chapter is organised methodically according to the subfunctions that contribute to self-regulation identified in Albert Bandura's SCT framework of self-regulation.

Lastly, the following sections of this research focus on presenting the findings that contributed toward the identification of key steps for the development of self-regulating guidelines for the use of GenAI.

Between October 2024 and December 2024, participants were recruited purposively, comprising various technology professionals who are knowledgeable in the area of GenAI models but also willing to contribute toward the regulation of GenAI models (Nyimbili &

Nyimbili, 2024). The tables below provide summaries of the demographics, experiences and background of the research participants.

Table 3 Table Showing the distribution of the participants by age

Ages	Frequency	Percentage
26-30	6	29%
31-35	6	29%
36-40	4	19%
41-45	3	14%
46-50	1	5%
51-60	1	5%

Table 4 Table showing the distribution of the research participants by gender

Gender	Frequency	Percentage
Male	14	67%
Female	7	33%

Table 5 Table showing the characteristics of the research participants

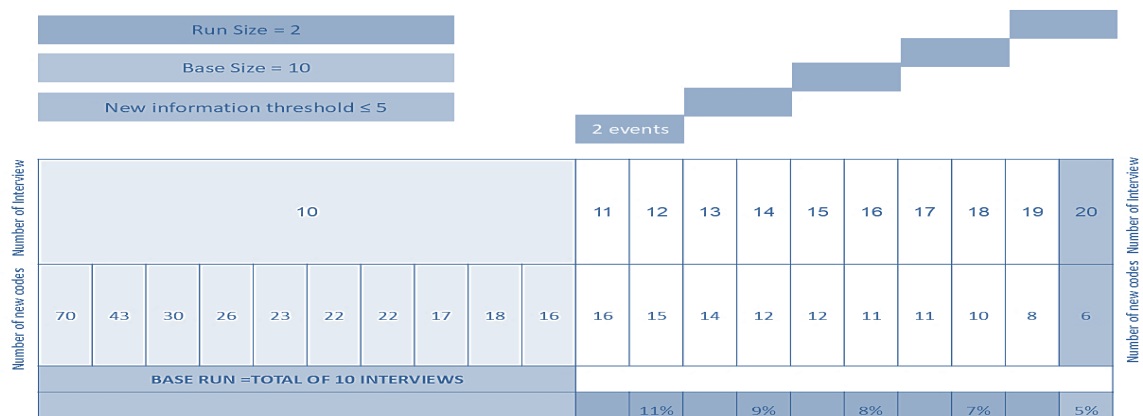
Participant ID	Gender	Age	Technological Background	Years Experience	Years of Experience in GenAI
Research Participant 1 (P1)	Male	30	IT Lecturer	12	2
Research Participant 2 (P2)	Male	35	Tech entrepreneur	6	1
Research Participant 3 (P3)	Male	43	Entrepreneur in Technology	12	3
Research Participant 4 (P4)	Male	56	Storage Engineer	30	0
Research Participant 5 (P5)	Male	29	Doctorate in Machine Learning and Head of Technology	8	3
Research Participant 6 (P6)	Male	40	Owner of a Tech Company	20	2
Research Participant 7 (P7)	Female	32	Founder of a Tech Company	7	2
Research Participant 8 (P8)	Male	36	Managing Director of a Tech Company	16	5
Research Participant 9 (P9)	Male	41	Software development in electrical engineering	18	5
Research Participant 10 (P10)	Female	31	Application testing specialist	5	1
Research Participant 11 (P11)	Male	42	Head Of Operations in a Technology Company	18	2
Research Participant 12 (P12)	Male	34	Project Manager in a Technology Company	15	2

Participant ID	Gender	Age	Technological Background	Years Experience	Years of Experience in GenAI
Research Participant 13 (P13)	Male	29	Coding and Development	6	2
Research Participant 14 (P14)	Female	31	Systems Integration Specialist	10	1
Research Participant 15 (P15)	Female	37	IT Personnel	15	4
Research Participant 16 (P16)	Male	38	Tech Training and Development	10	2
Research Participant 17 (P17)	Male	33	Software Engineering	10	2
Research Participant 18 (P18)	Female	27	Information Systems student and currently working as a software developer	6	1
Research Participant 19 (P19)	Male	47	Head Of Training and Development of a Tech Company	24	15
Research Participant 20 (P20)	Female	30	Tech entrepreneur	6	1
Research Participant 21 (P21)	Female	25	Modeller	5	1

4.1.1 Sufficiency of the Sample and Data Collected

Sufficiency of the data occurs where additional data collection yields diminishing marginal returns. The new information threshold is a qualitative measure to determine whether enough evidence exists (Guest et al., 2020). In this study, the acceptable threshold was set at $\leq 5\%$.

Figure 6 New information threshold calculations (Researchers own)



To attain this, a Document-Code Analysis codebook was extracted from ATLAS.ti and normalised to eliminate any redundancies; thereafter, a base number of interviews (10) was set, and for each run, the percentage of new information was calculated.

Achieving data saturation and sample sufficiency was therefore a significant milestone in this research study. To this end, additional research interviews would not contribute meaningfully to addressing the research question, and it is noted that some of the responses were now becoming redundant or were similar Guest et al., 2006; Saunders et al., 2018).

Equation 1: New information Threshold Equation

$$\frac{\text{Total from each Run Length} \times 100}{\text{Total Base Run}} = \text{New information threshold}$$

Typically, a small sample size allows for in-depth analysis and is selected purposively to provide rich, relevant information (Vasileiou et al., 2018). Notably, initially, the study was aiming to only recruit participants with a minimum of 10 years of experience working in technology. Given the above-mentioned, to ensure a more robust, valid, comprehensive and representative sample, experts with less than 10 years of working experience, whose exceptional credentials and expertise warranted their inclusion, were included.

4.1.2 Threat to validity of the findings

To reduce the threat to validity, the sampling strategy of the study incorporated diverse technological contexts (Vasileiou et al., 2018). Additionally, the relevance of the calibre of the sample, including their levels of experience in technology, was also considered. This purposive sampling strategy helped to eliminate any threat to validity, minimise biases and increase the transferability of the findings (Nyimbili & Nyimbili, 2024). Effectively, this strategy captured a wide range of perspectives, experiences, and insights, thereby enhancing the validity and reliability of the data (Brink, 1993).

[illegible]

Credibility of the findings was of paramount importance, and this attribute relates to the extent to which these research findings accurately captured the opinions of the research participants or are congruent with what really occurred (Stahl & King, 2020). The above word cloud was one of the methods in the analysis of the findings that enhanced credibility. The word cloud confirms the credibility of the study as it visually displays the frequently occurring words in the transcripts. The size of each word represents how frequently that word occurred in the interview. With that in mind, in this study, the credibility was established through prolonged engagements with the technological experts on GenAI. This is also confirmed in the word cloud. The researcher's immersion into their sphere of technology, by also conducting in-person interviews, also contributed to the credibility of the study. Furthermore, the researcher attended forums dedicated to technology and engaged in prolonged discussions with various participants on the self-regulation of GenAI in business customer experience. Notwithstanding,

these interactions enriched the credibility of the study. There was also the opportunity to view some of the GenAI business customer experience systems being deployed in South Africa (further emphasising the relevance of this research (Muñoz, 2024; Patel & Ragolane, 2024).

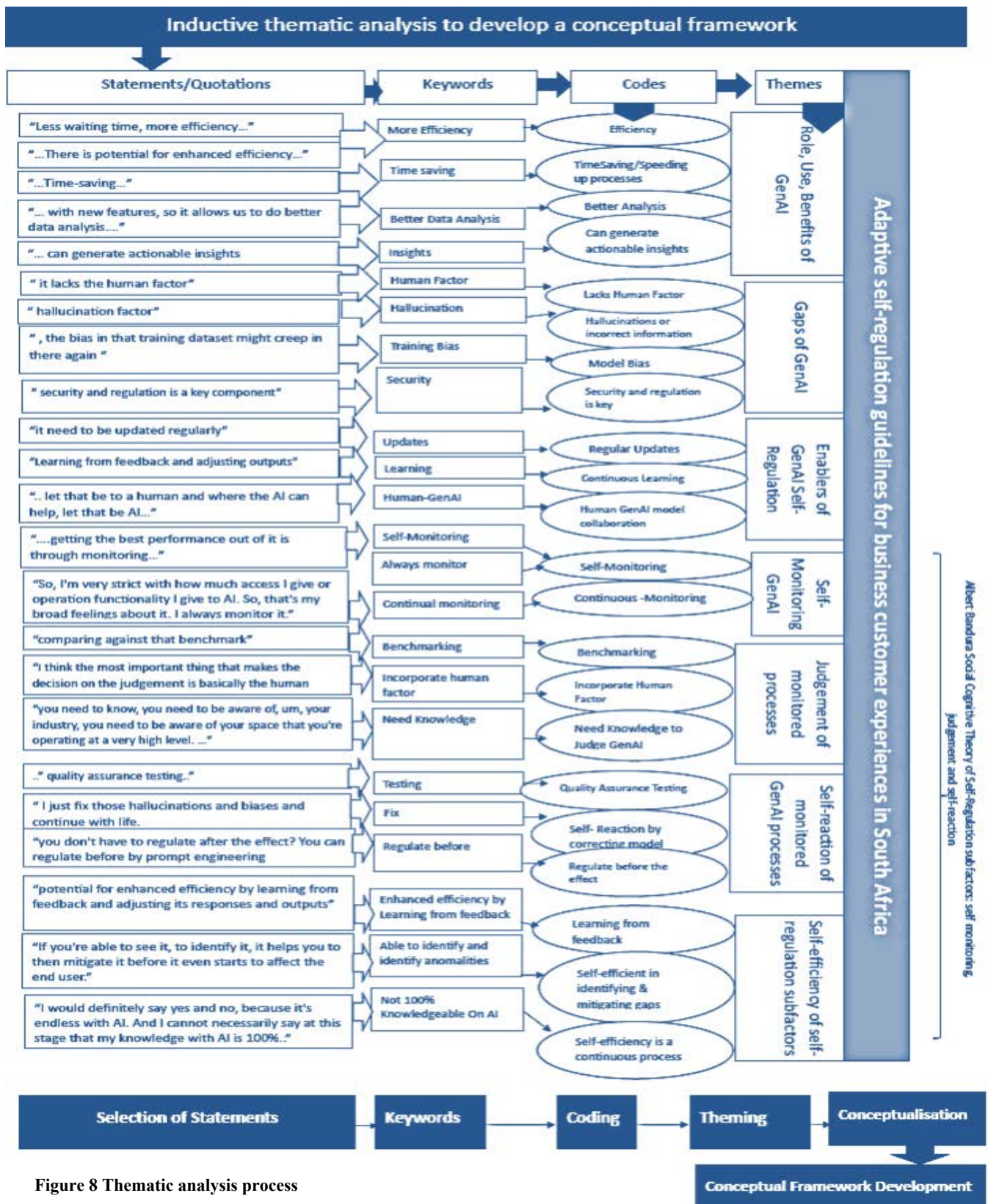


Figure 8 Thematic analysis process

One such forum was the Africa Tech Festival (11-14 November 2024) held in Cape Town, South Africa in November of 2024 (O’Leary, 2024). Through these interactions verbatim quotes were identified and used to develop a conceptual framework (Figure 8).

During these interviews, careful observations were also being made of the sentiments, attitudes, views around the GenAI, the business moral dilemma and the self-regulation of GenAI. These observations were also captured in the questions that were asked as follow-ups to the research questions during the interviews (Smit & Onwuegbuzie, 2018). The prolonged engagements and the observations led to any preconceived ideas or assumptions being clarified.

Therefore, triangulation was inevitably achieved through the interactions with different participants from diverse technological backgrounds. This process of triangulation using various sources further contributes to the credibility of the research (Bans-Akutey & Tiimub, 2021). Through triangulation, any research flaws or biases in this research study were reduced, as evidenced above (Turner, 2016).

Given the above account on the different efforts and investments that were made to achieve prolonged observations, engagements and triangulation, credibility in this research study was established. In addition to achieving credibility, confirmability and dependability were also achieved. Confirmability is defined as the extent to which the research findings can be confirmed by others to eliminate any research biases (Ahmed, 2025). To ensure confirmability, a trail of the research has been created and backed up in the form of various files and folders (O’Leary, 2024). This transparency therefore ensures that any other researchers can be able to replicate this research study and also undertake a verification of the findings, which creates dependability. Lastly, neutrality was also a critical component of trustworthiness, whereby the research findings are solely opinions of the research participants. This is highlighted in the chapter through the use of direct quotations from participants (Kakar et al., 2023).

Table 6 Table summarising the codes and themes.

Name of Code	Code Frequency	Theme	
Regular Updates	(4)	Key Steps of GenAI Self-Regulation	20
Continuous Learning	(4)		
Human-GenAI model collaboration	(7)		
More Efficiency	(7)	Role, Use, Benefits of GenAI	20
Time-Saving/ Speed/Fast	(30)		
Better Data Analysis	(4)		
Can generate actionable Insights	(4)		
Lacks Human Factor	(20)	Gaps of GenAI	0
Hallucinations/Incorrect information	(7)		
Model Bias	(9)		
Security and regulation are a key component/concern	(6)		
Self-Monitoring	(19)	Self-Monitoring GenAI	4
Continuous Monitoring	(2)		
Benchmarking	(2)	Judgement of monitored processes	
Incorporate Human Factor	(26)		
Need Knowledge to judge AI	(4)		
Quality Assurance Testing/Testing	(5)	Self-reaction of monitored GenAI processes	
Self-Reaction by correcting the model	(5)		
Regulate before the effect/pre-process	(7)		
Learning from feedback	(2)	Self-efficacy of self-regulation subfactors	
Self-efficient in identifying and mitigating gaps/use	(14)		
Self-efficacy is a continuous process /improvement	(2)		

4.2 Research Codes and Themes

The process of coding transformed and diffused the disorganised transcript data into organised ideas by assigning labels (codes) to the data, thus providing a clearer understanding of the findings (McLeod, 2024). For clarity, the researcher was able to compare data segments, identify similarities, and group similar phrases under a single code, thereby conceptualising and framing the research themes (code-groups) (Frieze, 2017). To generate the codes, three types of methods were applied: open coding, in vivo coding and descriptive coding. Open coding is where transcripts were coded by going through the transcripts line by line (Blair, 2015). In vivo coding is when actual phrases or quotes are taken from the research participants. Descriptive coding is whereby a paragraph or phrase from a research participant is summarised by using a short phrase or word to describe what the participant was alluding to (McLeod, 2024). At the end of the coding process, 420 unique codes were generated, and code saturation had also been reached (Rahimi & Khatooni, 2024).

The thematic analysis steps were followed to organise the findings, and the conceptual framework was adapted from Naeem et al., (2023). The steps included familiarisation with the transcripts, selection of keywords, codes and the main themes that will be presented in the findings chapter. In line with the primary research objective to identify the key steps study path to develop adaptive guidelines for the self-regulation of GenAI in business customer experience, several key recommendations emerged.

4.3 Theme: The role, use and benefits of GenAI

During the participants would articulate their opinions on the benefits of GenAI while also mentioning the gaps simultaneously. This instinct to recognise the innate gaps before the question demonstrates the innate awareness of the dual nature of GenAI technologies. Thus, this phenomenon aligns with the research's inductive reasoning approach whereby the participants' observations revealed the complex GenAI moral dilemma. Notwithstanding this dilemma, in South Africa, the integration and adoption of GenAI in business customer experience models has yielded pervasive benefits. Participants described a myriad of benefits, use cases and roles of GenAI. Specifically, Participant (P7) highlighted that it helps bring solutions more easily. While other participants recognised several other benefits such as saving time, efficiency, the ability to analyse large customer data and more. This underscores Bandura's self-monitoring and judgement subfunctions of self-regulation. Where businesses are monitoring what the output of the GenAI is, but also exercising judgement on whether it's beneficial or detrimental to customers. These predominant patterns of responses and codes will be further explored in the subthemes below.

4.3.1 Time Saving

A dominant motif that emerged around the benefits of GenAI was the time-saving attribute. The majority of the participants recognised GenAI's capacity to significantly reduce the time that is spent on tasks. As shown in the word frequency, the word "time" was pervasive in the interviews. This included related words like "quicker", "speed" and "faster".



Figure 9 Word frequency generated from the benefits of the GenAI theme

This emphasises the temporal benefits of the adoption of GenAI, being related to the quick processing speeds. Even so, one participant (P15) equally noted that, because of the speed of GenAI assistance, “going to a queue and waiting for stuff, like it's a waste of time”. This was further corroborated by other participants who cited that not only are customers saving time, but businesses save time and focus on their core business. They are now delegating generic and repetitive tasks to GenAI. For example, another participant cited that tasks such as answering frequently asked questions (FAQs) are streamlined. This means that time spent on previously repetitive tasks can now be automated online using GenAI (Sinha et al., 2024). Moreover, customers also enjoy the benefits of saving time in decision-making (Tiutiu & Dabija, 2023). Furthermore, another participant highlighted that GenAI platforms such as WhatsApp are more affordable, thus customers not only save time but also money. Another time-saving feature of GenAI identified was in the real-time interactions with the sales agent (Ahmed & Hussain, 2023).

The benefits of saving time are not only for customers but the business GenAI developers, who also cut down on coding time (Bruhin et al., 2024). Particularly (P5) noted that “the code can be near perfect”. This response was corroborated by several others who also mentioned the speed with which coding tasks are completed.

However, ethical concerns were raised by (P22) who noted that, “you'll get charged eight hours when this person can use Generative AI in like 15 minutes or 20 minutes”.

Also, in contrast, one participant expressed concern about the over-reliance on GenAI. The participant (P20) noted that “ it's very important that you also allocate time to do research to keep yourself informed and eliminate or rather reduce the dependency of Generative AI... ” This is because of the alarming consequences of customers not having researched or knowing GenAI. For example, customers are saving time but being exposed to the nefarious consequences, including ethical and data privacy side effects of GenAI (Singh et al., 2024). Therefore, the onus also falls on customers to reap the benefits but exercise caution through judgement on the level of exposure and risk they allow. This aligns with Bandura’s SCT of self-regulation, judgement subfactor. This was also recognised by participants, for example, (P17) highlighted that although businesses can collect customer logs or data to save customers' time, the information collected is susceptible to information security concerns. Thus, conforming to the need for adaptive self-regulating guidelines that are not outpaced by this technology.

Drawing from the responses on saving time using GenAI, there is also a relationship between the findings and theory. Bandura’s judgement subfactor of regulation describes the capacity to discern when there is something in need of self-regulation. This was the case that although participants were saving time, there were innate risks that required self-regulation.

4.3.2 Efficiency

Similarly, another salient trend that emerged with the role, use and benefits of GenAI was the efficiency. Participants consistently recognised the role of efficiencies attached to the benefits of leveraging GenAI. For example, (P18) highlighted that “there is potential for enhanced efficiency”. More so, participants underscored the role of GenAI in improving the efficiency of their business customers’ experiences. Interestingly (P2) notes that, “we're going back to the efficiency line, it helps with that...”. Additionally, (P5) was of the viewpoint that efficiency gaps can also easily be identified. They highlighted that a customer repeating the same question or prompt raises a that customers are not satisfied with the responses that they are receiving. In contrast to the efficiencies, the participants also recognised the ethical risks around the adoption of GenAI in delivering projects (Marie & Mathews, 2021). Understanding the interplay between the efficiencies of GenAI and business customer experience is in line with the exploratory nature of the research. Hence, GenAI efficiencies are competing with ethical

shortcomings in the model (Ferrara, 2024a). Therefore, human oversight or self-monitoring, as cited by Bandura, cannot be overstated.

Ultimately, as businesses can take steps to uphold moral and ethical values while maintaining efficiencies through adaptive self-regulation (Velasco et al., 2024).

4.3.3 Better Analysis

Participants also underscored the significance of better analysis while using GenAI. Specifically, the businesses are being empowered to distil and summarise large data about their customers to augment their business customer experiences. Notably, it was noted in one of the interviews that there is a level of objectivity with this approach as well. One participant expressed the prowess of GenAI models in tasks, in streamlining the summation of large reports (Ferraro et al., 2024). The participant (P1) highlighted the ease of the process, where “we can just upload your CSV files there, and then it will go and analyse the data”.

GenAI allows for complex and large amounts of information to be extracted and analysed, and also for the generation of text, images and synthetic data, tools which drive the business to stay informed (Singh et al., 2024). Equally (P15), also noted the ease with which complex big data can now be summarised would have taken longer to achieve. Thus, businesses are able to gain better analysis for their businesses, which leads to actionable insights.

However, the sharing of high-level sensitive customer data for analysis was a cause for concern among the participants. Thus, ethical concerns continued to be raised, thus validating the need for adaptive self-regulation. In this instance, the role of self-monitoring, as emphasised by Bandura, will supervise the extent to which the data is being exposed. Furthermore, the shared privileged information can end up being an output generated by the GenAI to third parties, further emphasising the importance of adaptive self-regulation (Sekine, 2025).

4.3.4 Gives Actionable Insights

Equally, GenAI-generated analysis provides actionable insights for the business. Contextually, one participant highlighted that GenAI models can be used to monitor sales performance in the business, which provides insights into the performance of their customer experience (Yusuff, 2024). Additionally, (P18) reiterated that, “it can generate actionable insights in a matter of seconds”. These sentiments illustrate the expanding use cases of GenAI in business customer experience, aligning with the interpretivism philosophical aspects of the research. Another research participant noted that emotional involvement can sometimes compromise a human’s

objectivity in their insights, especially when handling customer inquiries. Whereas, GenAI models provide a neutral and impartial interface, eliminating human subjectivity fuelled by emotions or other prejudices (Huang & Rust, 2018).

Interestingly, these comparable insights from GenAI also have a ripple effect on the economy (Sinha et al., 2024). This was further corroborated by insights from a McKinsey Report, their calculated estimates suggests that an annual contribution of \$2.6 trillion to \$4.4 trillion across 63 use cases is possible (Chui et al., 2023).

However, these insights are not without their limitations as (P10) noted that the use of can involve mining of personal information, violating privacy. Therefore, caution and judgement on what is being analysed one of Bandura's subfactors for self-regulation, is necessary.

4.4 Theme: The gaps of GenAI adoption in business customer experience

In addition to the benefits, the participants' contributions highlighted significant lacunae or gaps in GenAI that arise. The gaps that are inherent with the adoption of GenAI in business customer experience are unavoidable and need to be explored. In the research interviews, the participants indicated gaps such as the lack of human interaction, security issues that are further exacerbated by hallucinations or the lack of accuracy of some information and biases. The latter further demonstrates that GenAI deployment cannot go unregulated in business customer experience. Additionally, the different contexts of these unintended gaps are explored, aligning with the interpretivist philosophical design adopted in this research. To provide a more nuanced understanding of these gaps, the following sections provide an in-depth exploration of the identified gaps. These findings elucidate the various innate complexities surrounding the

recommended by Bandura, where self-monitoring is an important subfactor in self-regulation. Participants also recognised the cultural biases against African nations like South Africa. Western-developed GenAI models cannot assist in South African vernacular dialects, and this was raised as a concern (Nyaaba et al., 2024). For example (P14) highlighted that, “.... especially the languages like the African languages, it's got limited knowledge...”

Therefore, the oversight that is provided by self-monitoring and judgement of the quality of the GenAI models will be crucial toward adaptive self-regulation of the model.

4.4.2 Hallucinations

The participants noted that GenAI is still relatively new and lacks sufficient data, and is therefore susceptible to hallucinations. For example, (P2) noted that, “it still has a problem when it comes to the accuracy”.

This phenomenon was an area of concern with the participants as it compromises the integrity of the output to the customer.

Hence, as good practise (P20) highlighted, “I always even encourage my team to validate the data, because sometimes it may hallucinate.”

This innate nature of GenAI to hallucinate also requires self-monitoring to verify, validate and correct the data. Correcting the data is also linked with the self-reaction attribute in Bandura's SCT theory of self-regulation. These continuous changes require an agile approach to mitigating the hallucinations in real time. Thus, participants highlighted the need for Human-GenAI collaborative strategies whereby customers have an option to interact with the person when the model is hallucinating. Businesses, therefore, need to carefully consider their self-regulation as hallucinating GenAI can erode customer trust or lead to serious consequences or harm for the business.

4.4.3 Security Concerns

As shown in the word count, breach of security was one of the recurring motifs in the gaps associated with GenAI in business customer experiences. The participant's concern was regarding the vulnerability of customers' personal information when engaging with GenAI. For example, (P4) noted that “from a cyber security point of view, there is also a part of AI where people are very vulnerable,

The above-mentioned is a classic scenario of where customers and businesses become vulnerable to hackers. In an economy where the commodification of personal information is rampant. For example, with the Cambridge Analytica scandal, where personal information from Facebook was exploited for political gain (Hinds et al., 2020). This sharing of personal information in the GenAI with third parties exacerbates the vulnerability of customers. Hence, robust security measures need to be in place.

As a proactive measure, one participant highlighted the importance of customers restricting the sharing of their personal information (Noble, 2018).

Even more worrying for businesses is that not only are their customers a prime target, but their log records are also a target. Participants also noted the possibility of their GenAI models attracting hackers to the business. Therefore, businesses should actively be navigating between the optimisation of the benefits of GenAI while mitigating security risks. Security threats should stay on the radar of the business, and self-monitoring the GenAI model contributes to this surveillance.

4.4.4 Lacks Human Factor

It is clear from the findings that customers will always want to have the option to be assisted effectively by a human. Thus, suggesting the indispensability of human beings in customer experiences where GenAI fails. The word frequency diagram listed interaction (human interaction) as the most recurring theme. This predominant theme was corroborated by the theoretical framework that reinforced the necessity of human interaction, wherein the absence of their presence creates a gap. For instance, (P18) highlighted that, “there will always be a need for human intervention”

Moreover, aside from security and ethical concerns, other participants also yearned for the warm and empathetic aspects that GenAI cannot replicate. Other participants recognised that the human interaction offered resolution of complex transactions beyond the ability of the GenAI. Thus, there is a significant gap where GenAI cannot respond effectively.

Therefore, GenAI models and Human collaboration in business customer experiences were recommended by the participants. While GenAI can augment customer experiences, it cannot replace the unique aspects of human customer service. Thus, recognising the importance of emotional intelligence and empathy in business customer experience, technology has not yet been able to simulate it.

4.5 Theme: The enabling factors of adaptive self-regulation guidelines

Drawing from the primary objective of the research to identify key steps for adaptive self-regulation guidelines, participants also shared their recommendations. In line with Bandura's SCT of self-regulation, businesses have to self-react. The next section elucidates all the recommendations suggested by the participants. These recommendations are the enabling factors that contribute to the steps of achieving adaptive self-regulation.

4.5.1 Regular Updates

The possibility of GenAI models being trained on data from a specific point in history necessitates the need for regular updates. (P10) recognised that when GenAI is malfunctioning, "maybe it needs an update."

To do this, one participant recognised that there are tools that can be used to automate updates. Equally, (P3) highlighted that the GenAI models need to be trained continuously with current information. This continuous training ensures that the model remains relevant and up to date. Furthermore, this allows the business to refine its models by incorporating customer feedback. Also, the businesses are able to proactively adapt to evolving customer, demographic needs and evolving regulatory requirements.

By acknowledging the use of regular updates as a way of adaptive self-regulation, businesses can also build a customer-centric GenAI approach.

4.5.2 Continuous Learning

The process of continuous learning in the area of self-regulation undergirds adaptive practices within the business. Contextually, the businesses are iteratively learning their customers' interactions with the GenAI. Participants alluded to the importance of continuous learning on the part of GenAI system managers. One participant (P14) stated the relevance for users to "up-skill themselves". This raises a critical factor that ignorance of the quality of the GenAI's interaction with customers can also exacerbate some of the gaps. Theoretically, this too aligns with Bandura's self-efficacy subfunction of self-regulation. To this end, both theory and the findings align in that one needs to have confidence, ability, and the effectiveness to affect any self-regulatory measures.

Importantly, businesses stay abreast of GenAI best practices, trends, latest legislation, benchmark standards and more by continuously learning. Best practises, they become more empowered to self-regulate.

Equally, the GenAI models also require continuous learning/training and testing. One participant (P7) highlighted that, “if it's adaptive, that means that it's continuously learning and it's continuously adapting and improving”. This process is also part of the engineering of the GenAI. As explained by one of the participants (P5), another method of self-regulation can be in the prompt engineering of the GenAI.

Prompt engineering is defined as the systematic design, development, and refinement of input prompts to elicit desired responses from GenAI (Bozkurt, 2024).

Moreover, this engineering of the GenAI models facilitates perpetual updating and monitoring to ensure optimal performance. This proactive approach enables the models to adapt to evolving requirements and mitigate potential risks (Vaghmare & Dwivedi, 2024).

Another participant (P9) also further highlighted that there is a relationship between continuous learning and continuous monitoring. The concept of continuously learning through monitoring is also theoretically grounded in Bandura's theory. Therefore, by ensuring a culture of continuous learning in the business and embedding it in the GenAI, it fosters adaptive evolution of the business customer experiences. Thus, as they learn, the GenAI and businesses remain responsive to any potential emerging requirements or threats. Human–GenAI collaboration

A critical analysis of the findings shows that humans play an integral part in business customer experiences. Consequently, in the development of adaptive self-regulation, this element cannot be overlooked. One participant (P3) noted the importance of Human-GenAI collaboration in optimal business customer experience. Additionally, participants recognised the complementary relationship of GenAI and humans in business customer experiences. Specifically, (P7) noted that, “where the human factor comes in, let that be to a human and where the AI can help, let that be AI”. This perspective is further corroborated by the integrative thinking approach to problem solving. This approach recognises the combination of various elements and different approaches to foster innovation and problem-solving.

Therefore, the findings show that humans have unique capabilities, and GenAI has its own. For example, critical thinking, creativity and empathy in humans, while GenAI offers speed, and in some cases accuracy. Thus, the merging of these attributes can optimise GenAI's business customer experience. More so in adaptive self-regulation, the role of human oversight cannot be overstated.

4.6 Theme: Self-monitoring of GenAI models performances

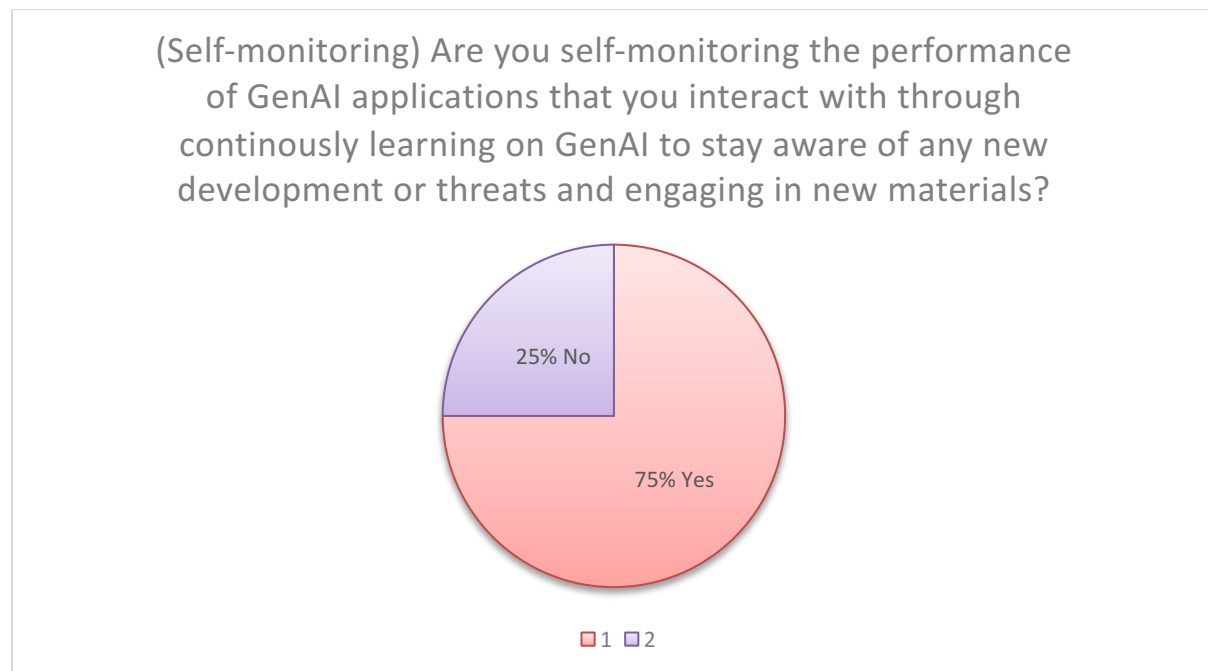


Figure 11 Results on the self-monitoring subfunction

The pie chart represented above visually illustrates the responses of participants regarding their self-monitoring behaviour. A majority of the responses (75%) indicated that they were self-monitoring. However, a minority of 25% indicated that they were unsure of the requisites of self-monitoring and unclear regarding the expectations. Therefore, there is a recognition of the significance of oversight over GenAI. The minority that was not fully cognisant of the implications of self-monitoring highlight the need for training to equip businesses in monitoring their GenAI. When participants responded on their self-monitoring behaviour, the predominant codes or subthemes included: self-monitoring, continuous monitoring and systems embedded to watch the system.

4.6.1 Self-monitoring

The findings in the research underscore the significant role of self-monitoring in enhancing efficiency while eliminating potential ethical risks. Contextually, self-monitoring involves careful observance and awareness of the GenAI and its ecosystem. Thus, the participants offered their opinions on how they perceive self-monitoring contributes to effective adaptive self-regulation. Participants emphasised the role of self-monitoring in augmenting the business customer experiences, enhancing efficiency and averting risk. One participant (P19) noted that adequate self-monitoring leads to “enhanced efficiency by learning from feedback and adjusting”. To add to this, (P11) recommended that for this to be effective, businesses should

adopt an agile approach where businesses are “ monitoring ... own results”. More so, (P8) underscored the relationship between self-monitoring and “getting the best performance”. Equally, this oversight, according to (P9), is “very important” for businesses to stay abreast of their GenAI business customer experience performances (Pasamonte, 2024). These perspectives of the participants are based on their own experiences. In line with the interpretivist approach of this research, these perspectives provided insight into the significance of self-monitoring.

Theoretically, the aspect of adaptive self-regulation is closely related to the acquisition of knowledge. In this case, the acquisition of knowledge on the real-time GenAI performance leads to the alteration of the subsequent behaviour of the model (Bandura, 1986). Contextually, self-monitoring the performance of the GenAI model is critical toward achieving efficiency, mitigating risks, and adaptively influencing subsequent behaviour (Almagrabi & Khan, 2024).

However, the implications of maintaining robust self-monitoring can stifle creativity and innovation. Additionally, self-monitoring can infringe upon the privacy of the customers and expose their information, which may also be a cause of concern (Bartneck et al., 2021). The potential for misuse of personal information gathered from monitoring customers by businesses was exposed by Facebook’s whistleblower (now Meta) (Bartneck et al., 2021; Sieber, 2019). More so, the inadequate self-monitoring of the customer-facing GenAI can jeopardise the integrity of the business. Nonetheless, the correct approach to self-monitoring can position the business strategically to foster customer trust and transparency.

4.6.2 Continuous monitoring

The perspective of continuous monitoring is divergent from self-monitoring because it amplifies the need for ongoing scrutiny of the GenAI performance. Self-monitoring can be limited during a specific period, for example, during the pilot phase, launch phase or testing phase. Thereafter, most systems are deployed and only monitored during maintenance, upgrade or service periods. According to participants, continuous monitoring can be supported by other applications or tools where performance logs are also kept.

Thus, participants clearly emphasised the importance of ongoing monitoring over time. Continuous monitoring allows for agile, adaptive self-regulation within the business. The former involves the timely identification of any bugs or gaps in the Genai. This view is supported by the participants' sentiments; for example, (P9) noted that, “ there's always

something new coming and we always are monitoring”. These observations from the participants’ experiences provide insights into the rapidly evolving nature of GenAI models. Therefore, this aligns with the interpretivist philosophical approach of reflecting participants’ experiences. Furthermore, recognising gaps and responding to them supports Bandura’s self-reactive subfunction of self-regulation.

To this end, businesses are able to close the gap in static regulation through continuously monitoring the performance of their GenAI business customer experiences.

4.6.3 Systems embedded to watch the system

Although necessary, the continuous human oversight can become an onerous, tedious task for the management or the business as they compete with a fast-evolving technology. Thus, participants underscored the role that embedded applications and tools play in closing this gap. Furthermore, this theme emerged in the research findings as complementary to human oversight.

The use of embedded tools to provide oversight allows the business to also explore new information they would have otherwise overlooked. Additionally, it allows businesses to align with set standards and best practises. This corresponds with the perspectives shared by (P17) that emphasised how these tools can be implemented by ensuring “a baseline” of how the GenAI should perform. This baseline or benchmarking creates a basis for discerning whether to flag an incident. This is also theoretically underpinned by Bandura, who emphasises the role of judgement in self-regulation.

Ultimately, the use of embedded systems to support human oversight and continuous monitoring endorses adaptive self-regulation of the GenAI. This perspective recognises the balance that is required between human judgement and technology oversight. This aligns with the holistic, integrative thinking problem-solving approach adopted in this study. Hence, businesses need to strike the right balance to foster a culture of adequate oversight over their GenAI models.

4.7 Judgement of the performance of GenAI models

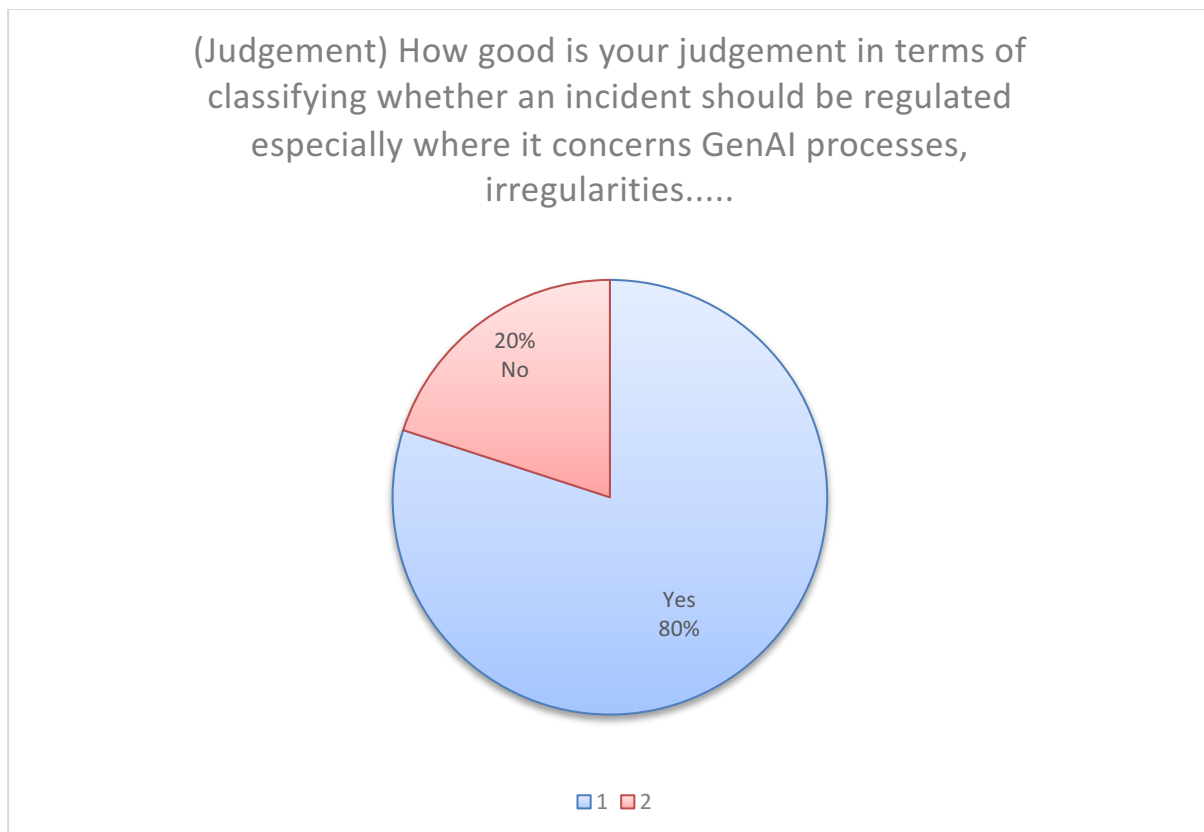


Figure 12 Results on the judgement subfunction

The findings of the study also underscored the value of exercising judgement in adaptive self-regulation. Participants were asked to share their perspectives on whether they could recognise irregularities with the GenAI and exercise judgement. 80% reported confidence in their ability to exercise judgement, while 20% expressed uncertainty. According to Bandura, judgement is a subset of personal standards, and performance is deemed as favourable or negative based upon standards (Bandura, 1986). These standards may also be personal standards formed from an observation of their environment. Thus, the perspectives and judgement of the participants were predicated on their standards from their lived experiences. For example, (P15) recognised the significance of familiar environments and spaces in shaping perspectives, as they desired that “if we'd only spoken about processes and irregularities within my space”. Furthermore, Bandura’s SCT recognises that judgement is contingent upon self-efficacy (one’s belief in their ability) in exercising judgement (Bandura, 1977). However, there can be a bias in judgement. According to (P2), humans are prone to bias. Similarly, the related subthemes included benchmarking, the need for knowledge and the incorporation of the human factor for effective judgement.

4.7.1 Benchmarking

The findings of this research recognised the critical role of benchmarking. Benchmarking is predicated against industry standards, global best practises or legislation among other sources. The theoretical underpinnings of the research, Bandura's SCT, also acknowledges the role of standards in shaping the judgement that precedes self-regulation. Notably, there was congruence between the theoretical underpinning of the research and practise. For example, one participant (P17) recognised that businesses adopting GenAI for their customers need a benchmark for them to be “always comparing against that benchmark”. The participant further implicated the use of Evaluations (Evals) to augment and support benchmarking. This process involves continuous assessment and evaluations to guarantee optimal performance of the GenAI. Additionally, the participants identified the implementation of alerts when there is misalignment with the benchmark as vital toward adaptive self-regulation.

Arguably, GenAI is still a relatively new technology. One challenge that businesses may face is acquiring adequate benchmarking standards. Some participants even raised the concern that they are still researching the technology and have inadequate knowledge. Another challenge that may arise is that benchmarking may deprive the business of its uniqueness. One participant (P6) was against any form of regulation, such as subjecting GenAI to judgement, where they indicated that this inhibits the purpose of the technology. This is because, by design, GenAI are created to generate novel content (Woolley, 2024). Nonetheless, the use of benchmarking can offer a competitive advantage, for example, compliance with a particular International Organisation for Standardisation (ISO) standard or others.

Ultimately, the ubiquity of GenAI in business customer experience underscores the importance of evaluating performance using benchmarks. This is imperative toward mitigating potential risks, ensuring accountability and fostering trust.

4.7.2 Incorporate Human Factor

These research findings accentuated the role of a hybrid and human-centred approach to self-regulation. Human judgement is always going to play a part in the validation of GenAI and ensuring performance is aligned with the established parameters. In addition, one participant (P7) recognised that GenAI has “limited information...compared to the human brain”. More so, there was congruence among the participants' perspectives on GenAI autonomy. They unequivocally recognised that an independent GenAI cannot recognise its technical glitches.

However, despite the role of human involvement in exercising judgement over the GenAI model, humans can introduce biases (Salazar et al., 2024). Thus, participants were cognisant of the likelihood of compromise in the judgement of the GenAI model.

Nonetheless, while there are challenges, adopting a hybrid approach where the assessment and judgement of the GenAI is balanced provides a holistic approach. This integrative thinking approach ensures that there is a fair assessment of the GenAI's performance to inform the self-regulation measures.

4.7.3 Need Knowledge to judge GenAI

The research participants who were in the minority and were not practising self-monitoring or judgement cited a lack of adequate knowledge. Hence, for effective oversight and judgement of the GenAI's performance, knowledge of the expected outcomes is critical. For example, (P19) noted that within an organisation adopting GenAI, “ your knowledge of the organisational policy as well” Is critical. Furthermore, (P2) recognised that, for the human oversight to pick up GenAI data breaches, “you would have to understand copyright law”. The critical role of knowledge of GenAI behaviour in a business cannot be overstated. For example, in one account, the participant gave an example of an airline whose GenAI model cost the business some income. Similarly, Air Canada's chatbot mistakenly offered a discount. The court ruled in favour of the customer, and Air Canada had to pay their customer for the discount offered by the GenAI customer chatbot (Ceruleo, 2024; Sookman, 2024).

The above-mentioned shows the complexities of GenAI, and hence, many participants noted that they are still learning and researching this tool to garner more knowledge. Their perspectives on lacking adequate knowledge provide a glimpse into why there could also be a gap in adaptively self-regulating GenAI.

Therefore, the findings point toward the need for businesses to have more knowledge of what GenAI's capabilities are to enable informed decisions and provide adequate measures that achieve adaptive self-regulation guidelines.

Furthermore, knowledge is required to anticipate risks and exercise control over the system. Thus, in the development of adaptive self-regulation guidelines, research to garner more knowledge will play a critical role. This includes change management, GenAI courses and upskilling as recommended by the participants.

4.8 Self-reaction

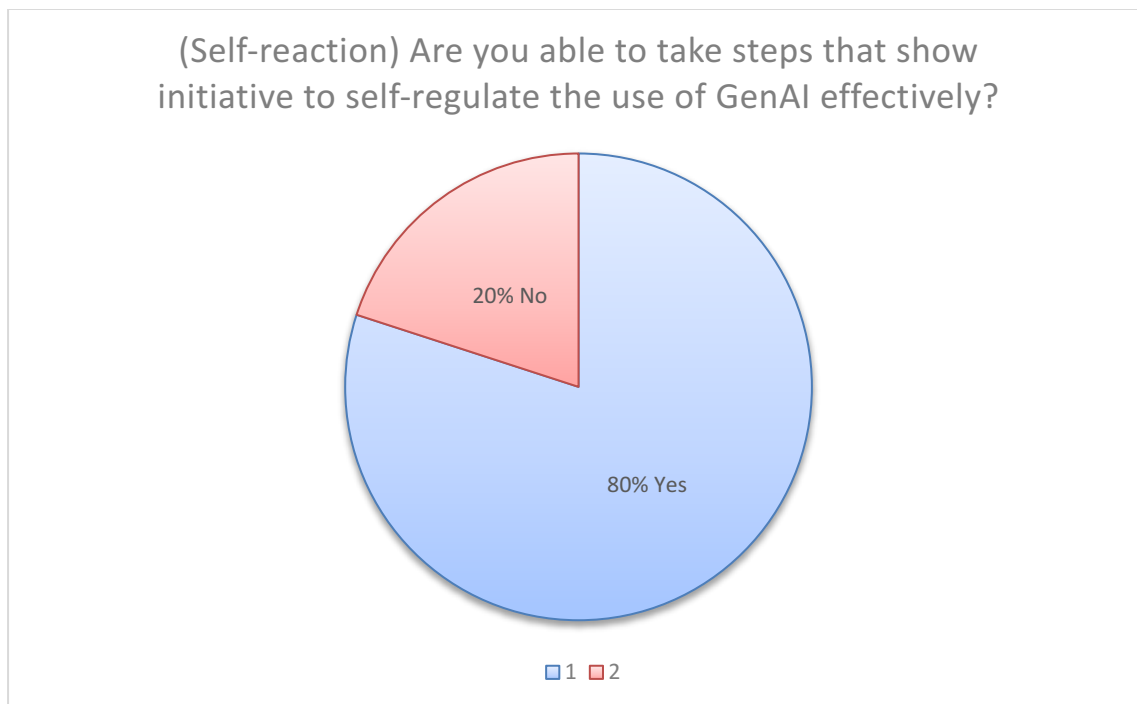


Figure 13 Results on self-reaction subfunction

The visual representation of the findings shows that a majority 80% are self-reacting to the gaps of GenAI. The participants alluded to recognising gaps and self-reacting by correcting the model, quality assurance testing, or by taking proactive measures to eliminate risk in advance (Yusuff, 2024). These common subthemes of self-reaction highlight the congruence between theory and practise. For example, Bandura's SCT theory recognised that judgement precedes self-reaction (Bandura, 1986).

Notably, self-reaction is influenced by the incentive or reward of the self-regulatory action (Bandura, 1986). This recommendation by Bandura can be considered in incentivising self-regulation to eliminate any resistance to adaptive self-regulation. For example, the findings show that some participants lacked motivation (P14), who cited that they will only practise self-regulation subfunction, "if it affects them. Thus, echoing some of the salient themes of a minority of the participants who were indifferent toward self-regulation habits.

Ultimately, self-reaction focuses on businesses responding to mitigate gaps as they arise. Non-responsive businesses may risk compromising the integrity of their business customer experiences.

4.8.1 Quality Assurance Testing

The research participants demonstrated an awareness of best practices that support the self-regulation of GenAI. For example, (P5) highlighted that in their observations, quality assurance testing was taking place in their models. The participant underscored the importance of this step in identifying and correcting anomalies. Furthermore, participants (P11) were of the view that peer review or a method of testing and certifying GenAI models was imperative. Certification as an incentive is congruent with Bandura's insights into the role of rewards in self-regulation. Equally (P15) warned against "unleashing" non-regulated models to the public. Hence, a rigorous testing framework, encompassing quality assurance protocols, penetration testing, and simulated hacking exercises, is crucial. This bolsters the system's integrity, detecting latent vulnerabilities and informing iterative self-regulatory enhancements (Aleti, 2023).

Ultimately, testing is a common assessment across many technologies. Hence, participants thought that the GenAI quality testing was also a protective measure for customers.



Figure 14 Correcting a GenAI model

4.8.2 Self-reaction by correcting the model

The research findings underscored the role of self-reactive measures that adopt self-correcting methods. For example, one can correct the Meta GenAI Business Assistant.

The research participants underscored the importance of responding to the GenAI when it hallucinates. For example, (P1) noted that they would advise the GenAI that the response to their prompt was “wrong”. Moreover, participants also recommended correcting the model. These lived experiences of the participants contribute to the interpretivist aspects of the research.

In contrast, sometimes these self-corrective messages to the GenAI can introduce biases. As noted by participants, where there is human involvement, biases can occur. Thus, it is necessary to have policies on guidelines on how they correct the faulty GenAI to avoid multiple interferences. This also promotes transparency.

4.8.3 Regulate before the effect

The research participants recognised the role of proactive methods toward adaptive self-regulation. One such method recommended by (P5) was to “classify the intent before feeding into the Generative AI”. Another participant (P15) also recognised the role of customers in restricting the sharing of all their personal information. Altogether, these perspectives underscore the role of proactive adaptive self-regulation. This means that self-regulation is embedded in the ecosystem of the GenAI from inception.

Alternatively, one of the participants (P17) highlighted the utility of implementing data masking techniques once the GenAI model has been deployed to protect sensitive information, which is another proactive self-regulation technique. Data masking is the process of replacing sensitive information with artificial but realistic information, making it seem or appear to be real, but the actual data has been hidden (Navandar, 2024). This concern over the misuse or violation of personal information was a notable recurring theme in the findings. Highlighting the lived experiences of the participants in constantly grappling with this issue. Therefore, the results underpin the importance of structures that anticipate any GenAI gaps and proactively mitigate the risks. In addition to reactive methods, this two-phased approach incorporates the integrative thinking method of addressing problems.

4.9 Self- efficacy

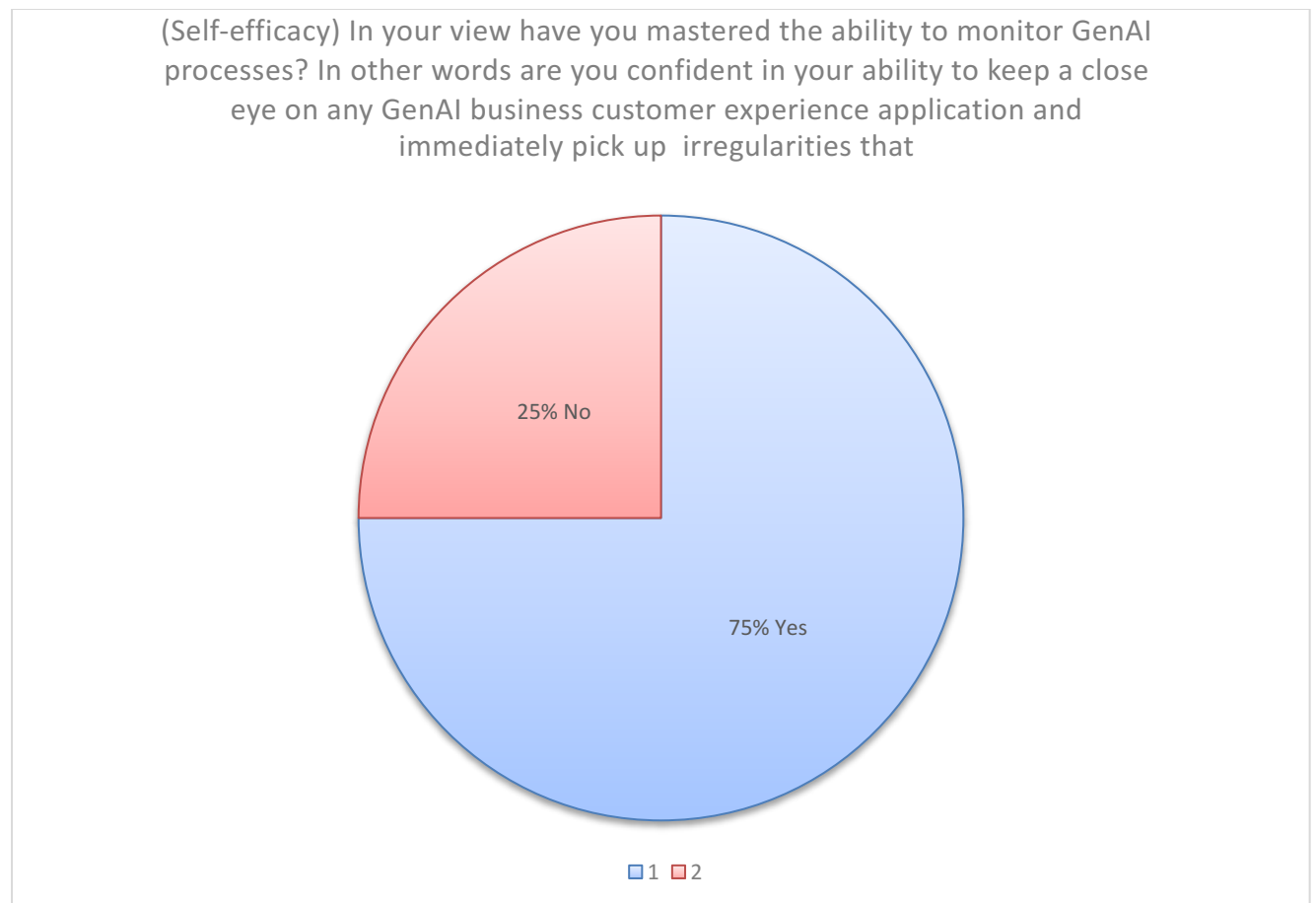


Figure 15 Results on self-efficacy subfunction

The visual representation of the findings revealed that a majority, 75% of the participants, were confident in their self-regulation abilities. The findings show that a minority (25%) of the participants were not yet confident, citing various reasons such as inadequacies in technical knowledge. Thus, underscoring the significance of the transfer of knowledge on GenAI as highlighted in section 4.7.3. The participants' experiences of GenAI is reflected in the assessment of their ability to comprehend and navigate GenAI self-regulation. Thereby providing an interpretivist lens to the research. Contextually, self-efficacy is the belief that one has in their ability to execute the self-regulatory function (Stajkovic & Stajkovic, 2019). This belief also partially influences their confidence in the other self-regulation subfunctions (self-monitoring, judgement and self-reaction) (Bandura, 1986).

Notably, one of the limitations of self-assessments in interviews is that it is subjective and different participants assess themselves differently. Hence, the responses were determined on their own personal opinions on their levels of confidence in self-regulation.

Nonetheless, this theme is very important and anchors the self-regulatory behaviour of businesses in their adaptive self-regulation of GenAI. To support this theme, other subthemes emerged, such as the evolving and continuous nature of self-efficacy, its importance in recognising gaps and in learning from the feedback.

4.9.1 Self-efficacy is a continuous process

The self-efficacy research findings are congruent with the theoretical underpinnings of the research. Particularly, the fundamental criterion of self-regulation is premised upon the belief that one has the commitment or mastery to achieve their goals of self-regulation (Bandura, 1986; Nabavi & Bijandi, 2012). This aligns with, participants' perspectives. For example, one participant (P7) recognised that mastery of GenAI is crucial as, "it's endless with AI. And I cannot necessarily say at this stage that my knowledge with AI is 100%". These sentiments mirror Bandura's findings in the SCT, where people regard their ability to self-regulate as an acquired skill gained through knowledge (Bandura, 1991, p268). Hence, participants much like Bandura's observation, judge their self-efficacy in terms of continuous improvement in the area of self-regulation of GenAI (Bandura, 1991, p268). Additionally, other participants recognised experience as crucial to the attainment of this mastery. For example, participant (P13) noted that. "... after eight years I would have ...the ability to pick up errors very quickly". This alignment between theory and practise shows the triangulation of data from both theory and real-world experiences. More so, these sentiments were common across the participants as they recognised the need to be experienced, qualified or knowledgeable. Hence, GenAI managers or system administrators' training and enhancement of skills and experience was recommended to facilitate adaptive self-regulation of GenAI (Katragadda, 2024).

Ultimately, congruence between theory and the findings underscores the significance of gaining mastery of experience in GenAI to effectively self-regulate it. This reinforces the relevance of companies instituting mandatory courses, research, certifications, training and other ways of knowledge transfer to empower their staff. Not only with they be empowered, but this step fosters a culture of adaptability and supports adaptive self-regulation of GenAI.

4.9.2 Self-Efficient in identifying the gaps

The research findings illuminated several gaps, and businesses are still exploring more gaps associated with GenAI in business customer experience. Equally, the participants also recognised the value of self-efficacy in identifying gaps in GenAI. Specifically, (P20)

highlighted that, "If you're able to see it, to identify it, it helps you to then mitigate it". This phenomenon was a recurring theme where participants underscored the significant role of identifying gaps as a prerequisite to adaptive self-regulation.

Notably, the identification of gaps can be a deterrent to customers. Specifically, (P14) noted that at recognising any bugs, they found other GenAI alternatives. Hence, the role of self-efficacy is crucial toward the timely resolution and maintenance of the GenAI in customer experiences.

However, the recognition of gaps is subjective to the GenAI's environment. For example (P14), highlighted language gaps and the Western-centric design of GenAI. In Western countries, they will not be able to identify the same gaps. For example, a GenAI in the United States can have features banned in South Africa. This has also been recognised by policymakers as a gap in the global regulation of GenAI (Christodorescu et al., 2024). Thus, as businesses are working toward self-efficient measures of identifying gaps, a holistic approach is required. This aligns with the integrative problem-solving approach in adaptive self-regulation. Additionally, the role of certifications and standards provides a universal benchmark on what constitutes a gap. This was an area that was still being developed in South Africa at the beginning of 2024.

4.9.3 Learning from feedback

The findings also highlighted the role of self-efficacy required when learning from feedback. Additionally, research participants further accentuated the role that feedback mechanisms have in driving effective GenAI business customer experience. Specifically (P18) noted that, "there is potential for enhanced efficiency by learning from feedback and adjusting its responses and output". Notably, participants also emphasised the need for iterative feedback loops between the models and customers (Yusuff, 2024). This collaborative approach enables professionals to refine the models' performance and address potential biases or errors (Järvelä et al., 2023).

The results suggest that the largest area of focus for a business should be in garnering customer feedback. However, this customer feedback contains personal information shared with their business's GenAI tools (Tompros, 2023). This was equally concerning to the participants. For example (P17), highlighted that, "you need to have a process for sensitive information." This is primarily because most GenAI require an account where sensitive email like email and passwords, are exchanged with the GenAI. Therefore, another participant (P18) thought that there "will always be a need for human intervention as there will be concerns around ethical

safeguards and transparency.” Furthermore, the participants recognised that the model can learn some undesirable traits from the trends of the customers' feedback, as was the case with Amazon. Their machine learned a bias toward male job candidates over time, and it was discontinued (Dastin, 2018). This represents a double-edged sword where, on the one hand, the feedback is vital, but on the other hand, it informs the model and could be misinforming the GenAI model. This further amplifies the significance of self-monitoring and self-efficacy in undertaking of achieving adaptive self-regulation guidelines.

4.10 Emerging Guidelines from Participants’ perspectives

According to Bandura, self-efficacy increases when a person is confident that they have control over regulating their environment. In addition to controllability, continued success in exercising their self-efficacy leads to them becoming more persistent in terms of self-regulation (Bandura, 1991, p270). This factor is relevant because the participants’ findings reflect their perspectives on their efficacy in their ability to self-regulate their GenAI environment. Thus, many of the recommendations from the participants mirrored Albert Bandura’s SCT of self-regulation subfactors. These include self-monitoring, judgement, self-reaction and self-efficacy. Furthermore, Bandura also describes the psychosocial functions in self-efficacy in a triadic causal structure. This structure underscores the role of one’s cognition (self-efficacy or beliefs), behaviour to mitigate gaps and the responsiveness of the environment to the regulation (Bandura, 1991). When managers perceive an environment can be controlled their behaviour aligns with their level of self-efficacy and controllability of an environment.

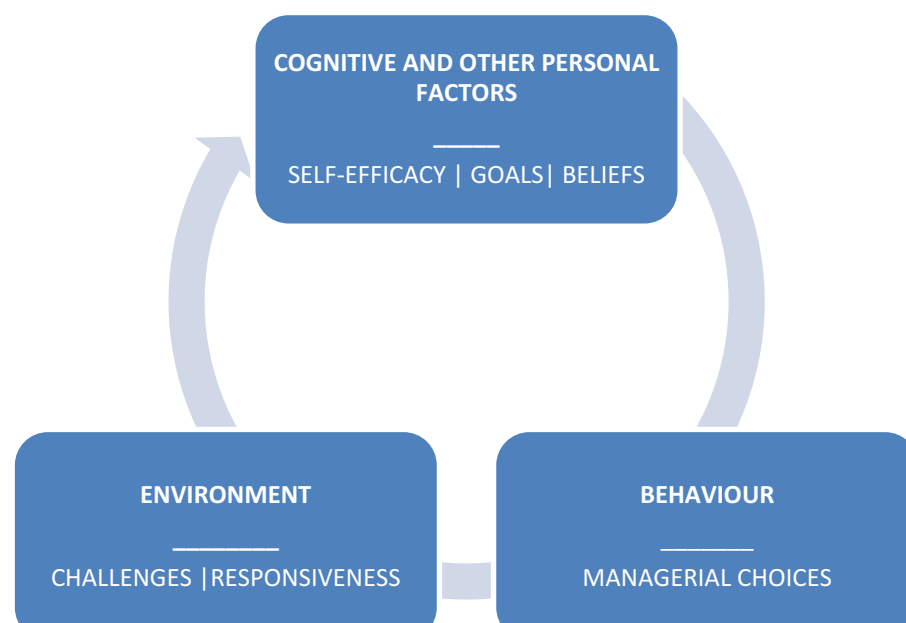


Figure 16 Researchers Own Bandura's Triadic Reciprocal Causation (Adopted from Bandura, 1991, p. 267)

Therefore, a majority of the participants recommended human oversight over the GenAI environment in business customer experience. This initial step of surveillance to identify gaps fosters transparency and is vital toward informing decisions. Judgement is also relied upon to ascertain the next steps based on the monitored performances. However, this judgement requires guiding steps or benchmarking to eliminate biases. Thus, businesses should not only monitor the GenAI performance but also react to what is causing gaps in the operating environment.

Secondly, participants recognised the role of certifications or standards in terms of motivating the self-regulation of GenAI. This converges with Bandura's findings on the SCT of self-regulation, where standards and goal-setting play a motivating role in self-regulation. This underscores the critical role of agile adaptive governance structures to mitigate the risk of any regulation lags. Businesses therefore, set goals or standards that guide their use of GenAI and how they self-regulate. In the literature review findings several businesses such as Accenture, Google and Amazon have set goals or guiding recommendations or policies that govern their GenAI on their websites (Porter et al., 2024).

Thirdly, the findings also reflect the significance of robust security measures to eliminate the risk of privacy breaches. As GenAI requires personal information in accounts such as passwords, security is critical. A majority of the participants were concerned about the potential gaps that arise when customers engage with GenAI. Recommendations were made, therefore to proactively plan and pre-engineer, and design safe-by-design GenAI models while making use of masking and other security features. Furthermore, quick self-reaction to any threat is important. Thus, the security effectively requires constant self-monitoring of GenAI performances, judgement over and flagged incidents and immediate self-reactivity. The ability to effectively execute this loop and adaptive self-regulation is determined by the controllability or responsiveness of the environment to regulation.

Therefore, participants also recognise the role of proactive agile methods of security. This dual approach of both reactive and proactive barriers contributes to mitigating any security gap.

Similarly, the role of human interaction was recognised as indispensable. Not only does GenAI fail to simulate human warmth and empathy, but there are gaps in inaccurate and outdated data. GenAI is trained on historic data, and humans can better assist with more accuracy in some instances. This disparity was recognised by participants who recommended augmenting

models to allow for the integration of human involvement in GenAI models. This hybrid approach also facilitates the process of oversight or self-monitoring of the GenAI.

Lastly, caution was given against a technology-driven approach to self-regulation. One participant also underscored the significance of the contributions from other fields of science, including psychology. This human-centred approach to adaptive self-regulation promotes the incorporation of various inputs from all the fields that interact with GenAI. This was a limitation of the study and can be an area of future research.

Ultimately, the participant's findings were in congruence with Bandura's research on SCT of self-regulation. Thus, demonstrating the alignment of theory and practise in the area of GenAI governance.

4.11 Summary

Through the application of the methodologies outlined in Chapter 3, this chapter presents the findings of the data collection. This exploratory study undertook an in-depth examination of the self-regulatory dynamics of GenAI in business customer experience. Grounded in Albert Bandura's Social Cognitive Theory (SCT), this research investigated the complex interplay between Bandura's self-regulatory subfunctions and the effective self-regulation of GenAI models.

The research problem revisited is that;

“How can businesses avert the regulation lag caused by the GenAI moral dilemma through adaptive self-regulation guidelines?”.

According to Albert Bandura's SCT framework, self-regulation is a multifaceted function influenced by individuals' self-monitoring, judgement, self-reaction, and self-efficacy subfunctions (Bandura, 1986). To investigate the self-regulatory dynamics of GenAI models in the context of business customer experience, this study solicited the perspectives of technology professionals. The research findings were in congruence with several underpinnings of the theoretical framework of the research (Bandura's SCT of self-regulation). This triangulation of theory and practise highlights that the participants had valuable insights and opinions on self-regulation from their observations and experiences. Thus, their responses conformed with the interpretivist approach of the research. These perspectives on adaptive self-regulation mirrored theoretical fundamentals such as self-monitoring, judgement, self-reaction and self-efficacy.

In contrast, one participant (P4) was against the regulation of GenAI. They noted that the regulation should be of the systems adopting the GenAI, not the technology itself. This response recognises some of the gaps and criticism around the self-regulation of GenAI. Another gap is the misalignment between policies, as what is acceptable in one country is prohibited in another (Christodorescu et al., 2024).

Nonetheless, the participants recognised that the implementation of adaptive self-regulation methods closes the gap created by the lag between the fast-paced technology and the development of regulation.

By implementing these methods, businesses can minimise risks and biases inherent in GenAI, thereby ensuring ethical GenAI practises. To that end, various recommendations emanated from the research participants, outlining strategic measures that facilitate self-regulation both before the launch of the GenAI model and after the model has been deployed.

The importance of ethical considerations in the development and deployment of GenAI models cannot be overstated (Al-kfairy et al., 2024). One of the substantive key findings was that there is a high investment cost required for the implementation of GenAI models, underscoring the need for businesses to possess adequate resources (H. Huang, 2023). Moreover, in light of the costs of regulating GenAI models, participants in this study emphasised the importance of businesses possessing specialised expertise to effectively monitor, control, regulate, and maintain GenAI systems (Yusuff, 2024).

Notably, the role and importance of human oversight in GenAI self-regulation were underscored by participants, who emphasised the need for professionals to engage in iterative feedback loops with the models and customers (Yusuff, 2024). This collaborative hybrid human-GenAI approach enables professionals to refine the models' performance and address potential biases or errors (Järvelä et al., 2023). However, once there is a dialogue and exchange with a business that involves personal information, it necessitates the need for security (Tompros, 2023). Also, participants recommended that businesses should also have governance structures in place that support the evaluation of GenAI performance.

A recurrent theme was the indispensable role of humans in business customer experience. For example, most businesses' chatbots allow customers the option to chat live with a human and not just a bot. This hybrid holistic approach is an integrative thinking approach to problem solving. Additionally, this approach is another method of regulation as the GenAI is not left entirely alone with the customers (Feng et al., 2024).

Furthermore, in the research interviews, some participants recommended testing and certifying GenAI models before deployment. Interestingly, another participant recommended that customers limit the information that they share with GenAI models. This sentiment was corroborated by other participants who also highlighted several security gaps of GenAI in customer experience. Thus, customers can collaborate with businesses to be proactive and stay aware of the security risks that they pose (Sekine, 2025).

In contrast, another participant criticised this research approach to having technologist-led – led self-regulation guidelines. The participant cautioned against the gaps it can cause in the self-regulation of GenAI models. They advocated for the inclusion of psychologists and allied professionals in the regulatory process. Given the profound impact of GenAI models on human lives, the inclusion of psychological expertise to ensure a more comprehensive and human-centred approach was recommended (Stone, 2024).

Table 7 Summary of the findings

Theme	Code	Illustrative Code	Bandura's SCT Link & Explanation
Key Steps of GenAI Self-Regulation	Regular Updates	"...it needs to be updated regularly..."	Self-Monitoring and Self-Reaction when outdated the GenAI the business reacts by having regular updates
	Continuous Learning	"What can we improve on so there's always that continual learning and continual monitoring?"	Self-Monitoring to observe and learn
	Human-GenAI model collaboration	"... an option where you can say, talk to a human so that you can get all the human answers that you need"	Self-Monitoring of GenAI for collaboration Judgement to discern what requires GenAI and what requires human
Role, Use, Benefits of GenAI	More Efficiency	"Less waiting time, more efficiency"	Self-efficacy to keep up with the efficiency of the model to self-regulate
	Time-Saving/ Speed/Fast	"... what used to take a lot of time can be reduced ..."	Self-monitoring the speed of performance of GenAI to adaptively self-regulate speed
	Better Data Analysis	"...allows us to do better data analysis..."	Judgement to adaptively self-regulate what information can or cannot be shared for analysis
	Can generate actionable Insights	"...gives generate actionable Insights..."	Judgement on the quality of GenAI insights to adaptively self-regulate
Gaps of GenAI	Lacks Human Factor	"...it lacks the human factor..."	Self-reaction of a human to self-regulate to avert a GenAI anomaly
	Hallucinations/Incorrect information	"...hallucination factor where generative AI sort of like makes up its own thing"	Judgement to discern if GenAI output is accurate or requires adaptive self-regulation Self-reaction to eliminate bias
	Model Bias	"..., the bias in that training dataset might creep in there again..."	Judgement to identify GenAI bias Self-reaction to eliminate GenAI bias
	Security and regulation a key components/concerns	"... cyber security point of view, there is also a part of AI where people are very vulnerable..."	Self-reaction to eliminate GenAI security risk and self-regulate timely manner when they arise
Self-Monitoring GenAI	Self-Monitoring	"... self-monitoring. I am also monitoring performance ..."	Self-Monitoring GenAI
	Systems embedded in the watching system	"...Systems embedded to watch ..."	Self-Monitoring GenAI
	Continuous Monitoring	"...continual monitoring..."	Self-Monitoring not once off but continuously
Judgement of monitored processes	Benchmarking	"...comparing against that benchmark..."	Judgement to discern if GenAI aligns with set benchmarks of standards
	Incorporate Human Factor	"...a human factor, we can say, okay, speak to a human instead of always AI finding the answer ..."	Self-reaction when GenAI models fail, humans need to adaptively self-regulate the model and also assist the customer
	Need Knowledge to judge AI.	"...you need to know, you need to be aware ...of your industry, ..."	Self-efficacy is required to build awareness of GenAI and its operating environment to adaptively self-regulate it
Self-reaction of monitored GenAI processes	Quality Assurance Testing/Testing	"...quality assurance testing..."	Judgement of quality by testing of GenAI to adaptively self-regulate it
	Self-Reaction by correcting the model	"... I just fix those hallucinations and biases and continue..."	Self-reaction to the errors
	Regulate before the effect/pre-process	"...mitigate it before it even starts to affect the end user..."	Judgement to prevent and self-regulate ahead of time
Self-efficacy of self-regulation subfactors	Learning from feedback	"...learning from feedback..."	Self-efficacy in learning from feedback and self-regulating
	Self-efficient in identifying and mitigating gaps/use	"... I think the only way to count on also for the positive of utilising generative AI is that you have to be a subject matter expert at the subject ... That's the only way that you're able to immediately tell that it is not going in the right direction..."	Self-efficacy in identifying gaps and self-regulating
	Self-efficacy is a continuous process/improvement.	"have to be continuously improved so that as it is implemented, it is representative of the gaps that need to be filled with self-regulation..."	Self-efficacy in agile adaptive self-regulation of GenAI

5 Discussions and the self-regulatory guidelines for businesses

5.1 Introduction

This chapter critically engages with the research findings delineated in the previous chapter. To derive more meaning from the findings, this chapter dissects the research themes with the theoretical underpinnings of the research. Importantly, Bandura recommended that when examining a moral dilemma, the relevant moral information must be extracted and weighed (Bandura, 1991, p277). To this effect, the participants' philosophies were extracted (Chapter 4) and are being weighed through a theoretical lens. Specifically, the chapter cross-examines the findings to derive deeper meaning and investigate opposing viewpoints for a balanced discussion.

Additionally, the chapter dissects the theoretical perspectives of the GenAI moral dilemma with those from practise, based on the experiences of the participants. Thus, aligning with the interpretivist methods of the research. This was to garner richer and meaningful insights into the research problem. Furthermore, to enrich the study, the benefits, gaps and governance of GenAI were discussed at great length through the lens of Bandura's SCT.

GenAI moral dilemma was explored in light of its benefits, gaps and governance. Notably, the perspectives of the research participants converged with the theoretical findings. For example, the congruence between the literature and the research findings on the benefits and gaps of GenAI. Specifically, the benefits of customisation, automation and delegation of mundane repetitive tasks. While the convergence in gaps appeared in recurring subthemes of biases, hallucinations, security threats and others. Hence, this triangulation aligns with best practises. Additionally, the limitations of this research will also be analysed. The chapter is concluded with the steps identified for the development of the adaptive self-regulatory guidelines. A summary of the structure has been visually illustrated.

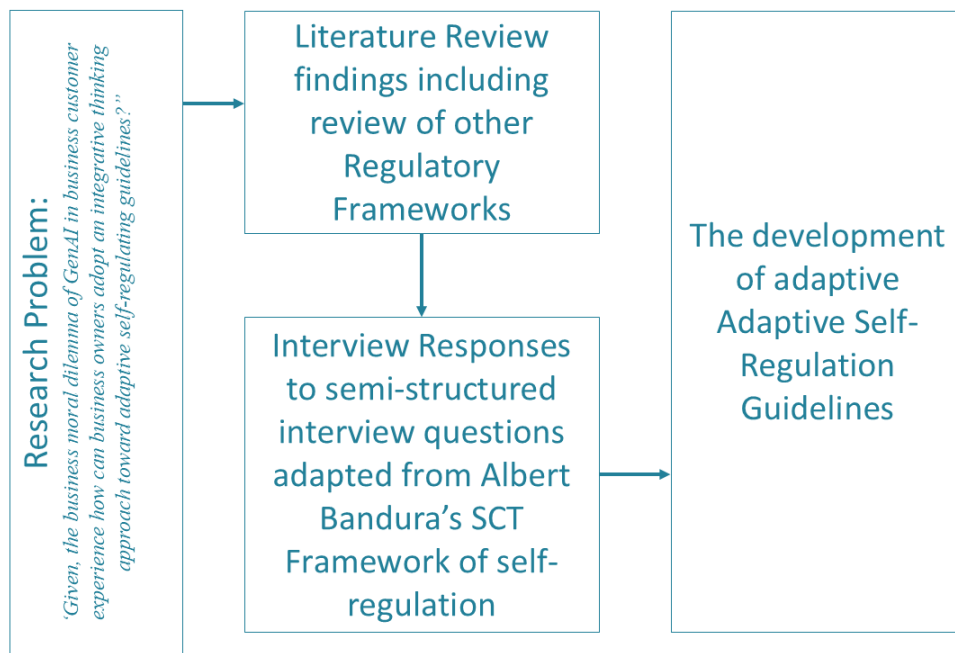


Figure 17 Mapping the results to the development of adaptive self-regulating guidelines

5.1.1 Discussions on the theme: role, use and benefits of GenAI performances

The research findings indicate that the adoption of GenAI has yielded several benefits. Importantly, businesses have to find the right balance where the benefits to customers outweigh any risks (Shukla, 2023). In addition to the benefits, the extant research highlighted that the use cases associated with GenAI in business customer experience are far-reaching. These include the adoption of GenAI in business customer experiences in health, fashion, construction, education, banking, finance, business and more (Golda et al., 2024). The academic body of literature also recognises the benefits of GenAI in customisation, automation, decision making and more.

In convergence with the literature findings, the research participants recognised the role of GenAI in the delegation of mundane tasks, large data analysis, automated customer responses, decision making, customisation coding, and more (Matta et al., 2022). Businesses are finding ways to leverage this technology to also cut down on inefficiencies and augment the overall customer experience. Theoretically, Bandura recognised that people will pursue an action that has positive consequences. Contextually, businesses are pursuing GenAI for the positive and beneficial outcomes in their business customer experiences. Importantly, Bandura also highlights that self-regulatory controls can be achieved when there are incentives for positive tangible outcomes (Bandura, 1991, 256). Thus, the pursuit of GenAI benefits while mitigating

the gaps is a goal that businesses work toward. Goal setting is also a motivating aspect of self-regulation.

In the research, several themes were extracted in line with the role, use and benefits of GenAI in business customer experience. The main recurring subthemes on its use and role were for time saving, efficiency, better analysis and for insights.

Critics of GenAI have also cited that the technology is making use of high computational power, that are associated with high emissions (Agrawal, 2024).

Also, due to the ever-evolving nature of GenAI in business customers, in future, the use-cases may have increased from the time of this research. Furthermore, what may be beneficial in the South African context may be prohibited in another country (Christodorescu et al., 2024).

Importantly, the research explored the practical ways customers and businesses are benefiting from GenAI. This aligned with Bandura's sentiments that in collective settings or organisations, rules or guidelines are learned from exploratory experiences (Bandura, 1991, p265). Therefore, the subthemes under this theme are also critically explored and analysed in the following subsections.

5.1.2 Subtheme: Time Saving

According to Bandura, organisations must strongly perceive that they have control over their environment for effective self-regulation (Bandura, 1991, p270). Contextually, control over time in concluding transactions is subjective, as each customer has different environmental factors at work. For example, weak internet, poor prompts are all different environmental elements that determine whether customers save time with GenAI.

Thus, the unpredictability of GenAI performance can have a bearing on how organisation set their goals in line with adaptive self-regulation. Notably, systems can be put in place to monitor and control the speed with which customers interact with the GenAI. This controllability influences the quality of the adaptive self-regulation (Bandura, 1991).

Notably, the research participants recognised that the adoption of GenAI leads to saving time. The use cases included saving time in coding, elimination of queueing and in getting responses to frequently asked questions and more. However, due to the limited capacities of GenAI, they ended up opting for a human to assist them. Thus, underscoring the relevance of a hybrid approach to business customer experience. This holistic approach is an integrative thinking

resolution to mitigating gaps arising from the GenAI. As this transformative technology is also still in its formative stages in customer experience, human oversight may remain relevant.

The personalisation of customer experiences is another potent benefit of GenAI. However, this has raised the most concerns on the security implications, including ethical and data privacy side-effects exist (Singh et al., 2024; Tiutiu & Dabija, 2023).

Although there are some time-saving attributes of GenAI, several gaps emerge that require human oversight (Schneider et al., 2024).

Lastly, judgement plays a critical factor in what should be incorporated or constituted in the GenAI to save the customer time at minimal risk. Hence, the elimination of human interaction to save time can come at a loss of privacy, as information is electronically exchanged across multiple channels. Thus, businesses should set time-saving goals that have low risk in their business customer experience. According to Bandura, setting goals that are attainable and have success can motivate self-regulation. In this case, adaptive self-regulation goals are set when there is a right balance between safety and the use of GenAI.

5.1.3 Subtheme: Efficiency

In addition to time saving, inherent efficiency was another common subtheme on the role, use and the benefits of GenAI in business customer experiences. The research interviews show that participants were of the opinion that GenAI can improve efficiency in various use cases. For example, by efficiently keeping track of feedback from the customers. Participants also recognised increased efficiencies through the streamlining of tedious tasks. These include expedited processes and provide instant access to pertinent information, thereby obviating the need for intermediaries (Seda et al., 2024). This increased accessibility and responsiveness enhance the business customer experience. Once more, concerns were raised about nefarious social engineering consequences, thus security and access control play a pivotal role (Ferrara, 2024b). This is because, as GenAI models in business customer experiences become more pervasive, as a tool to automate and enhance efficiency, the risk of sensitive information, including trade secrets, being compromised increases (Humble, 2024). Furthermore, GenAI efficiencies are debatable; critics have faulted GenAI for being prone to hallucinations and bias (Chadha, 2024; Ferrara, 2024a; Salazar et al., 2024). Additionally, concerns were also raised on the ethics surrounding a machine completing a task efficiently, where a person is being paid to do the job. These moral and ethical implications also highlight the significance of adaptive self-regulation. Unregulated GenAI use can exacerbate inefficiencies in society. For example,

deepfakes, phishing and other social engineering attacks can completely incapacitate businesses and customers (Ferrara, 2024b; Sekine, 2025; Zhou et al., 2023).

Ultimately, the regulated use of GenAI can drive efficiency. However, unregulated models can counteract progress and drive inefficiencies by threatening the security, integrity and trustworthiness of the business. Once again, judgement is crucial for managers to discern how to mitigate any possible risk in a bid to reap GenAI efficiencies.

5.1.4 Subthemes: Better Analysis and Actionable Insights

GenAI offers revolutionary strategic business analysis through the continuous monitoring of trends and customer spending patterns (Yusuff, 2024). The interview findings also revealed that leveraging GenAI models enables the analysis to facilitate further enhancements to business customer experiences (Kumar et al., 2024). The research and literature findings also revealed that better analysis is achieved by summarising large reports (Ferraro et al., 2024).

Hereto, GenAI's access to large computing power allows for complex analysis beyond a human level of computation (Singh et al., 2024). Thus, businesses are able to gain better analysis for their businesses, which leads to actionable insights. More so, GenAI monitors sales performance in the business, which provides insights into the performance of their customer experience (Yusuff, 2024). The research participants thought that GenAI models can provide objective and speedily available insights (İşgüzar et al., 2024). GenAI models are also capable of providing a neutral and impartial interface, eliminating human subjectivity fueled by emotions or other prejudices (Huang & Rust, 2018).

Notwithstanding the merits of GenAI automated analysis and insights, businesses are susceptible to risks. For example, the sharing of large files of sensitive data to third parties for political gain or other purposes. This was the case in the Cambridge Analytica scandal, where personal information was shared with third parties (Allen, 2018; Boldyreva, 2018; Cadwalladr & Harrison, 2018). Although breakthroughs are being made in data analysis, they come with risks. Therefore, businesses can consider developing their in-house analysis GenAI tools that are not accessible to the public. Despite these remedial innovations, businesses are still at risk of being hacked and other risks, as highlighted in the research findings. For example, businesses compete with social engineering attacks such as deepfakes, computing devices capable of deciphering security and passwords, malware and more (Sekine, 2025).

Unfortunately, this gap cannot be averted but actively monitored, as referenced by Bandura. Thereafter, implementing robust adaptive self-regulatory measures is crucial.

5.2 Discussions on theme gaps of GenAI adoption in business customer experience

According to Bandura, all the information is to be explored for a better understanding of moral dilemmas (Bandura, 1991). To this end, the research acknowledges that beyond the benefits, there are gaps and unintended harms of this technology.

Furthermore, the research findings and the research findings converged on the limitations or gaps of the adoption of GenAI. Specifically, in business customer experience, many gaps arise. Both the academic body of literature and the research findings recognised that these gaps included biases, hallucinations, security risks, among other moral and ethical concerns.

Of concern is that some of the gaps of GenAI are innate to the nature of GenAI. For example, a bias in the training or the data that is constantly being received, as was the case for an Amazon-discontinued model (Dastin, 2018). Equally, participants underscored the irreplaceable nature of humans in business customer experiences. They articulated that their warmth and empathy were not something that a machine could simulate. Thus, a hybrid human-GenAI approach was a common recurring suggestion.

In addition, the research participants recognised that the Western-centric GenAI models already have biases recognised in South Africa (Zhou et al., 2023). For example, the limitations in terms of language. More so, most businesses have no control over historical data. This further exacerbates the lack of transparency and bias in the accuracy of the historical data used for training (Matta et al., 2022).

Controllability and self-efficacy are very critical toward self-regulation as implicated by Bandura's SCT (Bandura, 1991). According to Bandura, if the perceptions are that the environment is somewhat controllable, they exercise their self-efficacy, which leads to a high motivation to self-regulate. Moreover, the more success achieved in this control through self-regulation creates persistence. Persistence and vigilance against the gaps that arise in GenAI fosters a culture of adaptive self-regulation. This agile approach against a fast-paced technology will not only mitigate risks but also close regulatory gaps.

Lastly, the abovementioned unintended harms of GenAI implicate the relevance of a transparent, accountable, safe, secure and human-centred approach when deploying GenAI.

Furthermore, the adaptive, proactive and timely holistic response to addressing any gaps will avert any regulatory lags between development and governance.

Ultimately, the absence of human factor, biases, hallucinations and security concerns are some of the common subthemes that emerged.

5.2.1 Subtheme: Bias

GenAI harbours great competitive advantages in business customer experiences. However, as GenAI is becoming ubiquitous, certain biases emerge, including gender, racial, language and other societal constructs (Ferrara, 2024a). The implications of this are far-reaching, especially in South Africa. More so, the literature review findings and the research participants converge that biases are inherent to GenAI. Innately, GenAI is a product of humans, and humans carry bias; thus, from inception, accountability and transparency are required to account for equal representation in training data (Matta et al., 2022). Other sources of biases could appear from algorithms and training data bias, and bias toward the country of development (Ferrara, 2024a; Nyaaba et al., 2024). Therefore, biases exist throughout the lifecycle of the GenAI.

To combat this gap, further clarity was explored from the participants who equally reflected upon the different types of biases they have experienced, such as language bias, race and others. This further exacerbates the magnitude of these risks as the majority of the participants had lived experiences of biases. In addition, it was clear that there are biases associated with GenAI adoption, particularly in business customer experience contexts (Lecocq et al., 2024).

Notably, algorithms have been criticised for displaying biased results when searching for terms like "woman", highlighting the need for greater diversity and inclusivity (Noble, 2018). One study reported that upon testing Midjourney, Stable Diffusion and DALL-E 2 with the same prompt, black people's images were synthetically generated in 9%, 5% and 2% of the results (Zhou et al., 2023). Of great concern is that this is a common occurrence. A customer is at risk of receiving biased content, or facing other prejudices that arise from the GenAI, for example, if a model is biased toward a certain gender (Lecocq et al., 2024).

However, GenAI models themselves, if correctly regulated, can provide a neutral and impartial interface, eliminating human biases fuelled by emotions or other prejudices (Huang & Rust, 2018). Participants were of the view that if due diligence is applied in the model's supervision, it could eliminate the possibility of biases.

Ultimately, the risk of GenAI bias can lead to dire consequences. These include denial of job opportunities, influencing wrongful perceptions of certain types of people and underrepresentation of the content of minorities, among other injustices (Ferrara, 2024a). Addressing this level of bias requires a holistic, integrative approach that fosters diversity, fairness and transparency. This approach was mirrored during South Africa's draft for a national AI policy, where contributions were made from various spheres (Motsoeneng, 2024). Furthermore, the mitigation of these biases requires robust strategies that foster inclusivity, fairness, privacy, transparency and diversity among other ethical and moral considerations. These mitigation strategies should evolve at the same pace as the technology, ensuring adaptive self-regulation of the GenAI against biases.

Globally, in terms of multilateral governance, the 'Bletchley Declaration' and the 'G7 Hiroshima Process International Code of Conduct for Organisations Developing Advanced AI Systems' ("G7 Code") address GenAI risks. They further advocate for human-centric, responsible, fair design and use of AI. The Bletchley Declaration specifically deemed "bias-mitigation" as critically important. Furthermore, it calls for countries to build upon shared knowledge of the GenAI risks and to support other developing countries with their AI capacity building (Christodorescu et al., 2024).

Given the above, Bandura recognises the role of collective societal influences when businesses exercise judgement over their GenAI performances. Their role is described as a form of "*collective comparison*" where there is an evaluation of the GenAI against publicly acclaimed standards (Bandura, 1991).

5.2.2 Subtheme: Hallucinations

GenAI has the propensity to produce seemingly accurate results that are inaccurate. This phenomenon is referred to as hallucinations (Ferraro et al., 2024). Once again, the lived experiences of the participants also reflected that they had encountered hallucinations. Some of the participants were of the opinion that they were able to correct the GenAI. This is congruent with Bandura's reference to controllability and efficacy. When self-efficacy is practised successfully to augment the environment, it motivates further exercise of that efficacy (Bandura, 1991, p. 258). Therefore, participants who had corrected the GenAI had experience successfully augmenting the hallucinations. These lived experiences and the findings from literary works researched findings dissected on the commonality of hallucinations (Akolkar, 2024; Latifi, 2024). Common examples of hallucinations include

inaccuracies of GenAI generated transcripts or notes from meetings, and in synthetically generated photos of people.

As the participants were also significantly concerned about the recurring hallucinations affecting business customer experiences (Williamson & Prybutok, 2024). For example, the case where Air Canada GenAI hallucinated offering a plane ticket at a fraction of the cost to a customer, which resulted in litigation (Cerullo, 2024; Sookman, 2024).

Evidently, of all the GenAI gaps, hallucinations are the most difficult to identify as they appear realistic. This is also further exacerbated by the opaque design of the GenAI models, where it is difficult to ascertain their integrity (Schneider et al., 2024). This may affect the controllability of the GenAI environment, a critical factor for self-regulation raised by Bandura.

It is therefore clear that self-monitoring, as implicated by Bandura, is equally important for validation of the GenAI's performance against hallucinations. Equally, educating customers is also paramount to equip them to identify hallucinations and alert the business. One participant highlighted that feedback is therefore imperative in businesses identifying gaps, such as hallucinations.

Thus, Human-GenAI strategies need to be in place whereby customers have an option to interact with the person when the model is hallucinating. Furthermore, adaptive responses to feedback from customers are imperative to achieve adaptive self-regulation.

5.2.3 Subtheme: Security concerns

In its Council of Recommendations of Artificial Intelligence, the OECD recommended a secure, robust design (OECD, 2019). This comes as tensions surrounding the security of GenAI have been mounting into debates on what should be prioritised in terms of GenAI governance. One such debate recorded by the World Economic Forum was between the school of thought that governance should focus on the self-regulation of 'known' harms versus the long-term harms of GenAI (Larsen et al., 2024).

One example of known security gaps is derived from the exchange of private information for tailor-made customer experiences. From their experiences, participants recognised that customised goods and services come at a security cost. To enable this level of personalisation requires accurate personal information, including passwords, to create an account. This sharing of sensitive information, such as passwords, raises security concerns (Sekine, 2025). Participants recognised the risk of businesses that attract a lot of personal data being hacked.

Additionally, the utilisation of GenAI exacerbates other ethical shortcomings, such as malicious outputs, necessitating a nuanced consideration of its implications (Golda et al., 2024). According to Bandura's triadic structure, the responsiveness of the environment to managerial choices determines the self-efficacy (Bandura, 1991). Contextually, where businesses are successful at governing their security and the GenAI environment is responsive to the regulation measures, it increases their self-efficacy in regulation. This increased self-efficacy motivates continued self-regulation. Therefore, businesses that have robust firewalls and other successful security measures are more likely to believe that they can tackle any GenAI threat and be motivated to exert control over their GenAI environment.

Additionally, a majority of the participants recognised several security concerns, such as the leaking of the customer's personal information and also the sharing of sensitive business information by the GenAI (Sekine, 2025). This is in convergence with the findings of the literature review. One example being where a GenAI used to help create deep-fakes, an impersonator defrauded a company \$243,000 (Ferrara, 2024b). Another concern is that businesses collect personal information that can be exploited by third parties, as seen in the Cambridge Analytica Scandal (Hinds et al., 2020). Security concerns are also a human rights issue, which has been an area of concern (Sieber, 2019).

Ultimately, security concerns can be mitigated in several ways. One participant highlighted a 'privacy-preserving technique where they curate the information they share (Noble, 2018)'. This shifts the burden away from the business to the customer.

Moreover, in line with OECD recommendations, participants also recommend the secure by design approach. Similar to the experts' opinions, literature suggested that security concerns can be addressed through the use of 'Adversarial Defence Mechanisms.' Adversarial defence refers to training the GenAI on examples of adversarial engineered attacks. However, this effect has also been compromised by the evolving nature of attacks against these defences (Golda et al., 2024). Thus, self-monitoring as implicated by Bandura continues to play a crucial role in adaptive self-regulation. This approach, supported by robust governance structures such as policies and technical security measures, provides a holistic approach to security concerns.

5.2.4 Subtheme: Lacks Human Factor

One of the ongoing tensions surrounding GenAI, identified by a World Economic Forum AI Governance report is the possibility of complete autonomy that may eliminate the human

factor. However, this has been dismissed as speculative (Larsen et al., 2024). Nonetheless, the human agency of GenAI in customer experiences is something that GenAI has not yet been able to simulate. Furthermore, global regulatory frameworks such as the Bletchley Declaration called for a human-centred approach to the design of artificial intelligence models,

Notably, Bandura also refers to a triadic causation structure where the self-efficacy influences the managerial choices and the GenAI environment (Bandura, 1991). Contextually, the human element is key in self-regulation, especially when the environment can be self-regulated.

In addition, the participants' lived experiences with GenAI also mirrored those of extant research.

For example, when a GenAI makes an error that a human could have avoided (Cerullo, 2024; Sookman, 2024). Hence, the complete autonomy and absence of a human lead to gaps. Additionally, participants recognised the role of humans in customer experience. This collaborative approach enables professionals to refine the models' performance and address potential biases or errors (Järvelä et al., 2023). Aside from business concerns, other participants also desired the warm and empathetic aspects of human beings. These limitations underscore the need for effective human-AI collaboration (Katragadda, 2024). Participants recommended a human-GenAI approach where the GenAI is not left entirely alone with the customers (Feng et al., 2024).

Ultimately, theory and practise converge around the collaboration of humans and GenAI in effective business customer experiences.

5.3 Discussion on the enabling factors of adaptive self-regulation guidelines

Globally, the GenAI self-regulation landscape is developing. There has been a diverse approach to the regulation of self-regulation across many nations. Effectively, some countries adopted a risk-based approach, others a rule-based approach, while others adopted an outcomes-based approach to self-regulation (Larsen et al., 2024). Nonetheless, globally, there has been a significant attempt to close the gap created by the lag in GenAI adaptive self-regulation (Larsen et al., 2024).

Hence, this section of the results explores the relationships between the theory and practise through the lens of Bandura's theory. According to Bandura, self-regulation comprises four main subfunctions, namely self-monitoring, judgement, self-reaction and self-efficacy.

Furthermore, Bandura recognises a triadic causation structure where self-efficacy, behaviour and the GenAI environment interrelate.

To this end, the research findings conveyed a consensus amongst the research participants when it came to applying all the subfunctions of Albert Bandura's SCT framework. By exercising self-monitoring, businesses are able to observe the required self-regulatory controls in their GenAI environment.

Furthermore, as businesses keep their GenAI under scrutiny, they affect judgement on whether to flag any potential risks. Judgement of the observed performance leads to self-reactive actions, usually in response to any gaps. As the business observes its self-regulatory performance outcomes, it becomes more self-aware of the responsiveness of the GenAI environment. Previous successes in self-regulation contribute toward their self-belief or self-efficacy in mitigating the GenAI risk factors (Bandura, 1991, pp. 269–270). This is in line with the triadic causation loop proposed by Bandura. Effectively, as businesses are becoming more confident in self-regulating their self-efficacy influences their behavioural decisions around GenAI and subsequently the GenAI customer environment.

Consequently, the judgement subfunction is pivotal because of the role of humans in arbitrating the GenAI's performance and how to self-regulate adaptively. The response to self-regulate is what is reflected in the self-reaction subfunction of self-regulation by Bandura., The implications of the research findings suggest that self-regulation is integral for businesses to harness the benefits of GenAI while mitigating the gaps. Contextually, self-regulation refers to voluntarily setting standards, or guidelines that govern, monitor or control the design or the development and deployment of GenAI (Gunningham & Rees, 1997; Ozhiganova, 2018). By enabling self-regulatory measures, GenAI applications become safe, transparent, explainable, and aligned with their business values. Ultimately, the research theme of the enabling factors of self-regulation is aggregated from several subthemes, which will be explored below. These subthemes are arranged according to the subfactors recommended by Bandura and additional subthemes from the research participants.

5.3.1 Discussion on subthemes recommended by participants: Regular Updates

The research participants recommended that one key enabling factor for adaptive self-regulation was regular updates of the GenAI. Outdated information affects the effectiveness of the GenAI (Yusuff, 2024). GenAI models needed to be trained continuously with up-to-date

information and given new data updates. Fostering a culture of regular updating through regular training, sharing of experiences ensures alignment with the business growth, ethical principles and societal values (Williamson & Prybutok, 2024).

Although from the perspectives of the research participants, this closes gaps for outdated information, other risks remain. For example, regulation updates or consent may be geographically relevant to a particular region and not applicable elsewhere (Shukla, 2023). Nonetheless, the participants recognised that the data training and regular updates maintained the model at optimal levels. According to Bandura, the controllability of the GenAI environment boosts self-efficacy and positively affects self-regulation (Bandura, 1991).

Effectively, in alignment with the research problem, adaptive self-regulation is also enabled by regular updates. For example, top technology companies like Meta have been updating their GenAI models to improve transparency (Pavón, 2025).

Ultimately, research participants underscored the significant contribution of regular updates in enabling adaptive self-regulation. Despite concerns about some of the risks that remain, such as updates failing to correspond with all the legislation around the world. This measure is still a method that businesses can initiate as a key step in achieving adaptive self-regulation for their GenAI.

5.3.2 Discussion on subthemes recommended by participants: Subtheme: Continuous Learning

Furthermore, the research participants also recognised the significance of the role of continuous learning. This enabling step of continuous learning encompasses a never-ending evolving nature of learning the GenAI model. The process of continuous learning is central to adaptive self-regulation of GenAI. According to Bandura, learning goals are linked to enhancing knowledge and ability. Enhanced knowledge and ability, and awareness of the GenAI model influence self-efficacy or the belief that the GenAI can be regulated adaptively (Bandura, 1991, p. 268). Therefore, participants underscored the necessity to “upskill” and stay abreast of the latest trends and understand the GenAI model. This augments customer experience by providing knowledge on patterns, trends and preferences. Therefore, through self-monitoring, businesses can continuously learn and align the GenAI model with their objectives (Ortega-Arranz et al., 2025). In contrast, where there is a failure by businesses to have strong governance structures for learning and education on GenAI, it creates a gap. Moreover, the participants underscored the significance of continuous learning through academic training.

The GenAI models also require continuous retraining or learning updated information. This process was referenced by the research participants as prompt engineering. Prompt engineering is defined as the systematic design, development, and refinement of input prompts to elicit desired responses from GenAI models (Bozkurt, 2024). This proactive approach enables the models to adapt to evolving requirements and mitigate potential biases (Vaghmare & Dwivedi, 2024).

Bandura cautioned that where there are no internal standards or knowledge, external influences will influence the behaviour. Thus, the businesses should instate internal methods of learning or standards on GenAI to educate the business on adaptive self-regulation (Bandura, 1991, p. 278). This avoids external influences in their GenAI objectives, vision and goals.

Ultimately, as a country, South Africa is also on the learning trajectory, as demonstrated by the widely consultative process taken for the National AI Policy. The consultations extended toward academics, legal practitioners and various stakeholders (Motsoeneng, 2024). Furthermore, a report by the State of California recommended learning from other jurisdictions to weigh the risks and benefits of GenAI (James, 2023). Thus, to maintain a culture of adaptive self-regulation, South African businesses need to foster a culture of holistic, continuous learning.

The abovementioned was also further corroborated by several participants who wanted to stay abreast of new GenAI knowledge. One highlighted the relationship between continuous learning and continuous monitoring, which creates a self-regulatory effect.

5.3.3 Discussion on subthemes recommended by participants: Subtheme: Human–GenAI collaboration

Lastly, another enabling factor recommended by the research participants for achieving adaptive self-regulation was human-GenAI collaboration. Through the lived experiences of the research participants, it was emphasised that GenAI cannot substitute humans. Furthermore, the theoretical underpinnings of the research also recognised the imperative role of human oversight over the GenAI. Thus, there was triangulation between the research participants' perspectives and theory. Both support the integration of human-GenAI collaboration or oversight that enables adaptive self-regulation (Feng et al., 2024). Human beings play an integral, almost irreplaceable role in enhancing business customer experiences. Hence, Gen-AI and humans collaborate to holistically self-regulate the business customer experiences.

Although the participants recognised that there was an irreplaceable role of humans in customer experiences, others preferred the GenAI experience. These mixed reviews underscore the need to facilitate effective hybrid human-GenAI collaboration (Katragadda, 2024). For example, on the one hand, some participants were of the school of thought that GenAI was much faster and efficient, whereas others preferred the warmth and empathy of a human. Once more, these experiences show that there is a need for an integrative thinking method toward meeting all the customer requirements. This means that, as opposed to total exclusivity and selecting one method over the other, businesses need to balance and integrate both GenAI and human factors.

Ultimately, in achieving adaptive self-regulation, the role of humans is imperative in complementing the GenAI. Furthermore, the National AI Policy also converges with Bandura's theory by reinforcing that businesses adopt a human-centred approach to GenAI that promotes human oversight (South Africa's National AI Policy Framework, 2024). Additionally, the Bletchley Declaration, which involves several nations around the world equally advocating for a human-centric approach to GenAI (Christodorescu et al., 2024). The next section explores the role of self-monitoring and the rest of the enabling subfactors of self-regulation recommended by Bandura. These subfunctions by Bandura's SCT of self-regulation include self-monitoring, judgement, and affective self-reaction (Bandura, 1991). Therefore, in this technological moral dilemma, the theory will be adopted to investigate how users and developers of GenAI tools can self-regulate their tools through self-monitoring, judgement and self-reaction methods.

5.3.4 Discussion on the enabling factors of self-regulation recommended by Bandura: Subtheme: Self-monitoring

Adaptive self-regulation cannot be achieved if the business is unaware of its GenAI performance. Thus, self-monitoring influences the process of self-regulation in several ways. According to Bandura, these include: playing a diagnostic role of analysing the GenAI risks, motivating self-reactive behaviour and setting self-regulation goals (Bandura, 1991, pp. 250–251).

Therefore, the research participants also recognised that self-monitoring the GenAI is beyond an audit of the technology's performance but and diagnosis of the gaps or risks (Pasamonte, 2024; Varsha, 2023). As mentioned in previous sections, GenAI is capable of synthesising new information (Aleti, 2023). Therefore, businesses self-monitor the data and the new content that their GenAI produces to diagnose any anomalies. This ensures that they mitigate the gaps but

that they constantly stay abreast of the quality of their business customer experiences. This human oversight has not only been underscored by Bandura's theory but by the research participants and legislation (Bandura, 1991; Christodorescu et al., 2024). The implications of self-monitoring are far-reaching for businesses as the monitored performances inform their reactions and decisions on their business customer experience and self-regulation. Additionally, oversight is crucial to protect customers' experiences and foster transparency (Chavali et al., 2024).

Most self-monitoring is at a specific point in time, usually at testing, but the research participants also recognised the need for adaptive and agile continuous monitoring. Thus, from the research participants' lived experiences, the evolving fast-paced nature of GenAI constantly requires monitoring. This is because some of the errors a GenAI commits have dire consequences. This includes identity theft, financial fraud, and reputational damage as seen in the Air Canada case (Cerullo, 2024). Also, because technology is always being developed and changed, continuous evaluation and monitoring of GenAI, beyond just for the testing phase or launch phase, is important (Hoffmann-Riem, 2020; Pasamonte, 2024; Yusuff, 2024). More so, customer requirements, political influence, business requirements, the overall GenAI environment are also always evolving. Therefore, continuous human self-monitoring fosters a more holistic, integrative and robust culture of adaptive GenAI self-regulation (Johnson & Hoover, 2024). Strategically, the continuous monitoring of trends, customer spending patterns, and customised sales and services can boost business performance (Yusuff, 2024). Additionally, through self-monitoring, businesses can align with their customers' feedback (Daqar & Smoudy, 2019).

In contrast, self-monitoring can expose customer information to potential misuse by third parties, as was the case with Facebook (now Meta) (Bartneck et al., 2021). Equally, not monitoring can also expose the business to crime. Hence, businesses are constantly grappling with the issues related to do with privacy.

Moreover, this continuous monitoring can also become unattainable due to the high costs involved, as recognised by one of the research participants (Huang, 2023). In practise, continuous manual human monitoring can become burdensome unless efficiently delegated. Thus, to meet the onerous demands of continued monitoring, GenAI tools can also be deployed to augment and automate this task. These tools can complement human oversight to monitor logs across diverse datasets, which helps ensure that the chosen algorithm performs

consistently (Ferrara, 2024a). The use of surveillance systems to support human oversight was another sub-theme that was also recognised as part of self-monitoring (Varsha, 2023). Once again, caution is required when machines are monitoring and collecting data. Participants also recognised the need to audit the GenAI models continuously, also because of the risks such as hallucinations and biases. However, the role of human oversight can also allow bias in terms of the assessment of potential risk. Thus, businesses need to eliminate these risks by ensuring that they have standards or procedures for self-monitoring, especially for testing before deployment (Aleti, 2023). Ultimately, several conclusions can be drawn from the research findings and Bandura's theory about the role that self-monitoring. Firstly, self-monitoring is crucial as a diagnostic step for businesses to inform them of their gaps in terms of GenAI. Secondly, once businesses are aware of any gaps, they can set realistic goals on how to self-regulate. Thirdly, to augment human oversight efforts, other technologies can be adopted. Lastly, that self-monitoring is recommended by local and international best practises making it not only relevant but imperative to self-regulating GenAI.

5.3.5 Discussion on the enabling factors of self-regulation recommended by Bandura: Subtheme: Judgement

Observation of the GenAI performance initiates the actions of self-regulation. The actions that the businesses will take are influenced by judgement on how to react to the monitored GenAI performances. According to Bandura, this self-reactive action to mitigate the gaps is informed by the businesses' standards (Bandura, 1991, p. 253). Bandura's theory also converged with the perspectives of the research participants who were of the viewpoint that businesses need to benchmark standards. The participants expressed that they would require more organisational knowledge on policies and standards before exercising judgement.

Equally, participants also observed that the role of benchmarking offers best practises for businesses to follow when self-regulating. The research findings highlighted that when there is human judgement involved, there is a risk of human bias. Therefore, businesses can objectively exercise their judgement on the outcomes of their GenAI-monitored performances by benchmarking. Another participant also underscored the role of evaluations (E-Vals). Evaluations can also inform judgement by providing a risk evaluation of the impact of the GenAI on society (Tayade et al., 2024). The research findings further emphasised the role of judgement in assessing whether the GenAI model requires self-regulation.

The recognition of the role of evaluations, especially of the GenAI environment, mirrors the triadic causation structure by Bandura. Bandura recognises the influence of the environment on self-regulation. The responsiveness of the environment influences the choices the business will make and their belief in their ability to self-regulate (Bandura, 1991).

Ultimately, the research participants underscored the significance of objective judgement. As highlighted by Bandura, standards inform judgement. To this end, the participants reinforced the need to eliminate biases by using benchmarking methods such as standards. This convergence between theory and practise demonstrates alignment between the lived experiences of the participants and the academic body of literature. To achieve adaptive self-regulation judgement, it is recommended that businesses have a continuous, agile, standardised process. The next section delineates the role that self-reaction plays in achieving adaptive self-regulation. As highlighted, self-monitoring, judgement and self-reaction continuously interrelate.

5.3.6 Discussion on the enabling factors of self-regulation recommended by Bandura: Subtheme: Self-reaction

According to Bandura, one of the outcomes of self-monitoring is a desire to augment and respond to gaps, and goals are set to self-react ((Bandura, 1991, p252). Once the self-reaction goals have been met successfully, it builds a sense of self-efficacy (Bandura, 1991, p273). Therefore, businesses self-monitor, judge their performance, and set goals on how to react based on their self-efficacy. The role of self-reaction must be agile and adaptive to ensure the adaptive self-regulation of the business's GenAI. Self-reaction is influenced by the incentive or reward of the self-regulatory action. The results were mixed concerning the self-reaction to the gaps. The research findings were mixed, while others were confident that they would react to the gaps; others were indifferent. The implications of this apathy are twofold: either fatigue or a lack of capacity to do anything. This is because, from the lived experiences of the participants, where they were inadequately informed or knowledgeable, they had low self-efficacy in their self-regulatory abilities (Huang & Rust, 2018).

Moreover, to incorporate integrative thinking, participants underscored the need to not only self-react to the monitored gaps but to be proactive and anticipate gaps (Järvelä et al., 2023). Some of the proactive measures identified by the research participants were forward-thinking and agile, including secure by design features, data masking, prompt engineering and others. Furthermore, one participant also recognised the dual role of businesses self-reacting and

customers reacting; they proposed that customers limit the information that they share with GenAI to mitigate risks. Participants also recommended quality assurance testing of the system's performance, in response to any current gaps and to anticipate any risks (Aleti, 2023). The former results in a more rigorous quality-assured GenAI model for their business customer experiences (Aleti, 2023). Similarly, the participants also recommended mitigating gaps through peer review of the GenAI models. While other participants underscored the role of simply self-correcting the model when it has errors. However, with this self-reaction measure, there is a risk that the model can be amended from the correct information to being trained on incorrect information.

Notably, one participant cautioned against a technologist-led self-reactive approach but a more inclusive, multidisciplinary approach. This widens the reach and scope, providing a more comprehensive and human-centred approach (Stone, 2024).

Altogether, the research findings and the theoretical underpinnings of the research converge that the role of self-monitoring is crucial to inform self-reaction. Furthermore, reacting to any gaps should not only be reactive but also proactive. This holistic approach also supports adaptive self-regulation. Ultimately, the role of self-reaction is supported by all the other subfactors self-monitoring, judgement and self-efficacy. Effectively, a business will need reliable data on the GenAI to effectively self-regulate according to its business standards or best practices. Once again, the role of knowledge and training was reiterated and is an element that businesses should consider to educate their business on the governance of GenAI.

5.3.7 Discussion on subthemes recommended by Bandura: Self-efficacy

Self-efficacy is central to the entire self-regulation process and is the malleable belief that is formed on their cognitive ability to execute the self-regulatory function (Stajkovic & Stajkovic, 2019). Bandura recognises that self-efficacy also determines goal setting and partly influences how the other self-regulation subfunctions operate (Bandura, 1991, p. 257). The higher the perceptions, the higher the self-regulatory goals that are set. The inverse is true where the lower the self-efficacy, the less motivated they are to self-regulate. In congruence with the literature, the research participants who were ill-informed and felt inefficient demonstrated by their responses an apathy toward self-regulation (Bandura, 1991, p. 273). Inefficacious attitudes can also be attributed to past failures.

The research participants also recognised the ability they have to control the GenAI by correcting it. Bandura describes that where there is controllability of the environment, there is more self-efficacy. Furthermore, in the theory, it was highlighted that the belief that an environment can be controlled is not divorced from self-efficacy (Bandura, 1991, p. 269). Similarly, the research participants recognised that the more experience they have with the technology, the more their self-efficacy. In self-monitoring, pre-existing self-efficacy or beliefs reflect how a GenAI's performance is monitored (Bandura, 1991, p. 250). Equally, Bandura's triadic model recognises the relationship between cognitive factors such as self-efficacy, behaviour and environment in managerial behaviour. Contextually, the cognitive factors are anchored on beliefs that the business is able to change the GenAI environment. These personal beliefs influence the choices of self-regulation and the managerial behaviour toward their GenAI. The role of self-efficacy is therefore important as it influences the behaviour and changes to be made to the GenAI environment. Furthermore, the research findings confirmed the need for enhanced user education to bolster their self-efficacy levels (Katragadda, 2024).

Self-efficacy is also related to the perceived value that businesses have in self-regulation activities. For example, Amazon discontinued a biased GenAI model immediately (Dastin, 2018). This shows the value they place on their customers (Bandura, 1991, p. 269). Thus, research participants also underscored the significance of feedback from customers. This value on customer feedback is also crucial for monitoring and regulating the GenAI.

To this end, undergirded by theoretical foundations, the recommended steps are both aligned with theory and the lived experiences of the participants. To this end, participants were also of the opinion that to identify the gaps and effectively carry out self-regulation, there is a need for training or knowledge. Hence capacitation, training and development of professionals is required. A few were not sure if they could identify gaps. The implications of this can be twofold: either fatigue or a lack of capacity to do anything. Therefore, from the literary works and the research findings, it is critical to implement change management that removes barriers to self-regulation and fosters enhanced self-efficacy and technical support in the business (Heikkiläarchive, 2024).

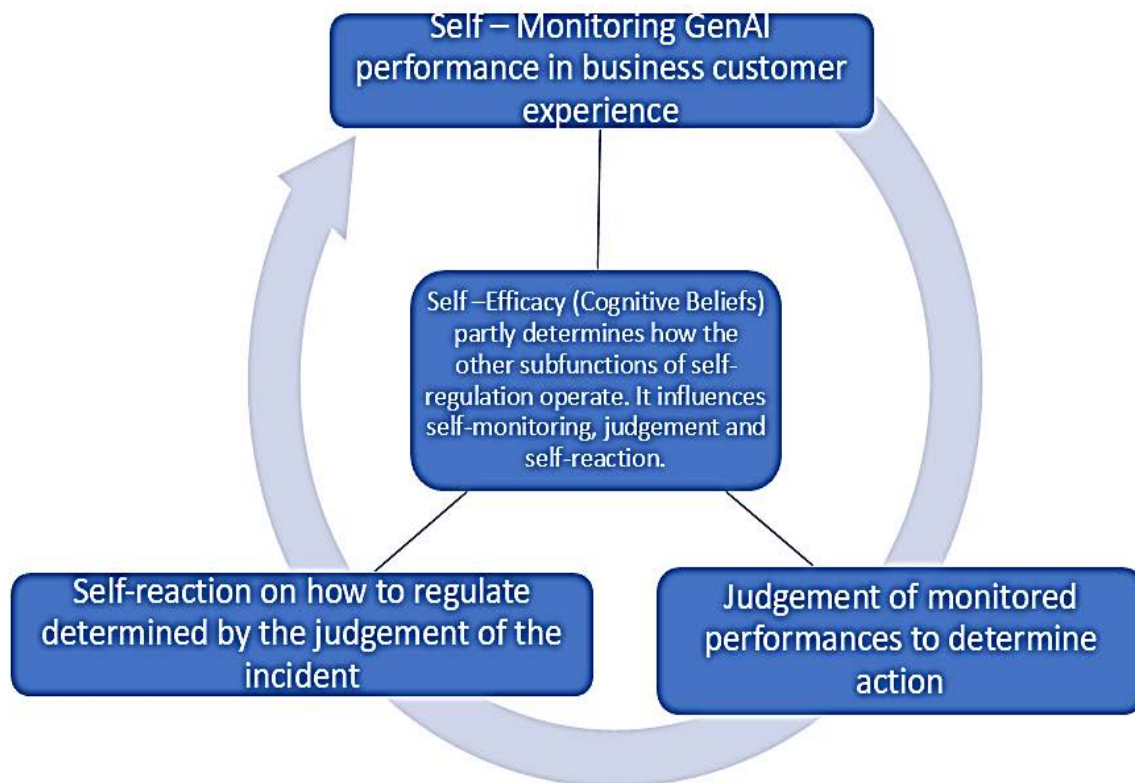


Figure 18 The role of self-efficacy in influencing the other subfunctions of self-regulation

However, participants recognised security risks when handling customer feedback (Tompros, 2023). This further amplifies the dichotomy where, on the one hand, GenAI offers solutions to customer experiences while, on the other hand, it has limitations and risks. Thus, self-efficacy informs the choices the business will make to strike the right balance of acquiring feedback while maintaining safety. Therefore, self-efficacy is pervasive in self-regulation. It is imperative to have good self-belief to effectively self-monitor, make good judgements on the GenAI and self-react.

In conclusion, the contributions of theory and practise informed that self-efficacy should be a priority in businesses.

5.4 Limitations

The research results had some limitations. One of the limitations was the disparity in the levels of understanding of GenAI among the participants. Some of the participants were still getting acquainted with this new technology, while others had in-depth knowledge, and there was a clear gap in the quality of their responses, where the more knowledgeable participants had more

information and insights. This is, however, not uncommon in studies of the nature of new technologies.

A critical gap identified in the literature review is the prevalence of static policies that fail to keep pace with rapidly evolving technologies (Lescrauwaet et al., 2022). This underscores the need for agile, adaptive approaches to self-regulation.

This study's findings corroborate existing literature, demonstrating a significant concordance between theoretical foundations and practical implications of GenAI adoption in business customer experience.

5.5 Mapping theoretical frameworks and research findings to develop adaptive self - regulating guidelines

The research gap is that the GenAI technologies cannot continue to develop faster than they are being self-regulated (Pollard et al., 2022). Thus, in line with the primary research objective, key steps were identified in the research findings and the literature review. Additionally, for best practises, other literature on the development of regulation interventions was also considered (identified in section 2.6.1).

Ultimately, an integrative thinking approach was applied to develop these guidelines by holistically considering various perspectives. For clarity, a matrix has been developed demonstrating what methods were adapted for this study from other regulation measures and the research findings.

Table 8 Matrix showing methods adopted from experts and other literature/ papers on developing guidelines

Author(s)	Research Methodology	Steps followed to develop guidelines or regulations	Focus	Steps Adopted in this research
(Olusegun, 2024)	Secondary Data Collection Primary Data Collection through interviews with Experts Thematic Analysis Content Analysis Fairness, Accountability and Transparency (FAT) framework assessment	Scope & Purpose of Guidelines Ethical Risk Assessment Development of Guidelines Training and Awareness Monitor and Update Accountability	Guidelines for AI in Digital Marketing	Secondary Data Collection Primary Data Collection through interviews with Experts Thematic Analysis Content Analysis
(Gopalakrishna et al., 2013)	Secondary Data Collection Primary Data collection through interviews with Experts for development of initial research and from experts Quote	Scope & Purpose Stakeholders Clarity and Presentation	Guidelines for guideline	Secondary Data Collection Primary Data Collection through

Author(s)	Research Methodology	Steps followed to develop guidelines or regulations	Focus	Steps Adopted in this research
	Extraction and Initial Matrix Thematic Categorisation Summary and Development of Draft Guidelines	Dissemination and Communication Editorial Independence	developers	interviews with Experts
(Bobrova & Perego, 2025)	Synthesising initial guidelines from experts, academic research and others Heuristic Evaluation to assess and evaluate initial guidelines Validation and refinement of guidelines with professionals	Development of initial draft guidelines Quote Extraction and Matrix Thematic Categorisation and subgrouping Opinions, contradictions and choice Summarising each topic and forming guidelines	User-Centric Design Guidelines for W3 Applications	Synthesising initial guidelines from experts, academic research and others
(Wang et al., 2025)	Secondary Data Collection Primary Data collection through interviews with Experts Summary and Data Analysis	Current Situation Analysis Guideline Development	Managerial Guidelines	Secondary Data Collection Primary Data collection through interviews with Experts Summary and Data Analysis
(Shittu et al., 2024)	Literature Review Stakeholder Engagement Contextual Analysis Development of Draft Guidelines Consultation and Feedback Pilot Testing Monitoring and Evaluation Implementation Strategies	Establishing a foundational framework based on core ethical principles such as transparency, accountability, fairness, privacy, and respect for human rights (tailored to Nigeria) Stakeholder engagement Develop Guidelines Implementation, Support adoption of guidelines Training to educate stakeholders on compliance requirements Implementation Monitoring and Evaluation Regular Reviews	Ethical guidelines for AI and digital transformation in Nigeria	Literature Review Stakeholder Engagement Contextual Analysis
(Janse van Rensburg, 2020, p. 2)	Awareness of problem Knowledge (Primary and Secondary Data Collection) Suggestion Evaluation Development	Reasoning and Reflection Requirements Design and Scheduling Guidance and Scaffolding Monitoring and Management Assessment	IT Higher Education	Awareness of problem (Research Gap)
(Falavigna et al., 2025)	Primary Data Collection through meetings Development of Guidelines		Guidelines for Health Centres	Primary Data Collection through meetings
National Policy Develop	Problems raised by Electorates Political Manifesto Processing through Medium Term Strategic	POLICY FORMULATION (Agenda settings: diagnosis of policy problems and policy analysis (SEIAS), Policy Design, Theory of	Framework for the Development of	Gap identified (Problem raised) Impact assessment, where the gaps

Author(s)	Research Methodology	Steps followed to develop guidelines or regulations	Focus	Steps Adopted in this research
ment (2025)	Framework Developing Policies and Laws Implementation	Change, M&E data) POLICY ADOPTION (Impact assessment, M&E data, Different types of evaluations e.g. diagnostics, design, implementation, economic and impact evaluation) POLICY EVALUATION (Impact assessment, M&E data, Different types of evaluations e.g. diagnostics, design, implementation, economic and impact evaluation) POLICY IMPLEMENTATION (Implementation plan, Resources & Capacity, M&E plan)	South African Policies	were explored in detail.
Experts / Research Participants	Semi-structured Interviews	Multi-disciplinary approach Inclusion of opinions of various professionals, including technologists, psychologists, for a human-centred approach.	Adaptive self-regulation guidelines	Identifying the gaps Pre-engineering the GenAI model Testing Peer review Regular Updates

In order to benchmark and to align with best practises, steps followed by other framework development methodologies were juxtaposed and compared against the methodologies for this research. Notable frameworks were consulted, including the development of National policies in South Africa. There was convergence between the methods that were adopted in the development of these frameworks, guidelines and other regulatory interventions and those of this research. Furthermore, the human-GenAI dual approach was a common theme in the research themes. This bolsters the role of the adaptive self-regulation guidelines, where both human self-regulation and the GenAI self-regulation create a more holistic and robust GenAI self-regulation structure to cater to their business customer experiences. As this research focuses on developing guidelines and GenAI models always evolve methods of automating models to self-regulate were not prescribed but included as part of developing the guidelines. Hence, only high-level steps of developing self-regulatory guidelines were included. The rest is up to the discretion of the regulators. Therefore, the next section develops guidelines given the steps and best practises that have been identified in this section.

5.5.1 Adaptive self-regulating guidelines: GenAI in business customer experience

In view of the holistic input from the literature review findings, the expert interview findings, and the theoretical framework grounding the research, the following steps were developed. To further provide more clarity for the avoidance of ambiguity, the guidelines have been mapped according to the theoretical subfunction of Bandura's theory and the recommended steps are explained in greater detail.

Table 9 The 10 steps identified from theory and literature for developing adaptive guidelines

<u>Research Participants' Findings</u>	<u>Adopted from Bandura's Social Cognitive Theory of Self-regulation (Bandura, 1991) and literature</u>	<u>Key Steps toward Adaptive Self-Regulation</u>
Multi-disciplinary approach, including other disciplines, not just technology experts.	Cognitive triadic causation (Cognitive beliefs, Behaviour, Environment). Self-efficacy is the belief that the environment can be changed. Various input from managers for the business GenAI influences the behaviour. Based on their self-efficacy, the managerial choices and behaviour influence the regulation changes to the GenAI business environment. The responsiveness of the environment also influences self-efficacy (Bandura, 1991).	1. Stakeholder engagement for wide representation and collaboration to develop guidelines. This also includes taking into account the GenAI business environment or ecosystem in which it has been deployed.
Human Factor is important for oversight and support.	Human self-monitoring (Bandura, 1991). Human-centred approach (Christodorescu et al., 2024; South Africa's National AI Policy Framework, 2024).	2. Human oversight and business self-monitoring of the GenAI to identify gaps.
Garner Feedback from customers.	Self-monitoring and staying aware of customer feedback.	3. Impact assessment of the monitored GenAI performances. Understanding how the GenAI is affecting customers' safety, security, society, business environment and other factors.
Correcting the GenAI model.	Self-reaction whereby the business responds to correct/mitigate gaps from the monitored GenAI performances. Self-efficacy (the belief in the ability) to change or correct the model (Bandura, 1991).	4. Develop and implement draft guidelines after stakeholder consultations. Consider how to correct monitored GenAI performances to self-regulate itself in this trial run.
Continuous Monitoring. Evaluations (E-Vals) of how the model is performing	Self-monitoring the GenAI even after implementing changes.	5. Monitoring and Evaluation, and updating of the implemented draft guidelines from the previous step.
Regular Updates.	Self-monitoring affects judgment on GenAI performances and the self-reaction loop.	6. Implementation of any updates to the guidelines iteratively.

<u>Research Participants' Findings</u>	<u>Adopted from Bandura's Social Cognitive Theory of Self-regulation (Bandura, 1991) and literature</u>	<u>Key Steps toward Adaptive Self-Regulation</u>
Upskill	Self-efficacy is based on the belief in the ability to self-regulate. Training and capacity building the business in line with GenAI (Bandura, 1991).	7. Training on the implemented updated adaptive guidelines.
Human oversight	Self-monitoring the progress of implementation of guidelines on the GenAI	8. Continued feedback and monitoring of GenAI models for updates
Evaluations, Quality Assurance testing. Benchmarking.	Self-efficacy and judgement (Bandura, 1991).	9. Continued adaption of guidelines based on continued feedback, standards, benchmarking performances of GenAI and testing the impact of the implemented guidelines. Training where necessary.
Continued Learning	GenAI regular appraisals to remain relevant and effective (South Africa's National AI Policy Framework, 2024). Self-reaction to emerging gaps (Bandura, 1991).	10. Repeat steps to stay current with evolving GenAI, thus achieving adaptive self-regulation

5.6 Summary

The chapter discusses the findings described in Chapter 4. The chapter provides an account for all the results in view of the theoretical underpinnings of the research. This demonstrates a convergent line between the findings from practise and theory. Thus, highlighting a fundamental alignment between the theoretical foundations and the practical implications of GenAI self-regulation. This chapter of the research also discussed the implications of the findings. Albert Bandura's Social Cognitive theory of self-regulation provided the lens through which the findings were cross-examined. According to this theory, self-regulation comprises four main subfunctions, namely self-monitoring, judgement, self-reaction and self-efficacy. Literature on how other guidelines were developed was reviewed. Furthermore, there is a triadic structure where the self-efficacy influences the choices or behaviour and the change to the GenAI business environment. Ultimately, the findings contributed towards the development of the adaptive self-regulatory guidelines.

Notably, 10 key steps were identified, aligning with the primary objectives of the research. An integrative thinking approach was adopted whereby all the various findings were considered in light of the business moral dilemma, and novel guidelines were proposed.

6 Contribution, Conclusion and Recommendations

6.1 Summary of the thesis

In conclusion, the research study recognises that harnessing the transformative power of GenAI is inevitable. In the area of business customer experiences, businesses are leveraging on these technologies for various uses. These technologies lend themselves to providing great innovative solutions to businesses. Examples include, the deployment of chatbots, personalised experiences, and more. Top tech companies such as Google, Accenture, and META have leveraged on these technologies. Hence, South Africa is aligning with international market trends as they are also adopting these technologies.

Despite, these innovative transformations organisations have to also confront several risks associated with GenAI. These risks are innate to the nature of GenAI and others as a resulting factor. For example, biases, hallucinations and security infringements. To exacerbate these risks, businesses are also lagging in regulating this developing technology. Therefore, businesses have to also make complex decisions to find a delicate balance.

To this end, part of the research objectives were to confirm the existence of the dilemma by identifying the benefits and the unintended harms (Göçen & Asan, 2023). Thereafter, to identify key steps from the research participants that eliminate the risk where technologies are developing and even updating themselves faster than humans can keep up the self-regulation (Kanbach et al., 2023).

To holistically address this moral dilemma, the research problem explored the role of adaptive self-regulation. Undergirded by Bandura's SCT of self-regulation, several notable factors emerged. These included the role of self-monitoring, judgement, self-efficacy and self-reaction. In addition to theoretically framing the research problem, an integrative thinking problem-solving technique was adopted. This is whereby the problem is addressed by encompassing all the elements from the opposing ideas to develop novel ideas.

The participants provided credence to the research problem, offering recommendations to the opposing tensions. This aligned with the interpretivism philosophy of this research by focusing on the lived experiences of the participants. Through the lived experiences of the research participants, the research was enriched with insights on the complex and multifaceted phenomenon of adaptive self-regulation in GenAI (Marie & Mathews, 2021). Furthermore, this also aligns with the human-centred approach recommended by various legislations. These include South Africa's National AI policy and the multilateral Bletchley Declaration.

This dual approach whereby theory and practise emerged, enriched the outcomes of the research. Furthermore, the diverging lines between theory and these perspectives confirmed the pertinent role of the academic body of literature in informing practise. This culminated in 10 key steps to develop adaptive self-regulatory guidelines. Thus, by taking an explorative approach and fully exploring these different opinions, new knowledge emerged. Lastly, as GenAI continues to evolve and become increasingly ubiquitous, researchers, practitioners, and policymakers must prioritise the development of effective adaptive self-regulatory guidelines.

By triangulating the literature review with the research findings, this study provides a nuanced understanding of self-regulating GenAI. Thereby contributing to the advancement of knowledge in this field (Bans-Akutey & Tiimub, 2021). Lastly, the consistency between the literature review and research findings highlights the importance of integrating theoretical and practical perspectives in adaptive self-regulation of GenAI.

6.2 Addressing the Research Question

The research question revisited is:

“How can businesses avert the regulation lag caused by the GenAI moral dilemma through adaptive self-regulation guidelines (integrative thinking approach)?”.

The research question was addressed by investigating the implications of the GenAI moral dilemma. This diverged with the theoretical underpinnings of the research that recognised that deeper insights should be examined and weighed when exploring a moral dilemma (Bandura, 1991, p. 277). Thus, an interpretivist philosophical approach was adopted where the perspective from the experiences of the research participants were considered. These perspectives delineated the implications of the GenAI moral dilemma. The insights from these technology perspectives acknowledged the benefits of GenAI and the inherent gaps of GenAI.

For example, although businesses are able to gather data for customisation, they can also become vulnerable to security threats, biases and hallucinations. To avert this anomaly, the research explored the role of adopting adaptive self-regulatory guidelines. This agile approach to regulation confronts the gaps that arise to optimise the GenAI performances by vigilant processes. These processes were undergirded by theory and in congruence with the insights of the research participants. These convergent methods included the role of human oversight, self-monitoring, self-efficacy, exercising objective judgement and immediate self-reaction. This continuous loop underscores persistent adaptive reactions to the GenAI's performance. Thus, the research problem is interrogated in a two-fold approach. Firstly, by outlining the scope of the research problem (moral dilemma) holistically. This holistic interrogation of the benefits and shortcomings of GenAI adoption in customer experience was exploratively achieved. This corresponds with the research design for the research. Secondly, the research problem was explored by converging the research findings with the theory. This dual approach aligned theoretical contributions with those of the research participants' lived experiences. Henceforth, an integrative thinking problem-solving technique was applied. This technique considers the different viewpoints to develop novel ideas.

Notably, these research findings were systematically organised and aggregated into themes according to the research objectives. The research objectives included the following;

- (i) To identify key steps for developing adaptive self-regulation guidelines for GenAI use in business customer experience, informed by Albert Bandura's Social Cognitive Theory of Self-Regulation.
- (ii) To determine the role, use, and benefits of GenAI in business customer experience.
- (iii) To explore the ethical and operational gaps, such as biases encountered in GenAI that present a business moral dilemma in customer experience.

Ultimately, the research analysis identified key themes that addressed the research question. Therefore, the "how" of the research question is prescribed by the identification of themes of achieving adaptive self-regulation of GenAI. The role of these themes in achieving adaptive self-regulation is discussed in the discussion chapter of the research. Ultimately, themes culminated in the development of the 10 key steps. Thus, to answer the research question, businesses can adopt adaptive self-regulation guidelines to avert the dilemma through the identified steps. These steps are highlighted below with an account of the referenced literature and research findings.

<u>Research Participants' Findings</u>	<u>Adopted from Bandura's Social Cognitive Theory of Self-regulation (Bandura, 1991) and literature</u>	<u>Key Steps toward Adaptive Self-Regulation</u>
Multi-disciplinary approach, including other disciplines, not just technology experts.	Cognitive triadic causation (Cognitive beliefs, Behaviour, Environment). Self-efficacy is the belief that the environment can be changed. Various input from managers for the business GenAI influences the behaviour. Based on their self-efficacy, the managerial choices and behaviour influence the regulation changes to the GenAI business environment. The responsiveness of the environment also influences self-efficacy (Bandura, 1991).	1. Stakeholder engagement for wide representation and collaboration to develop guidelines. This also includes taking into account the GenAI business environment or ecosystem in which it has been deployed.
Human Factor is important for oversight and support.	Human self-monitoring (Bandura, 1991). Human-centred approach (Christodorescu et al., 2024; South Africa's National AI Policy Framework, 2024).	2. Human oversight and business self-monitoring of the GenAI to identify gaps.
Garner Feedback from customers.	Self-monitoring and staying aware of customer feedback.	3. Impact assessment of the monitored GenAI performances. Understanding how the GenAI is affecting customers' safety, security, society, business environment and other factors.
Correcting the GenAI model.	Self-reaction whereby the business responds to correct/mitigate gaps from the monitored GenAI performances. Self-efficacy (the belief in the ability) to change or correct the model (Bandura, 1991).	4. Develop and implement draft guidelines after stakeholder consultations. Consider how to correct monitored GenAI performances to self-regulate itself in this trial run.
Continuous Monitoring. Evaluations (E-Vals) of how the model is performing	Self-monitoring the GenAI even after implementing changes.	5. Monitoring and Evaluation, and updating of the implemented draft guidelines from the previous step.
Regular Updates.	Self-monitoring affects judgment on GenAI performances and the self-reaction loop.	6. Implementation of any updates to the guidelines iteratively.
Upskill	Self-efficacy is based on the belief in the ability to self-regulate. Training and capacity building the business in line with GenAI (Bandura, 1991).	7. Training on the implemented updated adaptive guidelines.
Human oversight	Self-monitoring the progress of implementation of guidelines on the GenAI	8. Continued feedback and monitoring of GenAI models for updates
Evaluations, Quality Assurance testing. Benchmarking.	Self-efficacy and judgement (Bandura, 1991).	9. Continued adaption of guidelines based on continued feedback, standards, benchmarking performances of GenAI and testing the impact of the implemented guidelines. Training where necessary.

<u>Research Participants' Findings</u>	<u>Adopted from Bandura's Social Cognitive Theory of Self-regulation (Bandura, 1991) and literature</u>	<u>Key Steps toward Adaptive Self-Regulation</u>
Continued Learning	GenAI regular appraisals to remain relevant and effective (South Africa's National AI Policy Framework, 2024). Self-reaction to emerging gaps (Bandura,1991).	10. Repeat steps to stay current with evolving GenAI, thus achieving adaptive self-regulation

6.3 Key contributions

The key contribution of this research is threefold. Firstly, to the academic body of literature on GenAI customer experience. This research engages a topic that contributes new knowledge on the positive and negative aspects of GenAI in business customer experiences. Thus, providing a nuanced understanding of this dichotomy through the lens of South African Technology professionals.

The second contribution is towards the understanding of the role of adaptive self-regulation of GenAI models. This is due to the gap caused by the current state of technology advancements (Kanbach et al., 2023). GenAI business models are being proliferated at a rate faster than the pace of their self-regulation (Chouinard, 2024). Therein lies a gap or opportunity to contribute theory that addresses this gap. Therefore, in line with the exploratory nature of the research, the role of agile and adaptive behaviour toward GenAI self-regulation is explored. An in-depth analysis of the intricacies of GenAI governance, locally and internationally, is also acknowledged.

The third theoretical contribution is toward the advancement of knowledge and understanding of the development of GenAI adaptive self-regulatory guidelines. There is a gap in understanding how South African businesses can leverage these technologies while adaptively self-regulating. Before 2024, there were no policies that were for South Africans. However, with the advent of the 2024 South African National AI Policy, new knowledge is starting to emerge. This policy was driven by a wide consultative process. The Ministry of Communication and Technology garnered contributions across South Africa, including from the legal fraternity and from researchers. The study's outcomes can therefore contribute to future iterations of the policy (Hagemann, 2020).

The abovementioned contributions are relevant because most large companies in South Africa use GenAI (Hunkenschroer & Kriebitz, 2023). Therefore, a new genre of theory on adaptive

GenAI self-regulatory guidelines is required. Specifically, self-regulation that is equally aggressive, agile and constantly stays up to date with new risks.

6.4 Areas of Future Research

The direction for future research in this area should focus on understanding how GenAI can be regulated synchronously across many countries. This involves systemic regulation of GenAI that does not compromise values, policies or laws in another country. Further exploration is required on how multi-national agreements can close the regulation gaps created by different geographical, socio-economic factors, political and other agendas.

Other areas of research could investigate how GenAI developers can be regulated in terms of transparent, safe, trustworthy systems that can be audited. Alternatively, future research can also expand on mechanisms for integrating human oversight with AI self-regulation. Understanding how to achieve a dual integration or human-machine structure for automated self-regulation could be a key area of focus.

6.5 Limitations of the Study

This study has several limitations. Firstly, the study's scope on the use of GenAI was limited to technology professionals/experts in South Africa. Thus, as proposed by the research participants, a multidisciplinary approach is required for an equal representation across diverse fields. Secondly, the study's focus on GenAI adoption in business customer experience may limit the generalisability of the findings to other disciplines. For example, in developing adaptive self-regulation guidelines in medicine. However in terms of GenAI customer experience there is a possibility of generalisability across various domains that deal with any customers.

The study's timeframe is 1.5 years, which may not capture long-term effects or changes in GenAI development and self-regulation opinions. By acknowledging these delimitations, this research aims to provide a detailed understanding of the complex issues surrounding the self-regulation of GenAI business customer experience. This research also recognises the need for future studies to address broader perspectives and contexts.

6.6 Final Thoughts

This research provides pertinent insights into the perspectives of the research participants on the effects of GenAI adoption in South Africa. Contextually, in 2024, South Africa was still

developing their own National AI policy, underscoring the credence of the research gap. Notwithstanding, there is still a lot more that can be done in terms of educating South Africans on GenAI. Particularly, the participants recognised the implications of users protecting their personal information from harm when using GenAI. Furthermore, businesses, institutions, and different societal groups can benefit from a nuanced understanding of these GenAI technologies. The research findings also recognised that there is still limited knowledge on how to adaptively self-regulate. Therefore, businesses should consider fostering an environment that encourages learning in various areas related to GenAI. These include moral, ethical, security factors and other aspects.

Furthermore, the research methodologies align in practise with some of the development steps adopted in policy development in South Africa. This intentional alignment is premised upon ensuring congruence between the South African businesses and local and international best practises. For example, several multinational agreements and policies have also taken a human-centred approach to GenAI governance. Thus, highlighting the severity of issues to do with morals and ethics surrounding GenAI in business customer experiences.

Notwithstanding the technological focus of this research, a multidisciplinary approach can also be considered for future research. This will garner more insights from the educational, medical, science and other fields. Similarly, collaboration of researchers from different spheres of the world to investigate GenAI is also ideal. The nature of this type of research is just the beginning to close the gaps created by GenAI.

The fast development of GenAI in its regulation remains an area to be closely monitored. The success of these adaptive self-regulation guidelines is also a subject matter to be cross-examined.

Lastly, the governance of GenAI remains very topical across the world. From this research, various insights can be drawn, fostering responsible GenAI use, values, training, and upskilling the workforce. Peruchini et al., (2024) noted that there is still ample opportunity for further growth and investigation, particularly in light of developing new GenAI models. In light of these developments, adaptive self-regulation remains critical for equitable and fair benefits to all.

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8 Appendices

Appendix A – Field procedures

1. Using my network - willing and able participants for the interviews were identified.
2. Initial contact made for possible consent for conducting the interviews and using responses for research purposes.
3. Scheduled a convenient interview time in a relaxed and quiet setting.
4. Each interview commenced with a brief introduction of the intentions of the research, explaining the type of questions that will be presented.
5. The interviewee will be informed that the interview is recorded and will be given the reassurance that the intention of the investigator is not to enquire about company specific, financial or private information only their personal views. Ensured that the interviewee understands that they are at liberty to withdraw from the project at any time, should they so desire. Their responses will be treated as private and confidential.
6. Ensured that the interviewee do not have a problem with being recorded.
7. Ensured that interviewees do not discuss interview content with other possible participants to avoid bias as far as possible.
8. During the interview ensured that as far as possible that the interviewee is at ease at all times.
9. During the interview the investigator's body language and other possible cues did not influence the interviewee's thinking or responses.
10. To minimise subjective bias the same open-ended questions presented to interviewees in similar order.

Appendix B - B Research Instrument/ Questions

Item	Source	Purpose of the question
Demographics		
What is your gender?	Adapted from Nikbin et al.,(2021)	To demonstrate a balance in the representation of demographics that participated in the research.
Male		
Female		
Other		
Would rather not disclose		
What is your age?	Adapted from Nikbin et al.,(2021)	To demonstrate a balance in the representation of age groups that participated in the research.
What is your technological background?	Adapted from Nikbin et al.,(2021)	To demonstrate appropriate level of exposure and expertise on the subject matter.
How many years of experience do you have in technology and also in GenAI for customer experiences?		To demonstrate appropriate level of experience on the subject matter.
*For each question. Please provide a short explanation of your response as this is a qualitative study.		
In your view what are the current benefits of using GenAI in business customer experiences in South Africa? Explain.		To provide clarity on benefits of using GenAI for business customer experience (provide perspective as both the customer and the backend developer).
In your view what are the gaps, or the shortcomings of the use of business customer experience GenAI applications? Explain.		To provide clarity on the inherent shortcomings or gaps that arise from using GenAI such as privacy threats, copyright infringements, manipulation of the machine learning data, accuracy, and any other concerns emanating from the use of GenAI.
Given the above identified gaps, from your what do you suggest can be done in terms of GenAI self-regulation?		To provide details on how the self-regulation can be a solution to the abovementioned gaps?
In your own opinion do you advise the use of GenAI in coding and have you also made use of it? For example, asking GenAI to write code for an application or loading code for correction in GenAI tools such as chatbots. Explain.		To provide clarity on the use of GenAI business customer experience tools where the customer is the developer. For example, making use Visio Studio AI features to write the ATM code. Also explain how you recommend ensuring the privacy and safety of the code to avoid it leaking into the public domain).

Item	Source	Purpose of the question
Have you developed any GenAI business customer application that was self-regulated adaptively? Explain.		To explain the GenAI business customer tools developed and the regulatory measures that are considered while developing the application.
What is your opinion of adaptive self-regulation of GenAI? Explain.		To explain the level of adaptiveness.
Bandura's Social Cognitive Theory		
<u>Questions on the Social Cognitive Theory Constructs</u>		
The questions will be based on the three main constructs highlighted by Bandura, Self-efficacy, self-regulation, judgement and self-monitoring (Albert Bandura,1991)	(Wood & Bandura, 1989)	
Self- efficacy		
In your view have you mastered the ability to monitor GenAI processes? In other words, are you confident in your ability to keep a close eye on any GenAI business customer experience application and immediately pick up irregularities that contradict regulation measures and can you immediately address or mitigate any risks effectively?		
Judgement		
How good is your judgement in terms of classifying whether an incident should be regulated especially where it concerns GenAI processes, irregularities, such as biases, inconsistencies, copyright infringements, security breaches and any other undesirable effects?	To expand on how they fare in terms of their judgement of GenAI irregularities. Definitions: *Fair in this case means a non-biased judgement. Accurate in this case means a judgement that has all the facts.	
Self-monitoring		
Are you self-monitoring the performance of GenAI applications that you interact with through continuously learning on GenAI to stay aware of any new development or threats and engaging in new materials?	To demonstrate self-monitoring.	
Self - regulation / self-reaction		
Are you able to take steps that show initiative to self-regulate the use of GenAI effectively?	To demonstrate the ability to self-react to mitigate any undesirable GenAI outcome.	
Any other comments?	Here you can provide any comments related to this study that can enrich the study.	

Appendices C Ethics Approval and Turnitin Report



Rhodes University Human Research Ethics Committee
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5 August 2024

5 August 2024

Rufaro KANGANGA

Email: g10K0892@campus.ru.ac.za g10k0892@campus.ru.ac.za

Review Reference: 2024-7941-8927

Dear Rufaro KANGANGA

Title: Adaptive self-regulating guidelines for the use of Generative AI in business customer experiences.

Researcher: Rufaro KANGANGA

Supervisor(s): Dr Matolwandile Mtotywa

This letter confirms that the above research proposal has been reviewed and **APPROVED** by the Rhodes University Human Research Ethics Committee (RU-HREC). Your Approval number is: 2024-7941-8927

Approval has been granted for 1 year. An annual progress report will be required in order to renew approval for an additional period. You will receive an email notifying you when the annual report is due.

Please ensure that the ethical standards committee is notified should any substantive change(s) be made, for whatever reason, during the research process. This includes changes in investigators. Please also ensure that a brief report is submitted to the ethics committee on the completion of the research. The purpose of this report is to indicate whether the research was conducted successfully, if any aspects could not be completed, or if any problems arose that the ethical standards committee should be aware of. If a thesis or dissertation arising from this research is submitted to the library's electronic theses and dissertations (ETD) repository, please notify the committee of the date of submission and/or any reference or cataloguing number allocated.

Sincerely,

Dr Janet Hayward

Chair: Rhodes University Human Research Ethics Committee, RU-HREC

cc: Ethics Coordinator

11 November 2024

Ms Rufaro Kanganga
Rhodes Business School
Rhodes University

Dear Ms Kanganga,

Re: Adaptive self-regulating guidelines for the use of Generative AI in business customer experiences.

This letter confirms that the RU-HREC has reviewed the proposed changes to your research protocol and your request to include in-person as well as online research interactions with research participants has been approved.

Approval Number: 2024-7941-8927

Sincerely,



Dr Janet Hayward

Chair: Rhodes University Human Research Ethics Committee

