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A Framework for Adopting Generative AI in Small and Medium-Sized Enterprises to Achieve Sustainable Value

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Abstract

Since 2022, the rapid advancement of Generative Artificial Intelligence (Gen AI) has offered substantial benefits for both small and medium-sized enterprises (SMEs). However, ambiguity surrounding how SMEs should approach Gen AI adoption presents significant barriers to successfully realizing its potential value. This thesis addresses these barriers by developing the Gen AI-SME Value Framework (GSVF): a practical tool that can support SMEs looking to maximize the value of Gen AI adoption. Research used to ground the framework, which divides the adoption process into five layers, comes from a systematic review of current academic literature and practitioner insights. To evaluate its utility, the GSVF was applied to 12 organizational contexts through semi-structured interviews with SME employees. Together, the extensive literature review paired with the practical applications enable SMEs to confidently use this framework for making more informed decisions that help them achieve net benefits from adopting Gen AI.

Keywords: Generative Artificial Intelligence, Gen AI, Small and Medium-Sized Enterprises, SMEs, Value Creation, Gen AI-SME Value Framework, GSVF, Technology Adoption, Semi-Structured Interviews

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Introduction

Generative artificial intelligence (Gen AI) has become a prominent component in the business landscape since its public emergence in 2022. With its ability to display human-like intelligence by using computational techniques to make content (Feuerriegel et al., 2023; Kalota, 2024), Gen AI can be viewed as the Swiss Army knife for digital workflows. As this technology becomes more accessible, small and medium-sized enterprises (SMEs) have begun to incorporate it into their workflows to support overall business goals.

However, despite widespread interest, the path toward understanding how to adopt Gen AI in a manner that enables sustainable value generation remains unclear. Currently, academic literature has mainly focused on the *who*, which involves defining SMEs and Gen AI, along with the *why*, as in determining the reasons to adopt Gen AI into SMEs. But with a lack of focus on the *how*, there exists limited support that can guide adoption decisions. This reality is especially precarious for SMEs, whose resource constraints often inhibit their ability to engage with projects that possess high-risk or high-uncertainty (Carayannis et al., 2024; Kallmuenzer et al., 2024). Thus, SMEs — which encompass most businesses and are deemed essential for economic success (Dörr et al., 2024; OECD, 2025, p. 8; Zamani, 2022) — are the organizations most in need of a decision support tool that enhances their ability to create sustainable value from Gen AI adoption.

To address the literature gap, this thesis proposes the Gen AI-SME Value Framework (GSVF). This framework, which is built from the established literature, has five structured layers designed to help SMEs maximize the value generated from adopting Gen AI. It is a sequential process that can become iterative if needed, and it consists of the Foundational, Strategic, Implementation, Performance Measurement, and Sustainability layers. Because adoptions vary significantly between specific tools and SMEs, this framework is not a set action plan. Rather, SMEs use the GSVF to support their decision-making process by analyzing how the steps they aim to take satisfy or hinder each framework layer. Ultimately, the benefits of using the GSVF come from the increased awareness of risk, alignment with business strategy, and emphasis of creating long-term value.

This research employs academic theory, practitioner perspectives, and empirical insights. A review of the existing literature, which focuses on the *who* and *why* of adoption, is first used to characterize SMEs, Gen AI, and the known reasons for adopting technology. Then the GSVF is introduced through both a detailed breakdown of each layer and a guide for recommended usage. Lastly, the GSVF is applied to 12 semi-structured interviews involving employees working for SMEs to process a sample of practical insights that can guide adoption. Together, these parts support the creation of a framework designed to help SMEs in their efforts to successfully adopt Gen AI.

Literature Review

To properly assess how SMEs can successfully adopt Gen AI, the following review of currently available literature is divided into three parts. The first section profiles SMEs, followed by an analysis of contemporary Gen AI technologies, and lastly an overview as to why businesses adopt technology.

Evaluation of SME Landscape

Definition and Scope

Small and medium-sized enterprises (SMEs) represent the backbone of the global economy. They are pivotal to the success of nearly every economy, and they account for a substantial share of both global employment as well as technological innovation (Dörr et al., 2024; OECD, 2025, p. 8; Zamani, 2022). As reported by the Organization for Economic Co-operation and Development (OECD, 2023, p. 64), SMEs account for 99% of the total business population. However, despite their great significance and frequent citation, the specific qualifications of an SME vary. For the OECD (2023, pp. 247–248), small enterprises contain between 10 to 49 employees, and medium enterprises have 50 to 249 employees. Meanwhile, the U.S. Small Business Administration categorizes all small businesses as having generally fewer than 500 employees (U.S. Small Business Administration, 2024).

Despite nuances in definitions, SMEs have clear differences that distinguish them from larger enterprises. Their primary differentiating factor is a smaller pool of resources, which limits their ability to manage operations, finance business decisions, and compete effectively (Carayannis et al., 2024). Other distinguishing characteristics include greater volatility due to changes in environmental forces and a tendency to act cautiously in markets. With high volatility, Conz and Magnani (2020) found that organizations operating on limited resources are less resilient to external shocks, so sudden turmoil in a market could force SMEs to downsize or even exit entirely. As for their relationship with risk, many SMEs exhibit risk-averse behavior in markets due to the costly — and sometimes fatal — consequences of project failure (Carayannis et al., 2024; Kallmuenzer et al., 2024). Thus, taken together, differences in resource scope, resilience to market volatility, and orientation toward risk distinguish SMEs from larger enterprises.

Organizational Strategy and Structure

The strategy and structure of an organization are essential components that describe it holistically. Understanding them is crucial for identifying the methods that businesses use to adopt technology such as Gen AI. With regard to SMEs, each component shares similarities with, but also significant differences from, their larger counterparts.

Strategy. Corporate strategy describes the overall plan of a company to achieve their mission and build toward their vision. Companies that focus on long-term strategies are best acquainted with handling the volatility, uncertainty, complexity, and ambiguity (VUCA) that often plagues them (Dörr et al., 2024). To achieve long-term competitive advantages, especially in changing environments, companies will practice foresight. Seen as a remedy for dealing with VUCA, foresight involves observing and hypothesizing environmental trends. From using this style of analysis, firms can derive implications for how to best allocate their resources (Rohrbeck et al., 2015).

SMEs tend to lack proper foresight and strategic long-term thinking. This reality is in part due to their financial constraints, as these inhibitors often force SMEs to strategize in the short-term using adaptive plans (Dörr et al., 2024; OECD, 2023, p. 63). With finances, many of these enterprises operate with a delicate balance in working capital, which describes the difference in their current assets and current liabilities. Due to this fragile balance, many SMEs are forced to turn their cash flow into equity to finance their current assets rather than investing in long-term fixed assets (Nicolas, 2021). If these enterprises wanted to take on long-term projects, many would need to secure additional financing by increasing short-term credit or long-term debt. Getting this financing would likely damage working capital due to the additional short-term credits. Thus, these short-term credits paired with limited assets restrain the ability for SMEs to strategize and invest in the long-term (Nicolas, 2021).

SMEs also have a dearth of foresight for reasons that extend beyond finances. For instance, time and staffing issues both plague long-term strategies. Many SMEs function with small leadership teams that must spend a majority of their time completing tasks that support daily operations instead of engaging in long-term planning. This internal pressure, caused by short-term needs, means that these enterprises often lack an adequate amount of time and people (Dörr et al., 2024). Additionally, limited managerial and cognitive abilities of decision-makers also cause many SMEs to restrict their strategic thinking to just the short-term. Issues with knowledge are usually a result of both finite methodological knowledge resources and inadequate prior knowledge among staff (Dörr et al., 2024). Altogether, the constraints that SMEs burden lead many of them to prioritize short-term plans over long-term strategies.

Structure. The structure of an organization typically reflects the strategy that it imposes. SMEs tend to organize themselves in organic, horizontal structures rather than the mechanistic, vertical structures often deployed by larger enterprises (Lussier, 2019, pp. 206–207). Having this flatter alignment supports their short-term orientation in multiple ways.

One of the main appeals of this structure comes from decentralized decision-making. In horizontal organizations, the vertical chain of command is thin, but the span of control, meaning the number of people directly reporting to a manager, is large. Because of this dynamic, employees lower on the chain of command have more authority to institute important decisions than they would under large, vertical corporations (Angeles et al., 2022; Lussier, 2019, pp. 207–208).

Another quality of most SME and horizontal organization structures is their flexibility and speed. Many of the communication processes are conducted informally to emphasize fast response time (Angeles et al., 2022; Lussier, 2019, p. 209). These characteristics that stem from a flat alignment are important for the short-term strategies of SMEs, as they can quickly adapt based on changing market conditions.

Organically structured SMEs do have certain weaknesses compared to mechanistically structured large organizations. For markets with stable environments, the uniformity and traditional command style present in mechanistic designs are usually beneficial qualities to an organization. Additionally, the smaller span of management, along with the better-defined roles, gives mechanistic styles an edge over organic styles in these scenarios (Lussier, 2019, pp. 207–209). Having this structure in a stable environment can often support companies that are focused on long-term strategies; however, due to numerous constrained resources (Beck & Demirguc-Kunt, 2006; OECD, 2023, p. 63), SMEs typically struggle with implementing such strategies.

Overall, the structural configuration of SMEs plays an essential role in shaping their strategic behavior. Characterized by decentralized authority, informal communication, and flexibility, SMEs align themselves to focus on short-term goals. But despite the benefits in this design choice, its limits in standardization undermine the ability of these organizations to properly orient themselves toward long-term planning.

Leadership and Culture

Leadership and culture are core elements that shape how SMEs operate. Similar to strategy and structure, these components give insight into the approaches that SMEs use to adopt technology, which is critical for understanding the behavior of these organizations as they integrate Gen AI.

Leadership. With SMEs, leadership styles typically follow one of two models defined by Burns (1978). In his work, Burns analyzed leaders by what actions they made and the effects those actions had on others. His seminal framing led to the categorization of the transactional and transformational leadership models. Transactional leadership follows a boss-subordinate relationship composed of established rules and expected compliance, whereas transformational leadership details a leader-follower relationship containing a shared vision, intellectual growth, and the creation of moral agents (Burns, 1978, p. 4).

Transactional leadership in SMEs often manifests in the forms of performance targets and short-term efficiency. Leaders using this style focus on motivating employees to complete tasks through rewards and consequences (Berisha et al., 2024; Song, 2025). Within numerous SMEs, transactional leadership styles have been found to positively impact sales growth and return on investment (Singh et al., 2024) along with employee performance, operational efficacy, and innovation (Song, 2025). These results align well with the goal-oriented nature of transactional leadership. However, because it tends to emphasize standardized procedures over employee wellbeing, transactional leadership in SMEs has occasionally been linked to stress and burnout (Berisha et al., 2024).

By contrast, SME managers that deploy transformational leadership emphasize intellectual stimulation, internal motivation, individualized consideration, and shared long-term objectives. Trends across multiple SMEs that incorporate transformational leadership have shown a statistically significant positive association with sales growth, return on investment, and number of employees (Singh et al., 2024) as well as having increased trust, innovation, performance, and employee retention (Song, 2025). Because of the vast benefits of transformational leadership, certain regions, such as Europe, see it as the dominant leadership style in SMEs (Berisha et al., 2024).

Altogether, leadership styles are a crucial mechanism for interpreting the risk and feasibility of adopting Gen AI. A transactional approach works best for implementations of Gen AI characterized by well-defined performance objectives containing narrow scopes. However, because this technology often necessitates extensive experimentation and learning, an overreliance on transactional management may result in higher stress along with less long-term value. Transformational leadership, by contrast, is better suited for the experimentation and learning phases in Gen AI adoption. Its promotion of employee trust and intellectual stimulation supports the complexity of implementation. Ultimately, the leadership style that an SME deploys will be an important factor in the success of Gen AI integration into the business.

Culture. A pivotal factor in an organization for determining their readiness to adopt technology is their culture. A popular framework used for understanding organizational culture is the cultural dimensions theory established in Hofstede et al. (2010, p. 31). This book contains sections that detail each of the six dimensions, which are the levels of power distance, individualism, masculinity, uncertainty avoidance, long-term orientation, and indulgence. Table 1 highlights common classifications for SMEs in each dimension.

Table 1: A breakdown of cultural dimensions in Hofstede et al. (2010) based on a typical SME

Cultural Dimension	Description of a Typical SME
Power Distance	*Low:* SMEs often deploy a structure that promotes decentralized authority (Angeles et al., 2022; Lussier, 2019, p. 209).
Individualism vs. Collectivism	*Both:* Aspects of each usually exist in an SME, but characteristics, such as the style of leadership and national culture, will ultimately affect this dimension (Markopoulos et al., 2021; Upson et al., 2023).
Masculinity vs. Femininity	*Both:* Levels of masculinity and femininity are highly dependent on the SME, but qualities of each are typically present (Markopoulos et al., 2021).
Uncertainty Avoidance	*High:* Most SMEs tend to be risk-averse, fearing that risky innovations could burden them with significant costs (Carayannis et al., 2024; Kallmuenzer et al., 2024; Markopoulos et al., 2021).
Long-term vs. Short-term Orientation	*Short-term:* SMEs usually focus heavily on daily operations rather than long-term planning (Dörr et al., 2024; OECD, 2023, p. 63).
Indulgence vs. Resistance	*Both:* Many factors can determine the levels of indulgence and resistance that an SME possesses, with one of the most significant being the culture of the nation (Upson et al., 2023).

Each of the six dimensions in Hofstede et al. (2010) that constitute organizational culture influences how decisions are made within SMEs. For deciding to adopt a technology like Gen AI, an attribute such as low power distance may support faster communication and inclusive decision-making. Although, other common SME attributes, including short-term orientation and high uncertainty avoidance, can present barriers to implementation. SMEs are frequently characterized by their slow, troublesome technology adoption process (Kallmuenzer et al., 2024; OECD, 2023, p. 63), and certain cultural factors are significant contributors to this phenomenon. Thus, cultural dynamics play an important role in shaping SME readiness to adopt Gen AI.

Importance of Value Generation in SMEs

Value generation can seem like an ambiguous term, especially given that value can include anything from measured impacts to perceived usefulness. Common components of business value include financial, time, quality, emotional, social, security, accessibility, informational, societal, and environmental value. Businesses, such as SMEs, often frame and measure value generation from technologies based on a subset of these components.

For SMEs, achieving positive value generation is an essential factor influencing how they adopt new technologies. Unlike larger enterprises — which can afford to make riskier decisions due to their greater pool of resources — SMEs often demand a higher level of certainty that the business ventures they pursue will add value. To properly assess the value of a project, financial components are usually the salient considerations, followed by other components of value (Carayannis et al., 2024). Unfortunately for SMEs, their limited working capital and high exposure to financial shocks force them to focus on smaller, safer projects, where the overall value generated may be reduced (Nicolas, 2021). This phenomenon, along with necessary time and energy investments, presents severe barriers to the large-scale adoption of Gen AI tools. Even though Gen AI can provide numerous benefits, a typical SME will have high uncertainty avoidance toward its assimilation. Thus, as highlighted by Carayannis et al. (2024) and Schwaeke et al. (2024), precarious value generation can deter SMEs from funding projects that involve AI integration.

Generative AI Technology Overview

Defining Gen AI and Machine Learning

Artificial intelligence (AI) is a popular term that describes computer systems that behave with cognitive abilities akin to humans. Part of the Fourth Industrial Revolution, AI can accomplish complex tasks such as deduction, pattern recognition, and interpretation of big data (Kalota, 2024). Generative artificial intelligence (Gen AI) refers to a subset of AI that is capable of creating seemingly new content. Unlike other forms of AI, Gen AI specializes in producing results that resemble human-created artifacts. Currently, Gen AI has the ability to generate text, images, audio, and videos based on training data (Feuerriegel et al., 2023).

At a foundational level, Gen AI models are built on machine learning (ML) architectures. ML refers to the class of algorithms that learn statistical patterns through iteratively optimizing parameters in a model designed to perform a task. The important quality of ML is that it allows machines to learn without direct human involvement in parameter optimization — giving them the ability to create output (Feuerriegel et al., 2023; Kalota, 2024). The output generated is probabilistic, meaning that it is synthesized based on what the machine estimates to be contextually relevant. Overall, this generative capability offers a powerful tool that can support humans with cognition and creativity (Glantz et al., 2024).

Common Technology Models

The main models currently used for Gen AI applications are large language, diffusion, and multimodal models. While other algorithms exist, such as generative adversarial networks, autoregressive models, and variational autoencoders, their overall footprint in the commercial space is considerably smaller. Thus, this literature review only covers the three most widely used models to date.

Large Language Models. One of the most prominent categories within Gen AI is large language models (LLMs). These models are trained on vast sets of textual data so that they can predict what words should come next within a sentence (Kalota, 2024). While there are many families of LLMs, generative pretrained transformers (GPTs) are among the most popular since their release in 2022 (Feuerriegel et al., 2023). They are commonly used for summarization, translation, code generation, question answering, and general writing. Ultimately, their high versatility is a significant factor contributing to their interest within organizations.

Diffusion Models. The capabilities of Gen AI extend beyond just text-based systems. Generation of images and videos relies on techniques from computer vision, a field within AI, while generation of audio occurs using similar methods. The process of probabilistically generating media is typically conducted via a diffusion model. In this type of model, machines are trained to reverse a process that gradually degrades the quality, also called increasing the noise, of training data. As a result, a machine can construct media by starting from complete noise and gradually removing it (Croitoru et al., 2023). Having complex diffusion models available to businesses allows for new problem-solving techniques along with the acceleration of creative workflows.

Multimodal Models. A newer development within Gen AI includes multimodal models which operate through numerous datatypes. These models are more versatile, as machines generate the most intuitive output rather than always using the datatype of the input. Some popular examples of multimodal models include Codex for text-to-code, MusicLM for text-to-music, and GPT-4 for image-to-text generation (Feuerriegel et al., 2023). These tools extend the usability of Gen AI by supporting complex workflows in ways that mirror human problem-solving processes.

Example Use Cases in SMEs

While Gen AI technologies typically have a general-purpose design, their true value is showcased when used for specific tasks. With small and medium-sized enterprises (SMEs), Gen AI can be applied to areas that involve knowledge work, content generation, or decision support. The following subsections highlight four areas that Gen AI has been used in SMEs, according to an OECD (2025, pp. 16, 23) report.

Marketing and Customer Engagement. A common purpose of Gen AI within SMEs is to support customer-facing tasks. LLMs can be used to generate advertising content, personalized messages, and product descriptions (Chan and Choi, 2025; Glantz et al., 2024; Ooi et al., 2023). Furthermore, their use in AI chatbots has become popular even in small businesses — with many chatbots resulting in an improved customer experience (Carayannis et al., 2024; Kallmuenzer et al., 2024; Rizomyliotis et al., 2022). Diffusion models also can support marketing efforts, providing advertising as well as inspirational content to users in both image and video formats (Chan and Choi, 2025). The overall appeal of Gen AI with marketing and customer engagement lies in its ability to rapidly produce content that aligns with the values of the brand. While there are challenges with hallucinations, privacy violations, and discrimination (Chan and Choi, 2025; Rizomyliotis et al., 2022), the numerous benefits of Gen AI have led to its use in these fields.

Operations and Process Support. Gen AI has greatly impacted SMEs with supporting and even automating certain business tasks. While it usually handles repetitive, rule-based objectives, Gen AI has begun facilitating work that has less structure and requires more creativity (Ooi et al., 2023). These tools can be applied to summarize meetings, generate reports, create designs for projects, conduct requirements analysis, draft emails, and more. Some SMEs see these use cases as particularly attractive because they reduce administrative and creative burdens that cost valuable time (Carayannis et al., 2024). While it cannot replace all operations and processes, the ability of Gen AI to facilitate many different tasks in an SME gives it significant value.

Information Technology and Software Development. Multiple researchers within the field of technology management believe that information technology (IT) is critically important, as more managers are digitizing their businesses (Kallmuenzer et al., 2024; Molete et al., 2025; Ooi et al., 2023). So, for SMEs, relying on Gen AI to support their IT and software management can be advantageous. In IT, use cases for Gen AI include code generation (Ooi et al., 2023), IT help desk support (Feuerriegel et al., 2023), and data analysis (Carayannis et al., 2024). As for software development, Gen AI can aid in creativity, market research, and streamlining development cycles (Glantz et al., 2024). Similar to other Gen AI applications, there are risks to deploying the technology in IT and software development fields, but its benefits can still leave a largely positive impact on an SME.

Management and Decision Support. Another significant area of Gen AI applications in SMEs is with support in management and decision-making. Generally, AI technology aims less to replace managers and instead focuses more on providing insights to complement human judgment (Górka et al., 2025). The ability of an LLM to generate predictive analytics, brainstorm options, create risk assessments, analyze market trends, synthesize big data, and identify growth opportunities assists with managing people and finances (Carayannis et al., 2024). Moreover, this technology enables SME leaders to rely on data-driven decisions rather than simply listening to the highest-paid person's opinion (HiPPO). While HiPPOs can be useful, they are often based on too much intuition and not enough data, making them risky to constantly leverage (McAfee and Brynjolfsson, 2012). Gen AI is not a perfect alternative either, as it can hallucinate or violate privacy agreements. However, because it is typically accurate, incorporating Gen AI technologies into SME management and decision support limits risk (Li, 2025) and positions a business toward greater success as well as sustainability (Carayannis et al., 2024).

Benefits and Challenges

Gen AI presents significant advantages and limitations for SMEs. To properly assess the different aspects of Gen AI, Table 2 applies a strengths-weaknesses-opportunities-threats (SWOT) analysis framework. This approach allows for a balanced evaluation of internal strengths and weaknesses along with external opportunities and threats that can influence adoption.

Table 2: A SWOT analysis pertaining to relevant Gen AI characteristics in SMEs

SWOT Component	**Analysis of Gen AI in SMEs**
Strengths (Internal Benefits)	• Enables easier scalability in both cognitive and creative tasks (Carayannis et al., 2024; Rajaram and Tinguely, 2024; Schwaeke et al., 2024) • Reduces administrative burden — which boosts productivity — by streamlining repetitive tasks, such as documenting and communicating (Ooi et al., 2023; Rajaram and Tinguely, 2024) • Enhances decision support through effective evaluations of big data (Carayannis et al., 2024; Feuerriegel et al., 2023; Li, 2025; Ooi et al., 2023; Rajaram and Tinguely, 2024) • Lowers barriers to entry for sophisticated analytical and creative tools by having cloud-based software-as-a-solution (SaaS) options, with many containing free tiers (OECD, 2025, pp. 12–13) • Capable of supporting differentiation strategies and offering personalized experiences (Carayannis et al., 2024; Rajaram and Tinguely, 2024) • Has applications in many industries (Carayannis et al., 2024; Feuerriegel et al., 2023)
Weaknesses (Internal Challenges)	• Generates probabilistic outputs that are occasionally unreliable, as instances of AI hallucinations can be inaccurate or misleading (Carayannis et al., 2024; Glantz et al., 2024; Ooi et al., 2023) • Wavers in quality when the available data is either insufficient or irrelevant, meaning that its effectiveness is highly contingent on the training and input data provided (Ooi et al., 2023) • Loses effectiveness when the SMEs using it lack the proper technical expertise, organizational culture, and internal policies required to maximize its capabilities (OECD, 2025, p. 41)
Opportunities (External Benefits)	• Often yields a competitive advantage to early adopters in an industry (Carayannis et al., 2024; Kallmuenzer et al., 2024), which is due to the positive aspects detailed in the Strengths section • Can improve organizational resilience through analysis and planning capabilities (Carayannis et al., 2024; OECD, 2025, pp. 6, 11) • Likely will increase accessibility and usability, meaning more SMEs can participate in adopting the technology (Carayannis et al., 2024, Feuerriegel et al., 2023)

Threats (External Challenges)	• Sometimes develops issues related to data privacy, intellectual property, and algorithmic bias, which can pose legal and ethical risks (OECD, 2025, p. 45; Rajaram and Tinguely, 2024) • Potential of needing to change strategies if new compliance regulations are introduced, which can be devastating for many SMEs, as they often lack compliance resources (Carayannis et al., 2024; Rajaram and Tinguely, 2024) • Can lead to a lock-in effect, where SMEs rely on third-party software that may negatively change in the future, such as price hikes or discontinued services (Rajaram and Tinguely, 2024) • May lack clear value generation and successful implementation strategies, leading to potential failures in adoption (Carayannis et al., 2024, Schwaeke et al., 2024)

Ultimately, the value of Gen AI is neither universally beneficial nor inherently detrimental. Instead, both internal and external factors greatly influence the effectiveness of the technology within a business. Given the resource constraints within SMEs, knowing how to effectively adopt Gen AI into their business is therefore crucial for success.

Analysis of Technology Adoption

Technology Adoption as a Multi-Level Process

Enterprise technology adoption is increasingly conceptualized as a multi-faceted undertaking shaped by the complex relationships between individual decision-makers, organizational characteristics, industry environments, and the technology being integrated (Reim et al., 2020; Schwaeke et al., 2024; Zamani, 2022). With so many intricacies involved, technology adoption is often viewed as more than just a simple snapshot event. After all, different theories exist to frame the various driving factors involved in the success of integration so that businesses are better informed.

For SMEs, the stakes of successful adoption are further heightened, as their profit and operational margins are smaller than those of large enterprises (Schwaeke et al., 2024). While the confined nature of SMEs does provide some benefits for technology integration, the significant internal resource constraints that they face can heighten perceived risk and slow adoption (Kallmuenzer et al., 2024). Moreover, external factors can also significantly affect their strategies for preparation, implementation, and sustentation. Given this convoluted set of components affecting adoption, properly understanding the integration of a technology, such as Gen AI, into SMEs requires analytical frameworks that account for both internal and external developments. So, the following two sections apply these types of frameworks to examine influences.

Analysis Through the Technology-Organization-Environment Framework

Introduced by Tornatzky and Fleischer (1990), the Technology-Organization-Environment (TOE) framework views technology adoption through three lenses rather than as a single factor. With a logical containerization of components, this model is currently the most popular for understanding why companies adopt technology (Zamani, 2022). The multi-dimensional structure of TOE makes it ideal for exploring Gen AI adoption, which introduces its own complexity and risk.

Figure 1 illustrates a TOE framework for adopting Gen AI into SMEs. This image is a summation of three peer-reviewed frameworks that incorporate either SMEs or Gen AI. Hughes et al. (2026) found statistically significant factors influencing Gen AI adoption in businesses, Schwaeke et al. (2024) analyzed 106 peer-reviewed articles that delved into how SMEs use AI, and Sánchez et al. (2025) created a TOE-DOI framework to also explain the factors impacting AI adoption in SMEs. All three of their models highlight important components for each of the three frames that encompass TOE.

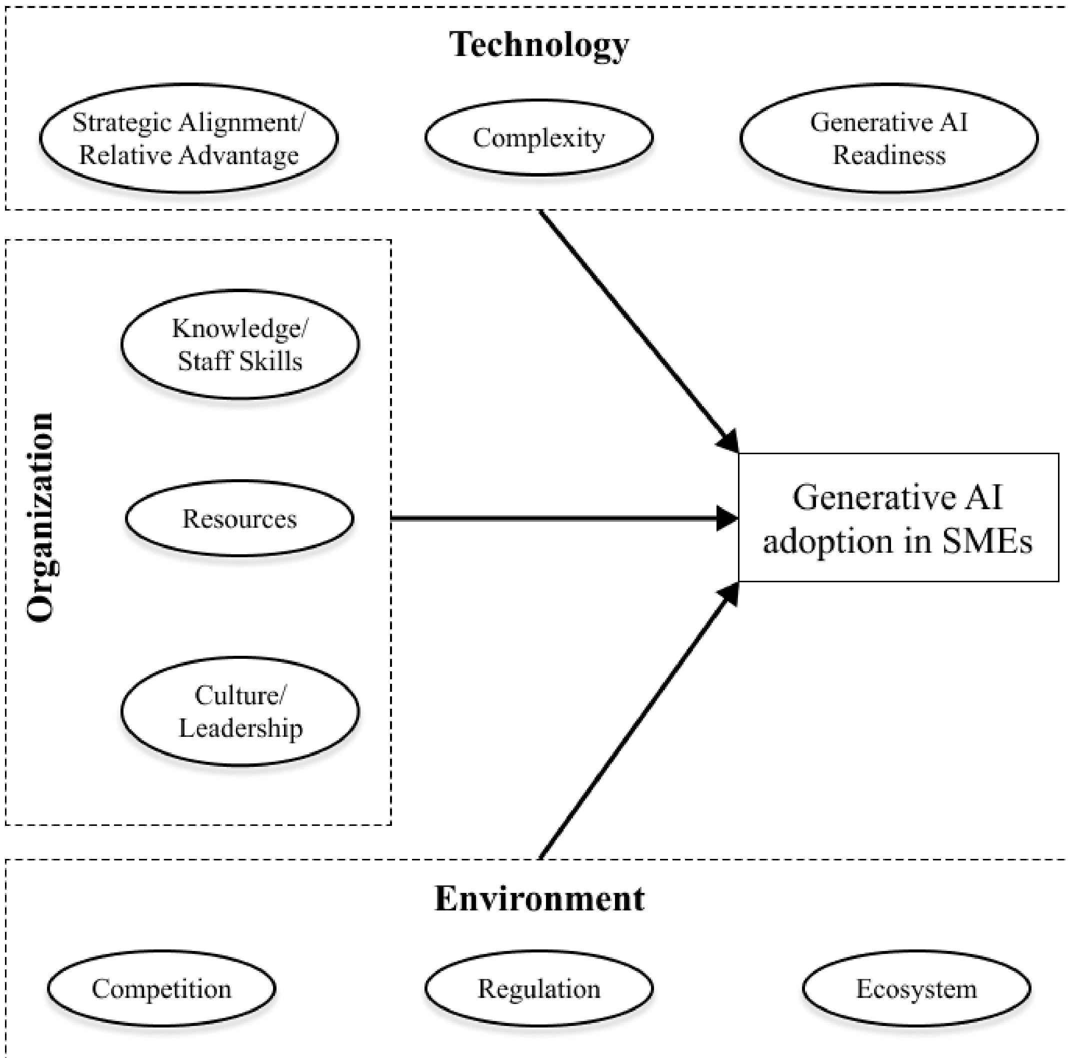

Figure 1: A TOE framework for depicting key factors influencing Gen AI adoption in SMEs, according to findings from Hughes et al. (2026), Sánchez et al. (2025), and Schwaeke et al. (2024)

Technology Factors. To adopt Gen AI, SMEs should ensure they are aligned with three salient technological factors found in Figure 1: strategic alignment as well as relative advantage, complexity, and Gen AI readiness.

With the first point, strategic alignment refers to the ability for Gen AI to follow business objectives (Schwaeke et al., 2024). A related aspect, relative advantage, reflects the degree to which adoption is perceived as beneficial to the organization (Hughes et al., 2026). These two concepts are similar in nature, as they both pertain to achieving long-term SME goals. Firms that have strong strategic alignment with Gen AI and envision its relative advantage are more likely to adopt it.

The second technological factor affecting adoption is complexity. Complexity typically refers to integration and learning challenges, but it can also deal with the difficulty in affirming or simply deciphering output. SMEs will have greater ease of adoption if their planned Gen AI usage carries low complexity (Hughes et al., 2026; Sánchez et al., 2025).

The final technological factor to consider is Gen AI readiness. This aspect evaluates the level of fit that Gen AI possesses within the existing technological infrastructure. In situations where Gen AI readiness is low, SMEs may perceive investments in proper infrastructure or training as excessive. By contrast, companies that show stronger capability in integration are more likely to adopt Gen AI (Sánchez et al., 2025; Schwaeke et al., 2024).

Organization Factors. Shown in Figure 1, the ease in adopting Gen AI for an SME partially depends on its knowledge as well as staff skills, resources, and culture as well as leadership.

Employee knowledge and skills are a pivotal organizational factor. In this context, knowledge is a holistic term encompassing everything from personal understanding to the level of information exchange that typically occurs (Schwaeke et al., 2024). Similarly, staff skills focus on the application of knowledge to solve problems (Hughes et al., 2026). SMEs that have high knowledge and staff skills will have a greater advantage in adopting Gen AI.

A second significant organizational factor is resources. Within organizations, resources can be subdivided into human, financial, time, intellectual property, physical, legal, and more. SMEs are well-known for their dearth of resources (Carayannis et al., 2024; Kallmuenzer et al., 2024), but those that have a greater wealth will have an easier time adopting Gen AI (Sánchez et al., 2025; Schwaeke et al., 2024).

The last major organizational factor impacting Gen AI adoption in SMEs is organizational culture and leadership. Most SMEs have a culture that supports decentralized decision-making, flexibility, and speed (Angeles et al., 2022; Lussier, 2019, pp. 207–209). If they can leverage these qualities to quickly communicate and learn, then their culture will facilitate the Gen AI integration process. With leadership, neither transactional nor transformational styles are necessarily perfect for adoption. While Schwaeke et al. (2024) mentions the benefits of promoting proactive learning, skill development, and adaptability — all hallmarks of transformational leadership — the significance of strong transparency mentioned by both Hughes et al. (2026) and Schwaeke et al. (2024) suggests that transactional leadership can also be effective. Ultimately, regardless of the specific leadership style, SME leaders that implement strong communication and positive learning environments will be better positioned for adoption.

Environment Factors. SMEs looking to integrate Gen AI into their business can be influenced by three external factors present in Figure 1. These components include industry competition, legal regulation, and ecosystem opportunities.

The percentage of competition that is adopting Gen AI can greatly influence whether an SME integrates their own solution (Sánchez et al., 2025). These external pressures are motivating because emerging technologies can give competitive advantages to firms that are early adopters (Schwaeke et al., 2024). Thus, the pressure from other companies can influence Gen AI adoption within an SME.

Another environmental factor that may impact the decision to integrate Gen AI into an SME is regulation. Given the current lack of a legal framework for Gen AI — along with the tendency for SMEs to suffer from legal insecurity — future regulations could drastically affect the rate of successful adoption (Schwaeke et al., 2024). However, the current impact of government policies may be less important compared to other factors. In the study conducted by Hughes et al. (2026), testing the causal relationship between regulation and adoption rates yielded an insignificant association. Although, while current regulation may not always be a pivotal factor, Hughes et al. (2026), Sánchez et al. (2025), and Schwaeke et al. (2024) recognized that future regulatory practices could still have some significant impact on the landscape of adoption.

A third environmental factor that can impact adoption is the ecosystem. The ecosystem describes external opportunities for SMEs to collaborate with other organizations to improve the potential of Gen AI. Leveraging these joint initiatives enables SMEs to avoid large internal investments in resources and provides SMEs with more diverse knowledge. Results from collaboration can be highly beneficial, such as instances of innovative product development and enhanced access to export markets (Schwaeke et al., 2024). Therefore, the opportunities made available through the ecosystem can lead to more successful adoption of Gen AI.

Analysis Through Complementary Perspectives

While the TOE framework offers a robust construct of major lenses for analyzing Gen AI adoption, it does not fully capture all aspects of integration. To truly have a holistic understanding of the reasoning and methods for adopting Gen AI in SMEs, it is best to incorporate the findings that other theories provide. The following complementary perspectives, summarized in Table 3, highlight how technology is adopted both individually and in social systems.

Individual Acceptance Models. A limitation of analyzing solely through the TOE framework is that it heavily focuses on adoption at a macro scale (Sánchez et al., 2025). This issue is mitigated by the Technology Acceptance Model (TAM) — one of the most widely used technology adoption frameworks (Zamani, 2022) — which assesses how individual perceptions within an SME influence adoption decisions. In TAM, the two most important variables for individuals adopting technology are perceived usefulness (PU) and perceived ease of use (PEOU). PU depicts the extent to which an individual believes integrating a system would personally benefit their performance; PEOU, by contrast, denotes the degree of belief an individual possesses in the simplicity of operating a system (Nurqamarani et al., 2021; Venkatesh et al., 2003; Zamani, 2022). While TAM does highlight other factors affecting adoption, according to Nurqamarani et al. (2021), PU and PEOU are the most common factors in the model that affect individual technology adoption in SMEs.

Building on the foundation of TAM and other models, the Unified Theory of Acceptance and Use of Technology (UTAUT) proposes four core constructs determining technology integration at the individual level (Venkatesh et al., 2003). Two of the constructs, performance expectancy and effort expectancy, are similar to PU and PEOU respectively. The other two constructs are social influence, which refers to the pressures and expectations set by others to adopt technology, and facilitating conditions, which describes the degree of individual belief in the existence of supportive organizational and technological infrastructure. UTAUT also provides four modifiers, age, gender, experience level, and voluntariness, which affect the relationships between the core constructs and the behavioral intention or usage behavior.

UTAUT can be highly applicable in the context of Gen AI adoption by individual SME employees, as Venkatesh et al. (2003) used UTAUT to explain 70% of technology adoption variance in organizational settings. However, not all four constructs or modifiers will equally impact Gen AI adoption. Some constructs will likely have greater weight, such as how Kim et al. (2024) found only effort expectancy and social influence to significantly impact the individual adoption of Gen AI in South Korean companies. Still, UTAUT, along with TAM, can be effective tools for analyzing the reasons driving SME employees to integrate Gen AI into their work. Taken together, they suggest that Gen AI adoption ultimately depends on whether an individual in an SME believes that Gen AI is valuable, usable, and socially supported.

Diffusion of Innovations Theory. Another complementary perspective to view Gen AI adoption in SMEs is through the Diffusion of Innovations (DOI) theory. Developed by Rogers (2003), DOI lists five main attributes that impact how innovations are communicated and integrated into a social system. Three attributes — relative advantage, compatibility, and complexity — are closely related to factors mentioned in TOE, TAM, and UTAUT. However, DOI also argues for the importance of observability, the degree to which results can be easily seen by others, and trialability, the level of experimentation available before full integration. Both observability and trialability are especially relevant for Gen AI adoption, as they help explain why the novelty of this technology often leads to greater uncertainty in its potential value. The inclusion of these terms within DOI therefore supports the understanding of how Gen AI spreads through social systems over time.

Ultimately, DOI is an important perspective to include because it reasons that Gen AI adoption can accelerate once organizations have a better understanding of the value in this technology. Thus, an essential finding from DOI is that the ability to easily observe results from the adoptions of other organizations along with the ability to test the technology before fully scaling up makes SMEs more likely to adopt Gen AI.

Table 3: The most essential factors influencing adoption for three complementary theories

TAM	**UTAUT**	**DOI**
- Perceived Usefulness (PU)	- Performance Expectancy	- Relative Advantage
- Perceived Ease of Use (PEOU)	- Effort Expectancy	- Compatibility
	- Social Influence	- Complexity
	- Facilitating Conditions	- Observability
		- Trialability

Insights from Practitioner Research

Industry-level insights produced by practitioner research are another important perspective for analyzing Gen AI adoption. While the scope of practitioner research typically encompasses organizations of all sizes, the information is still relevant to SME-specific adoptions. This section highlights two key insights on Gen AI adoption.

Total Adoption Rates. Figure 2, displayed in a report by McKinsey (Singla et al., 2025), illustrates the rapid growth of Gen AI use in organizations since worldwide surveying began in 2023. According to the report, the sample of respondents using Gen AI jumped from 33% in 2023 to 79% in 2025. General AI usage also accounts for a majority of respondents in 2025; however, McKinsey reports that 62% of general AI users are only experimenting or piloting with the tools. Essentially, the takeaway from this figure is that while adoption rates are high, only a minority of organizations have maximized the potential value from Gen AI adoption.

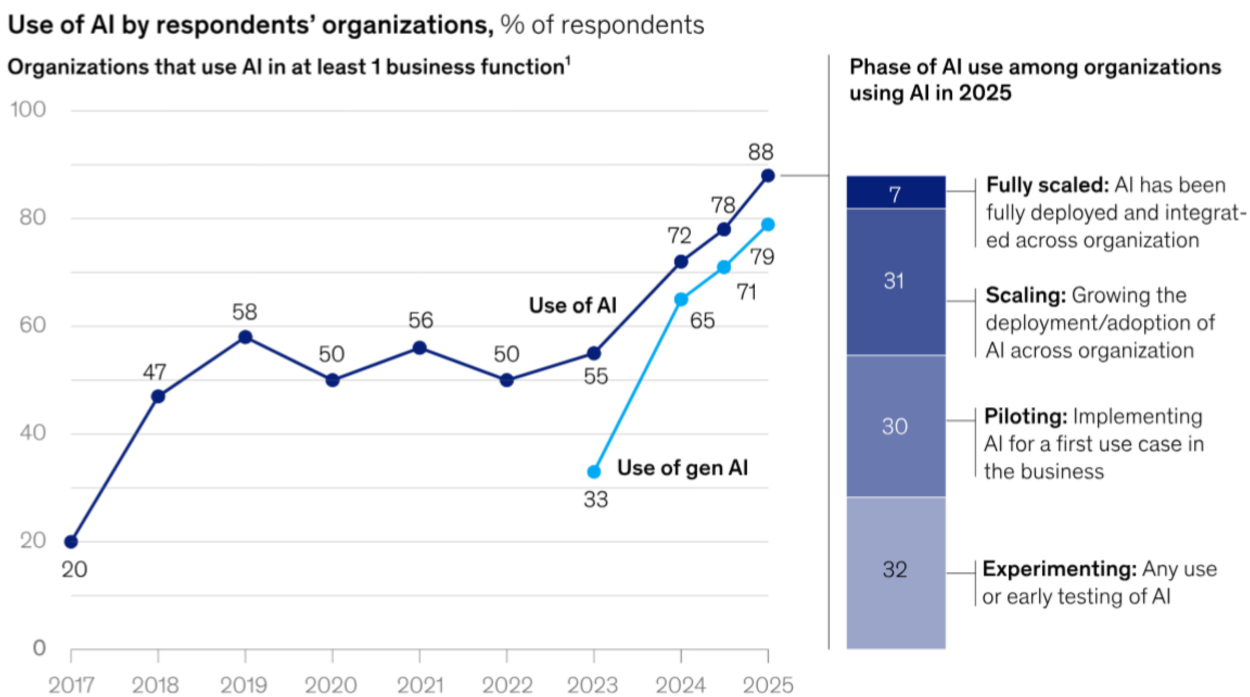

Figure 2: Worldwide survey results displaying yearly total adoption rates for AI and Gen AI along with the phases of AI integration for the 88% of AI users in 2025 (Singla et al., 2025)

Gartner Hype Cycle. Shown as a line graph comparing industry expectations over time, the Gartner Hype Cycle depicts the five phases that new technologies typically experience. According to a report from Gartner (Khandabattu, 2025), the hype surrounding Gen AI expectations has begun to fall as the technology has entered the phase called the Trough of Disillusionment: a natural point that occurs when the capabilities and limits for a particular technology become better understood. In the report, the Trough of Disillusionment for Gen AI has come with the claim that over 70% of CEOs for AI-leading companies are unhappy with their return on investment. Additionally, organizations classified as possessing low maturity are struggling to identify appropriate use cases that have realistic expectations. From this report, the main takeaway is that, as organizations begin to realize the limitations of Gen AI, many struggle to generate long-term sustainable value from adoption.

Summary of Findings. The practitioner insights from McKinsey and Gartner suggest that, despite the rapid acceleration of Gen AI adoption, numerous organizations are still struggling to convert experimentation into sustained value. Therefore, an important indication is that organizations — especially SMEs due to their high uncertainty avoidance and resource constraints — would significantly benefit from a structured framework that could guide them through strategically and realistically integrating Gen AI to capture long-term value.

GSVF Overview

Introduction to the Five-Layer Framework

Building upon the established theoretical foundations of SMEs, Gen AI, and technology adoption, this thesis proposes a five-layer framework designed to support SMEs in maximizing the value generated from Gen AI adoption. While existing models, such as TOE, TAM, UTAUT, and DOI, help explain why organizations adopt technology, they do not provide a roadmap within this scope for ensuring that adoption leads to sustained value. Thus, the Gen AI-SME Value Framework (GSVF) addresses this gap by acting as a decision support tool specifically designed for SMEs aiming to either initiate or further advance Gen AI integration into their organization.

Figure 3 presents the GSVF, which has five vertically stacked stages: Foundational, Strategic, Implementation, Performance Measurement, and Sustainability. These layers are sequential in logic, meaning that they progress upward as indicated by the arrows. This ascending movement resembles the construction of a stable structure, where each successive layer depends on the robustness and stability of the layers below. Modeling the five stages as a structure gives a visual depiction of how successful adoption occurs. For instance, if an SME tries to implement Gen AI with brittle foundational reasoning and poor strategic alignment, their structure is likely to crumble and result in a failed adoption. Therefore, based on the layout of the framework, sustainable value from Gen AI can only be achieved if an SME properly addresses its foundational need, strategic alignment, adequate implementation, and performance evaluation.

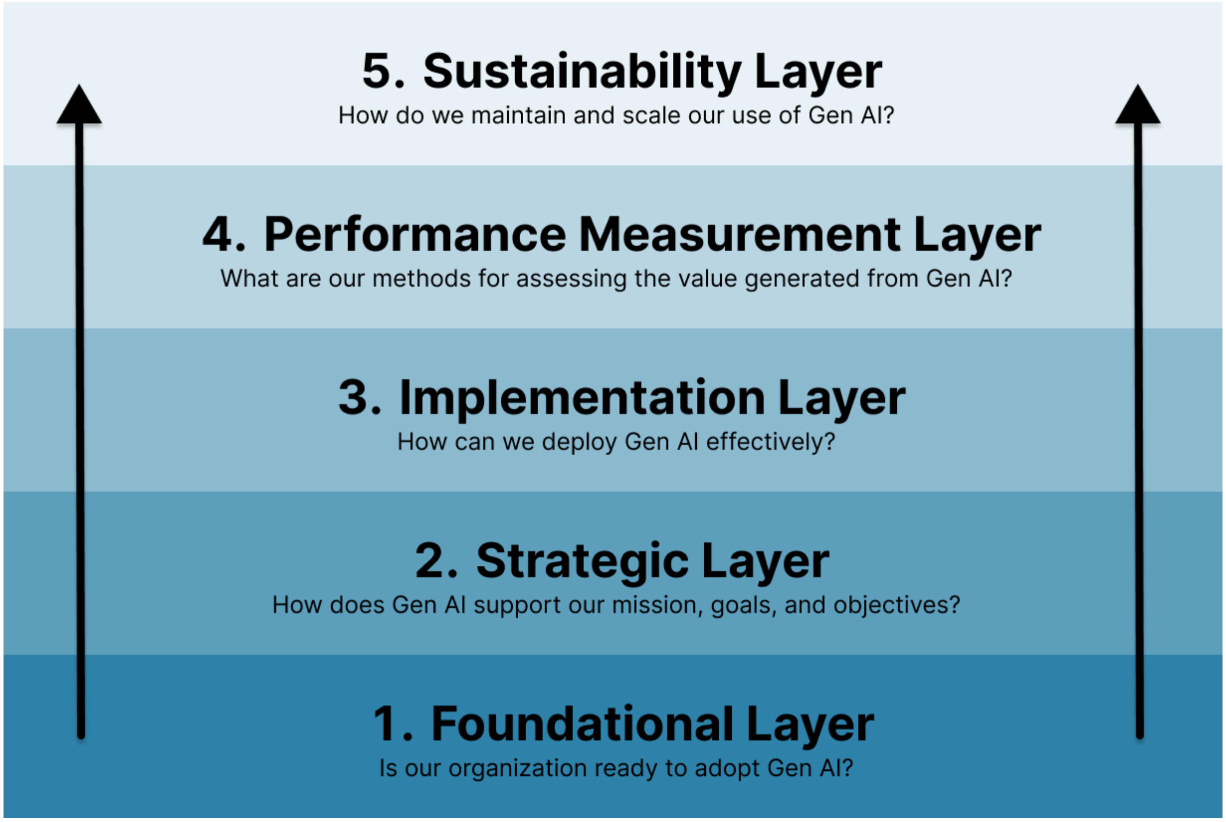

Figure 3: The framework for this thesis, named the GSVF, shown as a vertical five-layer stack

Description of Each Framework Layer

Foundational Layer

Serving as the bottommost piece, the Foundational Layer represents the overall organizational readiness to adopt Gen AI. This layer encompasses many of the principles that TOE, TAM, UTAUT, and DOI identify as important for technology adoption (Hughes et al., 2026; Nurqamarani et al., 2021; Rogers, 2003; Sánchez et al., 2025; Schwaeke et al., 2024; Venkatesh et al., 2003; Zamani, 2022). Specifically, the Foundational Layer focuses on the perceived usefulness (PU) of the technology; organizational leadership, culture, and resources; environmental competition; and social influence. Without adequate readiness, Gen AI initiatives risk underutilization, organizational conflict, and potential failure. Thus, the recommended questions in Table 4 highlight these research-supported principles so that SME decision-makers can evaluate whether they are ready to consider Gen AI adoption.

Strategic Layer

The next layer in the framework stack is the Strategic Layer, which ensures that the Gen AI tools have a relevant purpose for adoption. Here, any identified technology use case should have strategic alignment, as defined in TOE (Schwaeke et al., 2024), with the line-of-business goals and the overall enterprise architecture. Ignoring this alignment puts successful implementation in jeopardy, as the integration can be plagued with wasted resources, poor decision-making, and no clear vision. Applications that best contribute to this layer tend to support a competitive advantage and have strong Gen AI readiness, meaning they are highly compatible with the existing technology infrastructure.

Implementation Layer

Situated as the middle component, the Implementation Layer focuses on the operational execution of Gen AI adoption. By this point, an SME should have already identified its use cases for Gen AI, specified the tools they plan on using, and aligned all projects to the broader strategy of the business. The smoothest implementations at the individual level will naturally come from employees with high staff skills along with a favorable perception of trialability and ease of use (PEOU), as defined in prior adoption research (Hughes et al., 2026; Nurqamarani et al., 2021; Rogers, 2003; Venkatesh et al., 2003; Zamani, 2022). Employees who do not share these characteristics will find greater difficulty in integrating Gen AI into their workflow, which could lead to less value generated if they cannot surmount these challenges. So, this execution stage is critical to achieving sustainable success with Gen AI.

Performance Measurement Layer

Following the implementation process, the framework then addresses the Performance Measurement Layer. In this stage, SMEs create a method for tracking the value generated from using Gen AI. Organizations with the strongest performance measurement systems have the capability to link the value generation of each use case back to the strategic goals for adopting Gen AI. These institutions likely have high observability, as described by DOI (Rogers, 2003), with their use cases, simplifying the evaluation process. SMEs that do not have any formal methodology for measuring Gen AI performance can still realize sustainable value; however, that value must be clearly tied to key business objectives to achieve long-term success. In effect, this layer supports the transformation process from initial implementations to sustained success.

Sustainability Layer

The last and topmost layer in the framework stack is the Sustainability Layer. This piece describes the ability for an SME to get long-term value from Gen AI, and it is consequently dependent on the success of all other layers. Future external factors displayed in the TOE model (Hughes et al., 2026; Sánchez et al., 2025; Schwaeke et al., 2024), including new competition, government regulation, and ecosystem opportunities, will test the robustness of the five-layer adoption structure. SMEs that choose to properly address each layer will find most future changes in the Gen AI landscape more manageable, as they have aligned their adoption style to the academic research that supports successful long-term adoption. Ultimately, the goal for SMEs adopting Gen AI is to achieve success in this culminating layer.

Guidelines for Framework Use

While the GSVF provides the conceptual structure for understanding the stages of Gen AI adoption in SMEs, its main objective is to serve as an effective support tool for decision-makers. In practice, people can apply the framework by asking layer-specific questions that help diagnose issues and assess the ability of their SME to satisfy the goals of each adoption stage.

Table 4 displays a recommended set of appropriate questions that can guide decision-makers toward successful adoption. Here, the sample questions are designed to be answered in either a yes–no binary format, which is easier for unbiased analysis, or through descriptive storytelling, where the quality of the responses must be subjectively evaluated.

When the decision-makers in an SME believe that they have satisfied the current stage and can advance to the next stage of questions, an important point to highlight is that they may feel a need to revisit the current stage later. For instance, insights gathered from the Performance Measurement Layer may reveal weaknesses in the Foundational, Strategic, or Implementation layers. In cases like these, the framework should become iterative rather than purely sequential, as returning to previous layers to fix identified problems could represent the pivotal factor in achieving sustainable success in Gen AI integration. Ultimately, while the GSVF acts as a beneficial decision support tool, leaders within SMEs are still responsible for making the correct evaluations that guide the company to successful adoption.

Table 4: A recommended set of questions that address the primary goal of each layer

Foundational Layer
• What enabling factors support our ability to adopt new technologies? • What inhibiting factors make it difficult for us to adopt new technologies? • Have we had success in surmounting our inhibiting factors in past technology adoptions? If so, how? If not, why? • What specific Gen AI use case (or use cases) have we identified? • What specific Gen AI tool (or tools) do we plan to use?
Strategic Layer
• What are the mission, vision, and primary objectives of our company? • What value are we hoping to gain from our Gen AI use case (or use cases)? • How will the value generated from Gen AI adoption specifically improve our ability to fulfill the company mission, vision, and objectives? • Where are we applying Gen AI? Will adoption be for specific positions, lines-of-business, or enterprise-wide?
Implementation Layer
• What typically goes right or wrong with technology adoption at our company? How can we limit the challenges that we typically encounter? • What budget and technological resources do we have to adopt Gen AI? Are these resources sufficient for the given use case (or use cases)? • Do our employees have experience using Gen AI? If so, do we believe it is adequate for the given use case (or use cases)? • Should our organization offer, or even mandate, a training course detailing how to effectively use Gen AI? Why or why not?
Performance Measurement Layer
• What tools or metrics do we plan on using to determine the value generated by Gen AI? • How can we value subjective metrics, such as the perceived usefulness (PU) or perceived ease of use (PEOU)? • What thresholds have we established to evaluate whether Gen AI adoption has been a net benefit? • Should we have formal meetings to discuss Gen AI value generation? Why or why not?
Sustainability Layer
• What metrics do we believe are the most important for our company to generate sustained Gen AI value? • What contingency plans do we have in place if the value generated from Gen AI falls short of our desired thresholds?

• What external threats are there for our continued use of Gen AI? What limit do these barriers need to exceed for us to switch tools or outright abandon Gen AI? • Have we conducted a risk assessment to estimate the likelihood that an external threat which negatively impacts our Gen AI usage occurs?

Practical Application of the GSVF

Research Purpose

To properly evaluate the insights that can be generated from the proposed five-layer framework, a qualitative research study was conducted in the form of semi-structured interviews. Rather than testing predefined hypotheses, these interviews were instead designed to analyze each layer through the contexts in which SME employees address Gen AI technology. This style ensured that the GSVF was grounded not just in existing research but also in real organizational environments. After concluding the interview process, insights gathered from participants were used to assess how effectively the GSVF functioned as a diagnostic support tool.

Methodology

Participants and Design

The research included a dozen total participants (n=12) who currently worked in an SME. Interview participants were only considered if they used a laptop or desktop for work, but no prior usage of Gen AI was required. In each interview, the names and organizations of participants were kept confidential, with only a general description of their fields shown in Appendix A as Table A1. Participants were recruited through a combination of Penn State University alumni networks, personal contacts, and additional channels. The sample of participants was purposely diverse in industry, as this structure allowed a wide variety of jobs and markets to apply the GSVF.

Every interview was conducted over Zoom, a video conferencing platform, and lasted between 20 and 30 minutes. Participants talked about their personal experiences adopting digital technologies in their SME, with a main focus on Gen AI tools. If applicable, they also would extend beyond their involvement to describe the experiences of their entire team or business.

Participants were asked structured questions surrounding the five conceptual layers of the GSVF: Foundational, Strategic, Implementation, Performance Measurement, and Sustainability. The full list of structured questions is shown in Appendix B as Table B1. Also in the question list were optional bonus questions that were asked if appropriate and if time permitted. The third type of questions asked was not written in the question list, as it consisted of spontaneous follow-up questions used to probe specific topics further.

Procedure and Data Analysis

At the beginning of each interview, participants were provided with a brief overview that described the purpose of this research, defined Gen AI technology, and reminded them that no prior Gen AI experience was required. Participants were also informed that the call was confidential, but a recording would be kept for analysis. Following this introduction, the interview would proceed until either all questions were answered or the allotted time expired.

After all the interviews were conducted, the transcripts generated from the Zoom recordings were used for data analysis. To qualitatively analyze the data, a deductive coding matrix was developed in Microsoft Excel based on the five layers of the framework. The codes, displayed in Table 5, describe themes that can be answered either with a “Y” (yes) or “N” (no) depending on whether dialogue within the interview supported it. Each participant was assigned these binary values after manually reviewing the transcript line-by-line. The results of the thematic coding matrix, displayed in Appendix C as Table C2, served as the foundational structure for comparing results and discovering patterns.

Table 5: List of binary themes for each layer of the GSVF

Foundational Layer	
❑ 1-A:	Identifies Multiple Current or Future Gen AI Use Cases
❑ 1-B:	Mentions Budget Constraints as Barrier to New Technologies
❑ 1-C:	Mentions Time Constraints as Barrier to New Technologies
Strategic Layer	
❑ 2-A:	Frames Gen AI Value as Financial Benefit
❑ 2-B:	Frames Gen AI Value as Increased Efficiency or Saved Time
❑ 2-C:	Frames Gen AI Value as Improved Output Quality
Implementation Layer	
❑ 3-A:	Mentions Difficulties with Adopting Past Technologies
❑ 3-B:	Mentions Lack of Technical or Skills Infrastructure
❑ 3-C:	States Importance for Having Structured Gen AI Training
Performance Measurement Layer	
❑ 4-A:	Evaluates Gen AI Value Through Informal Judgment
❑ 4-B:	Discusses Technology Value with Team or Leadership
❑ 4-C:	Relies on Formal Metrics to Assess Technology Value
Sustainability Layer	
❑ 5-A:	Perceives Gen AI as Providing Ongoing Benefits
❑ 5-B:	Uses Gen AI Due to Organizational Need or Requirement
❑ 5-C:	Mentions Potential for Abandoning Gen AI

To deepen the analysis, a Python script was used to calculate co-occurrences between themes. Shown in Appendix D, the script examined how often pairs of themes appeared across the 12 participants, highlighting relationship correlations within and between layers of the framework. These correlations were used to further identify how the GSVF aligned with real-world experiences.

Following the computational analysis, Excel was used to generate visualizations of the findings from the matrix and co-occurrences. These include a bar chart for showcasing commonly discussed themes (Figure 4), a heatmap for illustrating co-occurrence theme frequency (Figure C1), and a bar chart grouped by the total co-occurrences between any two layers (Figure 5). These visuals complement the qualitative insights by providing a structured view of the data.

Finally, specific quotations were selected in Table 6 to represent key patterns and themes gathered from the interviews. These excerpts were chosen due to their ability to effectively showcase how the framework can help reveal key points that SME employees encounter with Gen AI adoption. Altogether, the coding matrix, co-occurrence analysis, visualizations, and quotes depict how the GSVF can be used to ensure that SMEs effectively incorporate Gen AI into their business.

Results

Shown in Appendix C as Table C2, the thematic coding matrix displays the combination of “Y” (yes) and “N” (no) values given by the 12 participants for all 15 themes. The dataset ranges from a low of eight “Y”s, given by P4, and a high of 12 “Y”s, which were the totals for both P8 and P10. Thus, every participant aligned with a majority of themes, but no participant agreed to all 15 themes.

Figure 4 illustrates the total “Y”s given for each theme. It is ordered vertically from lowest to highest theme presence, and each theme is color coded by framework layer. All 12 participants both framed Gen AI value in terms of increased efficiency or time savings (2-B) and perceived Gen AI as providing ongoing net benefits (5-A). Additionally, 11 out of 12 participants mentioned some level of difficulty when adopting past technologies (3-A); framed the value of Gen AI in terms of improved output quality (2-C); and identified multiple, meaning at least two, specific Gen AI use cases they either currently implement or may consider implementing (1-A). On the other end of the chart, the lowest value came from the future potential of abandoning Gen AI (5-C), where only four participants explicitly considered it.

Analyzing by framework layers, one conclusion from Figure 4 is that each layer had at least one theme with 10 or more responses. In terms of total participant responses, the maximum possible score is 36 responses. However, in this sample, the Strategic Layer had the highest with just 28 responses, followed by the Foundational Layer (26 responses), Performance Measurement Layer (25 responses), Implementation Layer (24 responses), and Sustainability Layer (21 responses).

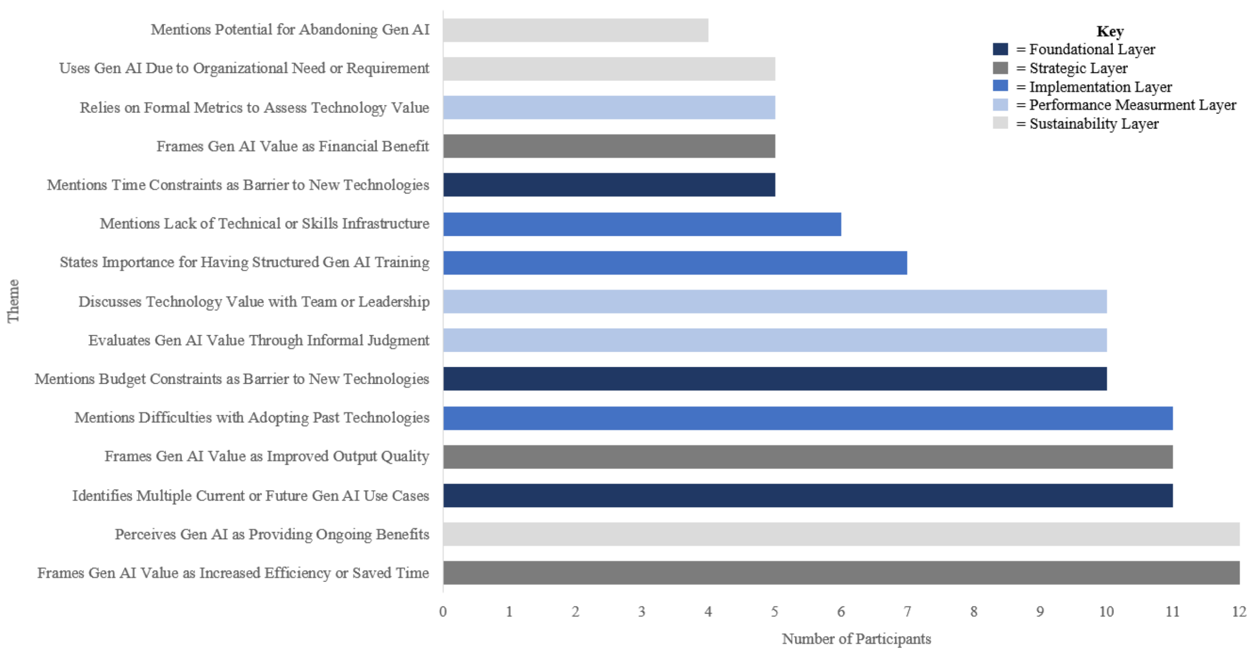

Figure 4: A bar chart comparing the total number of participant responses for each theme, with the bars color coded based on their framework layer

Figure C1, found in Appendix C, illustrates a heatmap of the results from co-occurrence analysis. In this figure, the number in a cell represents the total number of participants who mentioned both the theme on the horizontal and vertical axes of that cell. The range for cell values is zero to 12 responses. Values that are closer to zero are coded whiter, and values that are closer to 12 are coded greener. The only co-occurrence with responses from all 12 participants came from everyone mentioning that they both perceived Gen AI as providing ongoing net benefits and framed Gen AI value in terms of efficiency or time savings (5-A and 2-B = 12/12 respondents).

Figure 5 displays the co-occurrence results grouped by distinct framework layers. These calculations were made by summing the nine values found in each box of Figure C1, which represent all the co-occurrences for two different framework layers. An important point to note is that scoring a high or low total sum does not necessarily correlate with the ability of participants to properly address certain layers of the GSVF. Instead, this graph simply orders co-occurring layers based on how much resonance the participants had with the selected themes in those layers.

In Figure 5, the Strategic Layer is a part of the top three total participant sums. The highest value of the dataset came from the combination of Strategic Layer and Performance Measurement Layer themes, where 59 times there was co-occurrence. This fact is visually depicted in Figure C1, as the box containing co-occurrences for the Strategic Layer and the Performance Measurement Layer contains the greenest color overall. So, when comparing any two framework layers, this combination was the most likely to have any given participant support a theme from each layer.

On the opposite end, the Sustainability Layer is a part of the lowest three total participant sums. While theme 5-A, perceiving Gen AI as providing ongoing net benefits, always boasted at least five co-occurrences, themes 5-B and 5-C never had more than five co-occurrences. Thus, the low scores of 5-B and 5-C led to the Sustainability Layer having four of the five smallest bars in Figure 5.

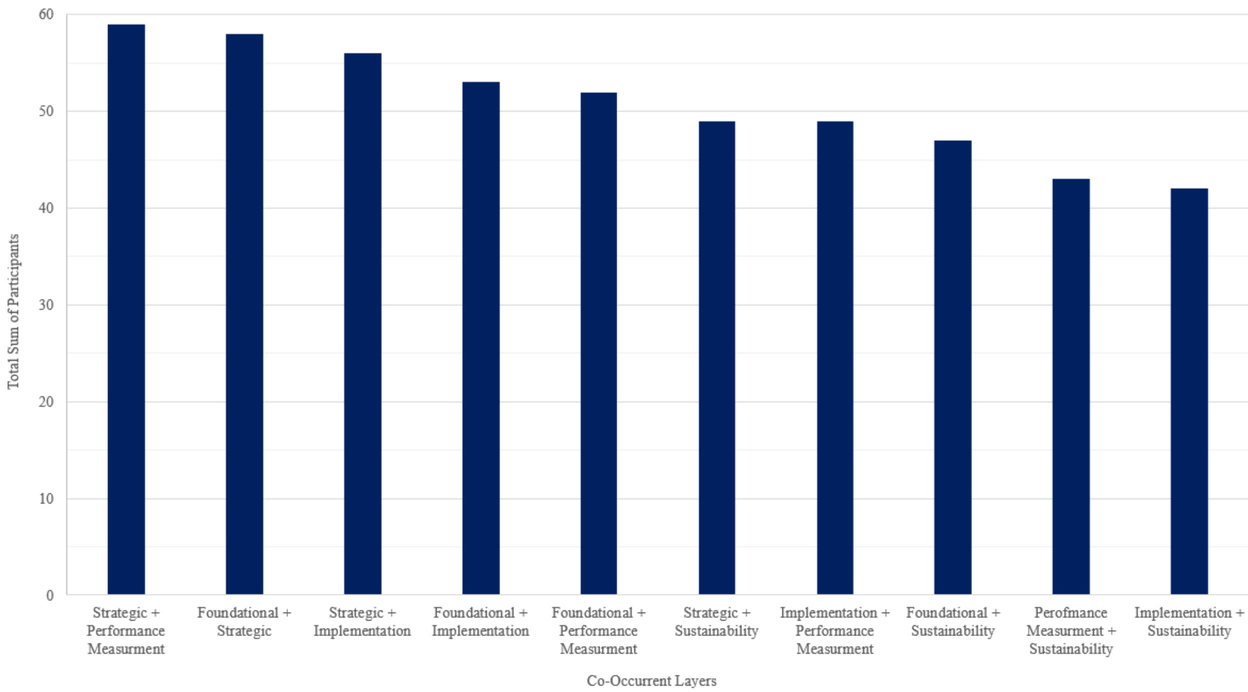

Figure 5: The summed results of co-occurrence analysis, grouped by framework layer

Lastly, Table 6 presents selected high-impact quotes from participants. These quotes are organized by framework layer, and they illustrate key insights that either positively or negatively relate to the overarching question of a given framework layer.

Table 6: A list of high-impact quotes from the 12 interviews. The Participant IDs match those displayed in Table A1

Framework Layer	Essential Question of the Layer	Impactful Quote
Foundational	Is our organization ready to adopt Gen AI?	• **P6:** “If we’re not using [Gen AI], we’re going to be dead… the value proposition’s really clear for me.” • **P10:** “Most of us are using them for everything, from… researching what we should do, to… writing 80% of our code… and then multiple teams are building, operationalizing the system, and handling all that.” • **P12:** “[With Gen AI adoption] there's still that little bit of a mental barrier of, like, yeah, I don't know if I want to just take a whole day out or a couple days out to figure this out, then move ahead.”
Strategic	How does Gen AI support our mission, goals, and objectives?	• **P5:** “[In one instance, the output was] completely made up by the AI and had nothing to do with what we were looking for… in the end, it was not useful at all, and it was sort of a waste of time.” • **P9:** “It would take our teams about an hour for each report… [Gen AI instead] created a 10-minute process where all they had to do was review it.” • **P10:** “The biggest thing is time, by far. I mean, for, like, the first time in my five years at [my company], we are beating timelines on our roadmap… and that's all due to AI.”
Implementation	How can we deploy Gen AI effectively?	• **P3:** “For more corporate-wide tools, our biggest challenges [of adoption] are compatibility with other tools that we're already using.” • **P7:** “If you're really intentional about [Gen AI] training, you're going to enable so much more than if you just handed [employees] the tool.”
Performance Measurement	What are our methods for assessing the value generated from Gen AI?	• **P1:** “[Gen AI] makes me look a lot smarter and saves me a lot of time.” • **P8:** “We don't have real metrics, but I would say if we're looking to bring something in…we've had discussions of, is this something that we can afford? Is it worth it?”

Sustainability	How do we maintain and scale our use of Gen AI?	• **P2:** “If [we] have to start paying for the basic versions [of Gen AI], there's no way we're going to keep it.” • **P7:** “We have exceptional buy-in [for Gen AI] at the top… if you have that buy-in, it makes a lot of things a lot easier, and it allows for a lot of different experiments along the way.”

Discussion

Overview of Discussion

This study sought to evaluate how employees within SMEs approached each layer of the GSVF by conducting 12 qualitative, semi-structured interviews. The interviews served as a complement to the theory established in the literature review about how SMEs operate, how they use Gen AI, and why they adopt Gen AI.

However, it is important to emphasize that all the data collected and analyzed can only provide interpretive — rather than causal — insights. None of the remarks or conclusions in this discussion declare a cause-and-effect relationship, as variables were not properly tested for causation. Instead, the points made here explore meaningful patterns that arose from the data and help contextualize the established theories provided in the literature review. As a result, the insights gathered demonstrate the effectiveness of the GSVF in identifying the current strengths and weaknesses of SMEs that are adopting Gen AI along with identifying future opportunities and threats to achieving sustainable success.

Interpretation of the Results for Each Layer

Foundational Layer. The themes in the Foundational Layer tended to resonate strongly with participants, as Figure 5 illustrates that three of the top five co-occurring sets involved the Foundational Layer. Generally, participants demonstrated a high understanding of the potential value of Gen AI technology, with Figure 4 showing that 11/12 participants identified multiple use cases (1-A). This finding suggests that the perceived usefulness (PU) defined by TAM, the performance expectancy in UTAUT, and the relative advantage mentioned in TOE and DOI are well established among SME employees (Hughes et al., 2026; Nurqamarani et al., 2021; Rogers, 2003; Venkatesh et al., 2003; Zamani, 2022). Having high PU and relative advantage for Gen AI is not surprising, as Table 2 lists six distinctive strengths and three distinctive opportunities identified by scholarly literature for Gen AI usage within SMEs. Strengths and opportunities were articulated by participants when asked how they used Gen AI, such as the comment from P10 who stated that most of their business saw usefulness in the ability for the technology to support research and write code (Table 6).

Themes 1-B and 1-C dealt with people who saw barriers to technology adoption in the forms of budget and time constraints, respectively. With budget constraints, there were unsurprisingly high reports (10/12 respondents), given that a key characteristic of SMEs is their lack of financial resources (Dörr et al., 2024; OECD, 2023, p. 63). Additionally, nine of those 10 respondents had co-occurrences with struggles adopting past technologies (3-A), suggesting that tight budgets may limit adoption capabilities. Thus, in terms of Gen AI, adopting the limited, but free, versions of tools may be all that certain SMEs can reasonably afford. As for time constraints, slightly less than half of respondents (5/12) mentioned it as a barrier to new technology adoption; however, all five of those respondents had time constraints co-occur with struggles adopting past technologies (1-C and 3-A = 5/12 respondents). While time constraints were less reported than budget constraints in this interview sample, both themes could reasonably inhibit the adoption of Gen AI due to the lack of organizational resources found in most SMEs (Dörr et al., 2024; OECD, 2023, p. 63).

Strategic Layer. Having a total of 28 responses to themes, the Strategic Layer produced the strongest overall alignment out of any layer. Unlike other layers that had varying positive and negative components within the themes, the Strategic Layer solely analyzed the different methods for determining the value of Gen AI. Participants who could easily identify how the technology was valuable to their organization were likely using it to effectively achieve the mission, vision, and objectives of the organization.

Shown in Figure 4 and Table C2, the two Strategic Layer themes with the highest responses were 2-B and 2-C, which dealt with framing Gen AI value in terms of improved time or efficiency (12/12 respondents) and improved output quality (11/12 respondents), respectively. Participants gave numerous examples as to how Gen AI was aligned with their business strategy, with one standout instance coming from P9 who mentioned the large time savings that Gen AI enabled for their presentation creation process (Table 6). Statements like this reinforce the notion that strategic alignment, as defined in TOE (Schwaeke et al., 2024), is a primary driver of adoption. Strategic alignment is critical for SMEs to achieve because it reduces the risk of project failure, and therefore, this component also reduces the likelihood that high uncertainty avoidance, as described in Table 1, inhibits Gen AI adoption.

In general, themes 2-B and 2-C reported high scores across the co-occurrence analysis (Figure C1), which is why the Strategic Layer in Table 4 is in each of the top three layer pairings. These themes had high correlations with theme 5-A, perceiving Gen AI as providing ongoing net benefits (2-B and 5-A = 12/12 respondents; 2-C and 5-A = 11/12 respondents). This finding is consistent with expectations, given that properly identifying the value of Gen AI often makes it seem more useful. Themes 1-A, 1-B, 3-A, 4-A, and 4-B also had at least nine co-occurrences with both 2-B and 2-C, but the surprising correlation comes from 4-A, which evaluates Gen AI value primarily through informal judgment (2-B and 4-A = 10/12 respondents; 2-C and 4-A = 9/12 respondents). Here, this correlation suggests that while participants tended to have multiple ways of defining Gen AI value, most of them had no objective way of measuring that value.

Unlike evaluating Gen AI through efficiency or time improvements (2-B) or quality improvements (2-C), framing Gen AI value as a financial benefit (2-A) had mixed results. Only five out of 12 participants mentioned financial benefits when evaluating Gen AI, likely due to the difficulty in demonstrating a financial return on investment compared to the simplicity in viewing better, faster output. Thus, there are likely more financial gains to Gen AI adoption than employees realize, especially given the high reporting for the benefits Gen AI provides in themes 2-B and 2-C.

Implementation Layer. The themes that constituted the Implementation Layer aimed at issues with technology implementation along with determining the importance of training to support employees. From the dataset in Table C2 and the graph in Figure 4, the only theme with nearly all 12 respondents came from 3-A (11/12 respondents), which addressed the difficulties in adopting past technologies. This result supports the finding in TOE and DOI that increased complexity can impede the success of an adoption (Hughes et al., 2026; Rogers, 2003; Sánchez et al., 2025). Although, according to Figure C1, difficulties with past technology implementations seem to not prevent Gen AI adoption efforts. After all, theme 3-A had high co-occurrences with identifying multiple use cases (3-A and 1-A = 10/12 respondents), providing two frames of value (3-A and 2-B = 11/12 respondents; 3-A and 2-C = 10/12 respondents), and perceiving net benefits (3-A and 5-A = 11/12 respondents). Thus, despite likely having challenges — such as the weaknesses and threats mentioned in Table 2 — many SMEs in the sample still appear to have a desire to implement Gen AI into their business.

Theme 3-B, mentioning a lack of technical or skills infrastructure (6/12 respondents), and theme 3-C, stating the importance for having structured Gen AI training (7/12 respondents), each had moderate agreement. All six people that saw infrastructure issues in their organization also mentioned budget constraints as a barrier to new technologies (3-B and 1-B = 6/12 respondents), which highlights the issues that SMEs face when operating from limited budgets. Although, given that numerous Gen AI applications used by participants operate on a software-as-a-service (SaaS) model (see Table A1), robust technology infrastructures are often not necessary. With a lack of skills, training could act as a remedy; however, the lukewarm agreement in theme 3-C reveals that not all SME employees feel as though structured training programs are essential in Gen AI adoption. Some participants were passionate about training, though, such as how P7 mentions in Table 6 that effective training can enable significantly more capabilities. Ultimately, the importance of developing skills infrastructure through training likely relies on the perceived ease of use (PEOU), defined by TAM (Nurqamarani et al., 2021; Venkatesh et al., 2003; Zamani, 2022), and the facilitating conditions, defined by UTAUT (Venkatesh et al., 2003), that an employee experiences. Thus, the mixed responses in 3-B along with the ambivalence in 3-C demonstrate how successful implementations often occur differently across firms.

Performance Measurement Layer. The themes in the Performance Measurement Layer aimed at understanding the methodology for evaluating the effectiveness of technologies, with a specialized focus on Gen AI. Despite having different scopes, theme 4-A, evaluating Gen AI mainly through informal judgment (10/12 respondents), and theme 4-C, relying on formal metrics to determine technology value (5/12 respondents), mostly contrast each other.

Generally, given that theme 4-A had 10/12 respondents, informal methods for determining Gen AI value were preferred. The quotes in Table 6 support this notion, with P1 even describing Gen AI as a tool that makes them look smarter and saves them time. The co-occurrence analysis supports the idea of suggested intelligence mentioned by P1, as theme 4-A had a high co-occurrence with discussing technology value with teams or leadership (4-A and 4-B = 9/12 respondents) and with perceiving Gen AI as providing ongoing net benefits (4-A and 5-A = 10/12 respondents). Together, these findings suggest that value is socially validated rather than systematically measured within many SMEs.

The importance of high social validation seen in theme 4-B, discussing technology value with a team or leadership (10/12 respondents), is consistent with characteristics mentioned in Angeles et al. (2022) along with Lussier (2019, p. 209), and it is aligned with the social influence dynamics described in UTAUT (Venkatesh et al., 2003). This pattern is likely reinforced by the high observability of Gen AI outcomes, as defined in DOI (Rogers, 2003). After all, benefits of the technology are easily recognized by participants; for instance, in theme 2-B, all 12 respondents see time savings or efficiency in Gen AI. As a result, high observability perceived through social validation may reduce the need for structured measurement systems when determining value. However, this insight also reflects a key Gen AI threat from Table 2: the risk of unclear value generation. While evaluating informally through social channels may be fine for some SMEs, others could struggle to optimize their usage or even justify long-term investments due to a lack of formal metrics.

Sustainability Layer. The themes in the Sustainability Layer cover various aspects affecting long-term usage of Gen AI. Despite having all 12 participants see Gen AI as providing ongoing net benefits (5-A), the low scoring in theme 5-B, using Gen AI due to organizational need or requirement (5/12 respondents), and theme 5-C, mentioning the potential for Gen AI abandonment (4/12 respondents), resulted in the Sustainability Layer having the three lowest co-occurrence layer combinations in Figure 5.

Specific co-occurrence analysis provides further insight into the imbalance between 5-A and 5-B along with 5-A and 5-C. At least 10 participants showed co-occurrences between theme 5-A and the following themes: 1-A, 1-B, 2-B, 2-C, 3-A, 4-A, 4-B. Notably, strong correlations with identifying multiple Gen AI use cases (1-A), framing Gen AI value in terms of improved time or efficiency (2-B), and framing Gen AI value as improved output quality (2-C) support the likelihood that most SMEs see long-term value in Gen AI. Moreover, the majority of sampled employees do not seem forced to use Gen AI (5-B), nor do they appear close to abandoning it (5-C). This insight explains why every co-occurrence for 5-B and 5-C encompassed less than half of all respondents.

The selected Sustainability Layer participant quotes in Table 6 accentuate important aspects of long-term success in Gen AI adoption. For P7, their claim about the significance of Gen AI buy-in from top executives aligns with the TOE model in Figure 1 that identifies culture and leadership as important factors in adoption (Hughes et al., 2026; Schwaeke et al., 2024). Ultimately, a supportive leadership group that can establish long-term objectives — as opposed to the short-term orientation, identified in Table 1, that commonly plagues SMEs — has a greater potential for achieving sustainable value. Meanwhile, P2 mentioned a deterrent to sustained value in the form of potential abandonment. Their quote signified the reality that many SMEs only adopt free versions of Gen AI due to their budget constraints. So, if environmental conditions were to deteriorate to the point where free plans were widely abolished, certain SMEs would be willing to completely abandon Gen AI.

Practical Implications

The findings from this study provide several practical implications, displayed in Table 7, for SMEs planning to adopt Gen AI for the purpose of maximizing sustainable value. These implications are based on the analysis conducted on the interview results from each framework layer. Ultimately, Table 7 demonstrates how the proposed GSVF can be applied in organizational settings to gain important insights.

Table 7: Practical implications for Gen AI adoption in SMEs based mainly on interview findings

#	Practical Implication	Supporting Evidence	Framework Layer
1	The GSVF serves as an effective diagnostic tool for assessing SME preparedness and effectiveness in adopting Gen AI	Culmination of all practical implications shown in this table	All layers
2	Approaches to Gen AI adoption vary between the SMEs that participants work for, which reinforces the need to have the GSVF act as a broad diagnostic tool rather than a set action plan	Only 2/15 themes had universal agreement from participants	All layers
3	Implementation challenges and barriers are common in technology adoption, but they do not prevent most successful Gen AI adoptions within sampled SMEs	High co-occurrence between reporting past technology adoption difficulties and perceiving ongoing net benefits from Gen AI (3-A and 5-A = 11/12 participants); 11/12 participants identified numerous current and future Gen AI use cases (1-A)	Foundational, Implementation, Sustainability
4	In the sampled SMEs, Gen AI is widely — but usually not fully — adopted, and most participants seem to use it out of their own desire to generate value rather than organizational mandates	11/12 participants saw multiple current and future Gen AI use cases (1-A); Only 5/12 of them reported required or needed use (5-B)	Foundational, Sustainability
5	With Gen AI, free SaaS solutions are popular among participants; however, there seems to be potential for abandonment if the solutions are no longer free or usable with little technology infrastructure	Universal tool usage within sample (Table A1); 4/12 participants mention potential for abandoning Gen AI (5-C), including P6 quote in Table 6	Foundational, Sustainability
6	Sampled SMEs are highly capable of identifying Gen AI value that supports their strategy, with time savings and quality improvement being the primary reasons for adoption	With Gen AI valuation, 12/12 participants identified time or efficiency improvements (2-B) and 11/12 identified quality improvements (2-C)	Strategic

7	Despite recognizing Gen AI value, SMEs often rely on informal and social validation instead of structured performance metrics, which makes demonstrating value generation less concrete	High co-occurrence between Strategic and Performance Measurement layers due to 9/12 and 10/12 co-occurrences between time or efficiency value (2-B), quality value (2-C), informal evaluation (4-A), and social discussions (4-B)	Strategic, Performance Measurement
8	Despite participants seeing other returns, financial returns on investment from Gen AI are less recognized, potentially due to limited formal evaluation metrics	Small co-occurrence for valuing financial returns and using formal metrics (2-A and 4-C = 3/12 respondents); 12/12 participants identified time or efficiency improvements (2-B) and 11/12 identified quality improvements (2-C)	Strategic, Performance Measurement
9	The importance of Gen AI training varies between sampled SMEs, as it typically depends on organizational contexts	7/12 participants viewed structured Gen AI training as important (3-C); Cultures can vary by SME (Table 1)	Implementation
10	Support from executive leadership can play a critical role in positioning Gen AI as a long-term investment that can generate sustainable value	P7 quote from Table 6; Importance of leadership and culture in SMEs for adopting Gen AI, according to TOE model in Figure 1	Sustainability

Limitations

This study had limitations that should be considered when interpreting the findings. One of the most significant qualifiers comes from the relatively small sample size of interviewed employees (n=12). While participants were selected from different backgrounds, as shown in Table A1, the findings reflect a limited set of perspectives. Therefore, results may not fully capture differences in Gen AI adoption that are specific to certain industries.

Second, the nature of using semi-structured interviews poses a limitation, given that it introduces the potential for self-reporting bias. Participants could have overstated, understated, or not stated the impact of certain aspects in their organization or their experience adopting technology. Additionally, with interviews focusing on individual experiences, answers often reflected perceived outcomes rather than objective organizational metrics, which could have skewed the results.

Third, there is a limitation with the reliance on a binary coding structure composed of “yes” and “no” values to assess the relationships that participants had with themes. While this structure is useful for identifying patterns and conducting analysis, it does somewhat oversimplify complex attitudes that constitute many adoption experiences. Furthermore, restricting the evaluation to 15 themes creates the possibility that other salient themes were excluded.

Lastly, a fourth limitation from this study is that there are no causal relationships that can be verified solely from interview responses. This limitation is a culmination of the other three limitations, as the small sample size, style of semi-structured interviews, and binary coding structure together cannot statistically prove any cause-and-effect relationships. Even though the GSVF is rooted in established theories — including TOE, TAM, UTAUT, and DOI — there still must be follow-up experiments to evaluate the causality of relationships between themes as well as other variables. Thus, while practical implications identified in Table 7 could be useful for SMEs that were not interviewed, there is no guarantee that these other SMEs can successfully extrapolate and apply the implications to their own context.

Future Research

Building on the identified limitations, there are several opportunities for future research. First, expanding the sample size of interviews to include a broader range of SMEs, especially from different regions and industries, would enable analysis from a more holistic perspective. Second, future studies that use a quantitative approach to test relationships and themes between framework layers could reveal important findings that support decision-making in SMEs. These experiments could isolate relationships that are hypothesized to have high significance for the success of SMEs in Gen AI adoption. Third, researching a sample of SMEs over a span of time could produce insights that are not visible within the snapshot of this study. After all, attitudes and experiences relating to Gen AI usage could shift dramatically for some SMEs in the next few years, so analyzing that data could present new findings. Lastly, research conducted on industry-specific applications of Gen AI could lead to more specialized versions of the GSVF. In this context, best practices and challenges could be identified and illustrated in a specialized framework that supports SME decision-makers in adopting the specific application.

Conclusion

This thesis was designed to address a critical gap in academic literature with regard to how small and medium-sized enterprises (SMEs) adopt generative artificial intelligence (Gen AI). Currently, there are strong explanations for *who* are SMEs and Gen AI as well as *why* organizations adopt technology. However, the dearth of literature exploring *how* SMEs can adopt Gen AI to achieve sustainable value results in little guidance for these types of organizations that are commonly plagued by limited resources. Thus, to effectively contribute to this overlooked area, the thesis introduced the Gen AI-SME Value Framework (GSVF). Structured as a sequential five-layer stack, the GSVF helps SMEs navigate the adoption process by being a tool that these organizations can rely on for decision support.

The insights generated from the 12 semi-structured interviews reinforce the applicability and relevance of the GSVF. For instance, participants widely recognized multiple Gen AI use cases (1-A = 11/12 respondents) and could link their current use cases to value that supported their strategy, such as through efficiency or time improvements (2-B = 12/12 respondents) or quality improvements (2-C = 11/12 respondents). However, these same participants often had difficulties adopting technology (3-A = 11/12 respondents), relied on informal judgment to determine Gen AI value (4-A = 10/12 respondents), and even had some consideration for abandoning the technology in the future (5-C = 4/12 respondents). These patterns, which highlight different benefits and challenges of adoption, illustrate the importance of the GSVF: a tool that aims to increase risk awareness, emphasize use case alignment with business strategy, and focus on generating sustainable value from adoption.

The implications of all this research point to the benefits of having a supportive diagnostic tool when adopting Gen AI. Instead of aimlessly experimenting with potential use cases, SMEs can leverage the GSVF with confidence, knowing that it was developed from academic insights and successfully applied to real organizational contexts. By using this tool, SMEs can begin to shift away from their typical short-term orientation and deliberately focus on achieving long-term value.

Ultimately, the growing presence of Gen AI in the business landscape presents both benefits and challenges for SMEs. Organizations that choose an unstructured approach to adoption likely face less clarity in the evaluation of risk, alignment with business strategy, and outlook on long-term value generation. By contrast, organizations that leverage a structured approach to adoption give themselves greater potential to turn Gen AI into a competitive advantage. This thesis contributes toward the structured approaches of adoption by presenting a framework that helps SMEs adopt Gen AI to achieve sustained value.

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Appendix A

Description of Participants

Table A1 gives an overview of the 12 participants who were interviewed. Given that these interviews were confidential, demographic data displayed in the table has been limited to protect the identities of the participants. Information regarding the “For-Profit,” “Industry,” “Role,” and “Estimated Company Size” columns was sourced from interview transcripts when available and from LinkedIn participant profiles as well as company profiles when not available. The information for the “Number of Gen AI Tools Currently Using” and “List of Gen AI Tools Currently Using” columns was sourced exclusively from interview transcripts.

Table A1: Overview of the 12 interview participants

ID	For-Profit	Industry	Role	Estimated Company Size	Number of Gen AI Tools Currently Using	List of Gen AI Tools Currently Using
P1	Y	Consulting	Leadership and Coaching Professional	1	6	ChatGPT, Copilot (Microsoft), Gemini, Meta AI, Otter.ai, GoDaddy Airo
P2	N	Menstrual Health	Advocacy Manager	11–50	3	ChatGPT, Gemini, Canva AI
P3	Y	Cybersecurity	Technical Engineer	51–200	1	Cursor
P4	N	IT Support	Executive Director	5–10	11	ChatGPT, Copilot (Microsoft), Gemini, Fathom, OpenAI (Azure), Canva AI, Guide.ai, NotebookLM,

						Ollama, Cursor, Codex
P5	Y	Bio-technology Research	Research Scientist	11–50	2	ChatGPT, Modern Vivo
P6	N	Community Foundation	Grant Operations Director	18	3	ChatGPT, Impala, Zoom AI
P7	Y	IT Services and Consulting	AI and Automation Director	140	7	ChatGPT, Copilot (Microsoft), Claude, Gemini, Gamma, Roost.ai, Azure AI
P8	Y	Bio-technology Research	Intellectual Property Leader	201–500	1	ChatGPT
P9	Y	Construction	Business Analytics Director	51–200	2	ChatGPT, OpenAI (custom APIs)
P10	Y	Information Services	Weather Analytics Director	201–500	5	ChatGPT, Claude, Gemini, Codex, Claude Code
P11	Y	AI Services	Customer Success Professional	50	2	ChatGPT, Gemini
P12	Y	AI Services	Environ-mental & Technical Specialist	51–200	3	Claude Code, Sybill AI, Gemini

Appendix B

Interview Question List

Table B1 shows the interview question list, which contains five structured questions (one from each category) along with one or two bonus questions that were asked if there was time. Each of the 12 semi-structured interviews lasted between 20 and 30 minutes, and all of them were recorded to generate a transcript.

Table B1: The interview question list, which was used to conduct 12 semi-structured interviews

- Foundational Layer — Organizational readiness to adopt Gen AI
  - *What factors make it easy or difficult for your team to try new technologies?*
  - Bonus questions:
    - *When your team considers new tech, what concerns or risks usually come up (e.g., practical, budget, time, skills, etc.)?*
    - *How familiar are you with Generative AI tools (e.g., ChatGPT, Anthropic, Stable Diffusion, Copilot)? How have you used them personally, if at all?*

- Strategic Layer — Alignment with mission, goals, and objectives
  - *What would/did "value" look like for your role if/when Gen AI was introduced? (Saving time? Fewer errors? Better communication? Creativity?)*
  - Bonus questions:
    - *What parts of your job or department's work do you think Gen AI could help with?*
    - *If your department had to choose where to apply Gen AI first, what would you personally pick and why?*

- Implementation Layer — Carrying out adoption effectively
  - *What kinds of support/training do you believe you (or your team) would need to use Gen AI confidently?*
  - Bonus questions:
    - *Have you been part of implementing a new tool or software in your department? If so, what was that experience like?*

-
  -
    - *What kinds of challenges do people on your team typically have when learning new technologies?*

- Performance Measurement Layer — Assessing the value generated
  - *How do you personally tell if a new tool is helping you do your job better?*
  - Bonus questions:
    - *In your department, what improvements matter most — saving time, improving quality, reducing repetitive work, etc.?*
    - *When your team tries a new tool, how do you discuss whether it's working or not? (Informally? Check-ins? Metrics?)*

- Sustainability Layer — Long-term integration (maintaining and scaling use)
  - *What would/has make/made Gen AI become a "normal part" of your work rather than a temporary experiment?*
  - Bonus question:
    - *What would make you stop using a Gen AI tool after a few weeks or months?*

Appendix C

Results from Data Collection

The following section lists three visuals. Table C1 is a reproduction of Table 5 and is included here to support the other two components in this appendix. Table C2 displays the binary-themed results for each of the 12 interviews. Figure C1 showcases the co-occurrence results in the form of a heatmap.

Table C1: List of binary themes for each layer of the framework with their ID (reproduced from Table 5)

Foundational Layer	
1-A:	Identifies Multiple Current or Future Gen AI Use Cases
1-B:	Mentions Budget Constraints as Barrier to New Technologies
1-C:	Mentions Time Constraints as Barrier to New Technologies
Strategic Layer	
2-A:	Frames Gen AI Value as Financial Benefit
2-B:	Frames Gen AI Value as Increased Efficiency or Saved Time
2-C:	Frames Gen AI Value as Improved Output Quality
Implementation Layer	
3-A:	Mentions Difficulties with Adopting Past Technologies
3-B:	Mentions Lack of Technical or Skills Infrastructure
3-C:	States Importance for Having Structured Gen AI Training
Performance Measurement Layer	
4-A:	Evaluates Gen AI Value Through Informal Judgment
4-B:	Discusses Technology Value with Team or Leadership
4-C:	Relies on Formal Metrics to Assess Technology Value
Sustainability Layer	
5-A:	Perceives Gen AI as Providing Ongoing Benefits
5-B:	Uses Gen AI Due to Organizational Need or Requirement
5-C:	Mentions Potential for Abandoning Gen AI

Table C2: Binary "Y" (yes) and "N" (no) values displayed for each theme across all 12 participants. The "TOTAL" fields only count the number of "Y" cells. The Participant IDs match those displayed in Table A1, and the Theme IDs match those displayed in Table C1

	Participant ID	**P1**	**P2**	**P3**	**P4**	**P5**	**P6**	**P7**	**P8**	**P9**	**P10**	**P11**	**P12**	***TOTAL***
Foundational Layer	**1-A**	Y	Y	Y	Y	N	Y	Y	Y	Y	Y	Y	Y	*11*
	1-B	Y	Y	Y	Y	Y	Y	N	Y	Y	Y	Y	N	*10*
	1-C	N	Y	Y	N	N	N	N	Y	Y	N	N	Y	*5*
Strategic Layer	**2-A**	Y	N	Y	N	Y	N	Y	N	N	Y	N	N	*5*
	2-B	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	*12*
	2-C	Y	Y	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	*11*
Implementation Layer	**3-A**	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	N	Y	*11*
	3-B	Y	Y	N	N	N	Y	N	Y	Y	Y	N	N	*6*
	3-C	N	Y	N	N	Y	Y	Y	Y	N	N	Y	Y	*7*
Performance Measurement Layer	**4-A**	N	Y	Y	N	Y	Y	Y	Y	Y	Y	Y	Y	*10*
	4-B	N	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	*10*
	4-C	Y	N	N	Y	N	N	Y	N	N	Y	N	Y	*5*
Sustainability Layer	**5-A**	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	*12*
	5-B	N	N	N	N	N	N	N	Y	Y	Y	Y	Y	*5*
	5-C	Y	Y	Y	N	Y	N	N	N	N	N	N	N	*4*
	TOTAL	*10*	*11*	*10*	*8*	*10*	*10*	*10*	*12*	*11*	*12*	*9*	*11*	

		1-A	1-B	1-C	2-A	2-B	2-C	3-A	3-B	3-C	4-A	4-B	4-C	5-A	5-B	5-C
		Foundational Layer			Strategic Layer			Implementation Layer			Performance Measurement Layer			Sustainability Layer		
Foundational Layer	1-A															
	1-B	9														
	1-C	5	4													
Strategic Layer	2-A	4	4	1												
	2-B	11	10	5	5											
	2-C	10	9	4	4	11										
Implementation Layer	3-A	10	9	5	5	11	10									
	3-B	6	6	3	2	6	6	6								
	3-C	6	5	3	2	7	7	6	3							
Performance Measurement Layer	4-A	9	8	5	4	10	9	9	5	7						
	4-B	9	8	4	4	10	9	9	4	6	9					
	4-C	5	3	1	3	5	5	5	2	2	3	4				
Sustainability Layer	5-A	11	10	5	5	12	11	11	6	7	10	10	5			
	5-B	5	4	3	1	5	5	4	3	3	5	5	2	5		
	5-C	3	4	2	3	4	3	4	2	2	3	2	1	4	0	

Figure C1: A heatmap showcasing the results from the co-occurrence analysis. The Theme IDs match those displayed in Table C1

Appendix D

Python Co-Occurrences Script

```python
#
# A Python Script for calculating the co-occurrence of themes across layers in the coding
matrix.
# Input: Dictionary 'data' which contains the coding matrix in the form of Y/N values.
# Output: A CSV file named "co_occurrences.csv" that lists the co-occurrence and count of
themes across layers, ordered by count descending (highest to lowest).
# @author: Ryan Wells (2026) — with support from Generative AI tool ChatGPT-5.2 to
understand how to use 'pandas' and 'itertools' for co-occurrence analysis.
#

import pandas as pd
import itertools

# Theme <-> layer mapping
theme_layers = {
    "Identifies Multiple Current or Future Gen AI Use Cases": "Foundational",
    "Mentions Budget Constraints as Barrier to New Technologies": "Foundational",
    "Mentions Time Constraints as Barrier to New Technologies": "Foundational",

    "Frames Gen AI Value as Financial Benefit": "Strategic",
    "Frames Gen AI Value as Increased Efficiency or Saved Time": "Strategic",
    "Frames Gen AI Value as Improved Output Quality": "Strategic",

    "Mentions Difficulties with Adopting Past Technologies": "Implementation",
    "Mentions Lack of Technical or Skills Infrastructure": "Implementation",
    "States Importance for Having Structured Gen AI Training": "Implementation",

    "Evaluates Gen AI Value Through Informal Judgment": "Performance Measurement",
    "Discusses Technology Value with Team or Leadership": "Performance Measurement",
    "Relies on Formal Metrics to Assess Technology Value": "Performance Measurement",

    "Perceives Gen AI as Providing Ongoing Benefits": "Sustainability",
    "Uses Gen AI Due to Organizational Need or Requirement": "Sustainability",
    "Mentions Potential for Abandoning Gen AI": "Sustainability"
}
```

```

# Stores all themes in a list
themes = list(theme_layers.keys())

# Creates the coding matrix
data = {
    themes[0]: ["Y","Y","Y","Y","N","Y","Y","Y","Y","Y","Y","Y"],
    themes[1]: ["Y","Y","Y","Y","Y","Y","N","Y","Y","Y","Y","N"],
    themes[2]: ["N","Y","Y","N","N","N","N","Y","Y","N","N","Y"],
    themes[3]: ["Y","N","Y","N","Y","N","Y","N","N","Y","N","N"],
    themes[4]: ["Y","Y","Y","Y","Y","Y","Y","Y","Y","Y","Y","Y"],
    themes[5]: ["Y","Y","N","Y","Y","Y","Y","Y","Y","Y","Y","Y"],
    themes[6]: ["Y","Y","Y","Y","Y","Y","Y","Y","Y","Y","N","Y"],
    themes[7]: ["Y","Y","N","N","N","Y","N","Y","Y","Y","N","N"],
    themes[8]: ["N","Y","N","N","Y","Y","Y","Y","N","N","Y","Y"],
    themes[9]: ["N","Y","Y","N","Y","Y","Y","Y","Y","Y","Y","Y"],
    themes[10]: ["N","N","Y","Y","Y","Y","Y","Y","Y","Y","Y","Y"],
    themes[11]: ["Y","N","N","Y","N","N","Y","N","N","Y","N","Y"],
    themes[12]: ["Y","Y","Y","Y","Y","Y","Y","Y","Y","Y","Y","Y"],
    themes[13]: ["N","N","N","N","N","N","N","Y","Y","Y","Y","Y"],
    themes[14]: ["Y","Y","Y","N","Y","N","N","N","N","N","N","N"]
}

# Converts the coding matrix to a DataFrame for easier use
df = pd.DataFrame(data)

# Converts Y/N to 1/0
binary_df = df.replace({"Y": 1, "N": 0})

# Calculates Y/Y (1 to 1) co-occurrences across layers
co_occurrences = []

# For loop that iterates through all possible theme combinations (without repetition) and
counts co-occurrences
for theme_a, theme_b in itertools.combinations(themes, 2):

    # Checks if both themes are Y/Y (1 to 1)
    count = ((binary_df[theme_a] == 1) & (binary_df[theme_b] == 1)).sum()

    # Adds co-occurrence to list
```

```
    co_occurrences.append({
        "Layer A": "[" + theme_layers[theme_a] + "]",
        "Theme A": theme_a,
        "Layer B": "[" + theme_layers[theme_b] + "]",
        "Theme B": theme_b,
        "Co-occurrence Count": count
    })

# Converts co-occurrences list to DataFrame
co_occurrence_df = pd.DataFrame(co_occurrences)

# # Sort results by co-occurrence count in descending order
# co_occurrence_df = co_occurrence_df.sort_values(
#     by="Co-occurrence Count",
#     ascending=False
# )

# Exports results to CSV file
co_occurrence_df.to_csv("co_occurrences.csv", index=False)
```