

ADDIS ABABA UNIVERSITY

COLLEGE OF BUSINESS AND ECONOMICS

DEPARTMENT OF MANAGEMENT

MSC. IN INTERNATIONAL BUSINESS

GENERATIVE AI ADOPTION AND FUTURE ORGANIZATIONAL PERFORMANCE IN MANAGEMENT CONSULTING FIRMS: THE DUAL MEDIATING ROLES OF EXPLORATORY AND EXPLOITATIVE INNOVATION, AND THE MODERATING EFFECTS OF ORGANIZATIONAL AGILITY AND ETHICAL DILEMMAS — EVIDENCE FROM ETHIOPIA

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DECLARATION

My thesis titled “Generative AI Adoption and Future Organizational Performance in Management Consulting Firms: The Dual Mediating Roles of Exploratory and Exploitative Innovation, and The Moderating Effects of Organizational Agility and Ethical Dilemmas — Evidence from Ethiopia” has been carried out under the guidance and supervision of my advisor, Zelalem Gebretsadik (Ph.D.).

The thesis is original and has not been submitted for any degree or diploma award to any university or institution.

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Date: 10/06/2026

CERTIFICATION

This is to certify that Natnael Kebede Engda has carried out this research work on the topic "*Generative AI Adoption and Future Organizational Performance in Management Consulting Firms: The Dual Mediating Roles of Exploratory and Exploitative Innovation, and The Moderating Effects of Organizational Agility and Ethical Dilemmas — Evidence from Ethiopia*" under my supervision. This research is his original work and has not been presented for a degree in any university, and all sources of material used for the study have been duly acknowledged. Thus, it is sufficient for submission to partially fulfill the requirements for the award of a Master of Science in International Business.

Advisor: Zelalem Gebretsadik (Ph.D.)

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APPROVAL PAGE

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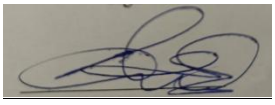
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Generative AI Adoption and Future Organizational Performance in Management Consulting Firms: The Dual Mediating Roles of Exploratory and Exploitative Innovation, and The Moderating Effects of Organizational Agility and Ethical Dilemmas — Evidence from Ethiopia

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ABSTRACT

The rapid advancement of Generative AI and its integrations within organizational operations have transformed how businesses operate and compete in dynamic markets. Despite this, empirical evidence on its effect on organizational performance remains limited. This study aimed to assess the effect of GenAI adoption (GA) on future organizational performance (OP) in the context of management consulting firms, while examining the mediating role of exploitative innovation (EXPLT) and exploratory innovation (EXPLR), as well as the moderating role of organizational agility (AGI) and ethical dilemmas (ETH). A quantitative approach was employed targeting 242 respondents from management consulting firms in Ethiopia, of which 219 responded (90.5% response rate). Data was collected using pre-tested questionnaires and analyzed using Smart PLS version 4.1.1.8. The measurement model of the study was validated using standard validity and reliability tests, while bootstrapping was used to test the significance of the structural model. The findings reveal that GenAI adoption has a positive significant effect on exploratory innovation, exploitative innovation and future organizational performance. The study also found that both exploratory and exploitative innovations each act as complementary partial mediators of the positive relationship between GenAI adoption and future organizational performance. In addition, organizational agility has been found to have a strengthening moderating effect on the relationship between GenAI adoption and exploratory innovation, exploitative innovation and future organizational performance, whereas the moderating effect of ethical dilemmas was found to be insignificant suggesting that ethical dilemmas neither amplify nor weaken the relationship in this context. These findings imply that adoption of GenAI contributes to improved future organizational performance both directly and indirectly through exploitative and exploratory innovation. This can further be strengthened when organizations have higher level of agility.

Key words: Generative AI adoption, future organizational performance, exploitative innovation, exploratory innovation, organizational agility, ethical dilemmas

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ABBREVIATIONS

AGI–Organizational agility

AVE–Average variance extracted

CR–Composite reliability

DIT–Diffusion of innovation theory

ETH–Ethical dilemma

EXPLR–Exploratory innovation

EXPLT–Exploitative innovation

GA–Generative AI adoption

HTMT–Heterotrait–Monotrait ratio

OP–Organizational performance

PLS–Partial Least Squares

RBV–Resource-based view theory

SEM–Structural equation modeling

VAF–Variance Accounted For

VIF–Variance inflation factor

CHAPTER ONE

1. INTRODUCTION

1.1 Background of the Study

In recent years, rapid advancements in artificial intelligence (AI) and its incorporation into organizational operations have transformed how businesses operate and compete in dynamic markets (Şahin & Karayel, 2024). Among the advancements within the field of artificial intelligence is a shift from simple machine processing towards Generative AI (GenAI) which is capable of carrying out sophisticated and creative tasks in a fraction of time (Banh & Strobel, 2023). This dynamic ability of GenAI has positioned it as a powerful tool for organizations across different industries, extending beyond conventional use to becoming an enabler of innovation (Naqbi et al., 2024).

Given its transformative capabilities, GenAI is not only redefining organizational processes but also driving economic implications. According to McKinsey & Company (2023), widescale adoption of GenAI could be one of the biggest drivers of global economic growth by enhancing productivity with estimated annual added value between $2.6 trillion and $4.4 trillion per year. Building on this potential, organizations are integrating generative AI into a wide range of activities with the aim of making processes more efficient, improving existing products and services or creating new ones, enhancing decision making and cost reduction (Benbya et al., 2020).

The growing enthusiasm over the adoption of GenAI by organizations requires an examination of the relationship between GenAI adoption and organizational performance. According to Wamba-Taguimdje et.al(2020), GenAI has been shown to positively benefit organizations by enhancing their ability to improve organizational performance at both the organizational and process levels. Additionally, GenAI is having a great impact on the organizational environment, as it can automate processes and increase productivity and efficiency (Hernández, 2024). While some scholarly research supports this claim, others contend that the adoption of GenAI may not always be positive. For example, the findings of the study conducted by Lui et al. (2022) indicate that organizations investment in AI has a negative effect on firm performance and value. Another study also suggests that adoption of GenAI would not directly translate into enhanced organizational performance but

rather negatively affect it without proper governance (Rana et al., 2022). The contradicting finding of these researches indicate that the relationship between GenAI adoption and organizational performance remain complex requiring further investigation. Furthermore, this unresolved findings are particularly important for firms with institutional complexity, knowledge intensive and project based industries such as management consulting where organizational performance depends on innovativeness of outputs and timelines (Greenwood et al., 2011; Alvesson, 2004).

Driven by the rapid economic growth and reforms such as the introduction of the Ethiopian capital market, the demand for consulting services in Ethiopia is growing (Girma, 2024). The rising demand is reflected in the entry of global consulting firms, such as Deloitte, and the expansion and enhanced participation of local consulting firms. Consulting firms typically engage in diverse and unique projects which are characterized by changing operating environment and client needs. As a result, their ability to succeed depends on proactively sensing and seizing new project opportunities by smoothly adapting and reconfiguring resources and activities to survive in the fast and highly competitive business environment (Ning & Kwak, 2022).

Globally, consulting firms rely heavily on knowledge-intensive activities, innovation, decision-making and productivity. By integrating GenAI, these firms are reshaping the traditional approach by minimizing cost and time, enhancing value creation and improving innovation (Jain, 2023). This raises the question of whether GenAI adoption influences future organizational performance within the context of consulting firms.

1.2 Statement of the Problem

The introduction of GenAI applications and its rapid advancement has resulted in its wide-scale adoption and integration across industries with the aim of improving operations and stimulating growth (Rubab, 2023). According to Şahin & Karaye (2024), the integration of GenAI is no longer optional but rather a prerequisite for survival. According to a report by LexisNexis (2025), management consulting firms are among the top adopters of GenAI with nearly 68% of the industry using GenAI to enhance their service offering and operations. However, there are debates surrounding GenAI's impact on consulting which tend to swing between two extremes with some arguing that it will render the businesses obsolete while others claim it will only make them more indispensable (Duncan et al., 2025)

In addressing this question, empirical evidence on the effect of GenAI on future organizational performance remains limited. Existing research has predominantly focused on organizational adaptation (Hernández, 2024; AL-Kfairy, 2025), opportunity and challenges (Rahman & Singh, 2024; Smith, 2025) and the impact of GenAI on internal organizational functions such as collaboration and employee engagement (Marimon et al., 2025).

In the limited body of literature where the effects of GenAI on organizational performance have been examined, the findings vary and remain inconclusive (Singh et al., 2024). Among this, several studies report positive firm performance as a result of GenAI use, including optimizing resource allocation, enhanced productivity, improved task performance due to automation of repetitive tasks and enhanced decision making (Albishri et al., 2025; Kumar et al., 2025; Kassa & Ketema, 2025). On the contrary, other research suggest that despite its benefit, GenAI may negatively affect firm performance especially as a result of overreliance. For example, Alavi et al. (2024), argue that despite GenAI being used as a tool to boost productivity, it poses a critical issue of knowledge misappropriation which potentially affects firms performance. This risk is further intensified with weak governance conditions such as inadequate oversight producing substandard outputs, increasing operational inefficiencies and eroding firm competitiveness (Rana et al., 2022). Collectively, these contradictory findings highlights the complex relationship between GenAI and future organzational performance and indicates the need for further research exploring unexamined mediating and moderating factors to address this gap.

In light of this, it is necessary to look beyond the direct effect of GenAI adoption on future organizational performance but rather consider additional factors and parameters through which these effects materialize. Existing literature provides evidence that digital technologies, such as GenAI, stimulate innovation capabilities of organizations by enhancing the firms capacity to generate ideas and concepts, detailing scenarios and automate routine task freeing up resources to engage in strategic tasks (AL-khatib & Wael, 2023; Xu et al., 2024; Holmström & Carroll, 2025). Similarly, studies on innovation indicate that innovation has a postive impact on future orgnazational performance (Suhag et al., 2017; Soomr et al., 2021) through both exploratory and exploitative innovation. When considered together, these findings imply the potential mediating effect of innovation on the relationship between GenAI adoption and organizational performance. Hence, examining exploratory and exploitative innovation as a mediator to have an improved

understanding of how GenAI adoption influences future organizational performance. Several empirical studies have tested this perspective by adopting innovation as a mediator to examine GenAI adoption and organizational performance (Li et al., 2025; Singh et al.,2024).

The unresolved nature of these findings along with the large scale adoption carries particular weight for management consulting firms, due to their knowledge intensivity and innovation being a major success factor (Lemus-Aguilar & Hidalgo, 2015). Despite this, the implication of GenAI adoption on organizational performance in the context of consulting firms is under researched, with majority of the research on this topic being focused on manufacturing and IT firms. Hence, this gap creates an avenue for further research.

1.3 Research Questions

This study addresses the following research questions in the context of management consulting firms in Ethiopia:

- What effect does the adoption of GenAI have on exploratory innovation?
- What effect does the adoption of GenAI have on exploitative innovation?
- To what extent does the adoption of GenAI affect future organizational performance?
- What is the effect of exploratory innovation on future organizational performance?
- What is the effect of exploitative innovation on future organizational performance?
- To what extent do exploratory and exploitative innovation mediate the relationship between GenAI adoption and future organizational performance?
- How do ethical dilemmas and organizational agility moderate the relationship between GenAI adoption and future organizational performance?

1.4 Objective of the Study

The general objective of this study is to assess the effect of GenAI adoption by management consulting firms on future organizational performance through the mediating role of exploratory and exploitative innovation and the moderating role of ethical dilemmas and organizational agility.

The specific objectives of the study are the following:

1. To evaluate the effect of GenAI adoption on exploratory innovation in management consulting firms in Ethiopia

2. To assess the effect of GenAI adoption on exploitative innovation in management consulting firms in Ethiopia
3. To investigate the direct relationship between GenAI adoption and future organizational performance in management consulting firms in Ethiopia
4. To determine the effect of exploratory innovation on the future organizational performance of management consulting firms in Ethiopia
5. To analyze the effect of exploitative innovation on the future organizational performance of management consulting firms in Ethiopia
6. To examine the mediating effect of exploratory and exploitative innovation in the relationship between GenAI adoption and future organizational performance
7. To assess the moderating effect of organizational agility in the relationship between GenAI adoption and future organizational performance
8. To explore the moderating effect of ethical dilemmas in the relationship between GenAI adoption and future organizational performance

1.5 Significance of the study

The effect of GenAI adoption on future organizational performance has been observed through numerous studies however this relationship is unexplored in the context of management consulting firm especially in developing countries such as Ethiopia. This study contributes to the existing body of literature by addressing identified gaps through the application of mediator and moderator variables which have not been widely examined in the past. It also contributes to the diffusion of innovation and resource-based view theories by extending their application to the subject that is being studied.

In addition to broadening the existing body of knowledge, this study helps guide future research by identifying unaddressed issues and proposing future research directions.

The study is also significant to organizations in the consulting industry as it helps them understand the dynamics of GenAI along with how its use can affect their organizational performance. It also helps them understand the challenges associated with it, especially in terms of ethical concerns and navigate through them.

1.6 Scope of the Study

The scope of this study is limited to investigating the relationship between GenAI adoption and future organizational performance. It examines the mediating effect of exploratory and exploitative innovation on this relationship. It also assesses the moderating effect of ethical dilemmas and organizational agility.

The research is limited to the management consulting firms based in Ethiopia. It targets 12 management consulting companies. The respondents of the study are employees that actively use GenAI and in both managerial and non-managerial roles to ensure representation from different levels of employees.

1.7 Limitation of the Study

This study has some identified limitations. The first limitation is that the management consulting industry in Ethiopia is highly scattered and usually serviced by a few numbers of individuals rather than having a large number of employees (Astatkie, 2016). This makes it challenging to adopt a large sample size and obtain data. Hence, this might affect the generalizability of study results to all management consulting firms.

The second limitation of this study is that responses may be affected by social desirability bias. Respondents may provide biased responses to adhere to ideas which are perceived to be socially acceptable. This type of bias may especially become a challenge when examining the ethical dilemma construct since respondents may provide answers which they believe are right rather than reflecting the actual scenario. A strong data collection instrument is used to minimize the effect of this limitation.

Another limitation is that it the study scope is limited to companies in Ethiopia due to time and budget constraint. This limitation may result in potential generalizability of findings to companies in different geographic locations.

Furthermore, the research adopts a cross-sectional research approach which examines the potential relationship between GenAI adoption and organizational performance at a specific time. This may make it difficult to understand the nature of the relationship over longer periods of time.

Lastly, convenience sampling was used to select the 12 management consulting firms, which may introduce self-selection bias and non-representativeness of the sample. As a result, this limitation may affect the external validity and restrict the generalizability of the results (Memona et al., 2025).

1.8 Operational Definitions

Artificial Intelligence refers to the simulation of human intelligence in machines that are programmed to perform tasks requiring cognitive functions such as learning, reasoning, and decision-making (Helm, et al., 2020)

Generative AI (GenAI) is a set of models designed to learn the hidden underlying structure of a dataset and to generate new data points in the form of text and pictures (Bordas et al., 2024)

Exploratory Innovation a type of innovation that focuses on searching for knowledge and expertise to develop new products or services that are distinct from what the organization currently offers (March, 1991).

Exploitative Innovation a type of innovation that focuses on the improvement of a firm's products or services by utilizing existing knowledge and resources, such as technologies and tools (March, 1991).

Organizational ambidexterity refers to the ability of an organization to simultaneously pursue both exploratory and exploitative innovation by balancing efficiency and incremental improvement in existing markets with flexibility and experimentation in new ones (O'Reilly & Tushman, 2013)

Organizational Performance is the set of both financial and non-financial indicators capable of assessing the degree to which organizational goals and objectives have been accomplished (Kaplan & Norton, 1992).

Organizational Agility is an organization's ability to anticipate change in its environment and proactively respond in a timely and efficient manner to consolidate its competitiveness (Nafei W. , 2016).

Ethical Dilemmas refer to situations in which decision-makers face conflicting moral obligations, where choosing one course of action necessarily involves compromising another valued principle (Tenbrunsel & Messick, 2004).

1.9 Organization of the Paper

This paper is organized into five chapters. The first chapter provides introduction into the topic under study. This chapter contains background, statement of the problem, research questions, study objectives, scope, significance and limitations. The second chapter explores empirical literature and an analysis of different scholarly works. The third chapter presents the methodology for conducting the study and includes target population, sampling method, data collection tool, research design, method of data analysis and result of the pilot test. The fourth chapter presents data, analysis, discussion of findings and interpretation. The last chapter consists of implications and summary of findings, conclusions and suggestions for future research.

CHAPTER TWO

2. LITERATURE REVIEW

2.1 Generative Artificial Intelligence

Generative Artificial Intelligence (GenAI) is a result of one of the recent developments in Artificial Intelligence technology, which has transformed from simple traditional data-driven AI tasks towards automated generation of creative and unique outputs (Banh & Strobel, 2023). According to Ronge et al. (2025), GenAI is defined as a data-driven system characterized by four core aspects which are flexibility, interaction, multimodality and productivity which extend beyond simple automation. This machine learning system uses computational techniques to understand patterns in existing data and generate novel content in various formats such as text and images (Feuerriegel et al., 2024).

GenAI has become a prevalent organizational phenomenon with its integration gaining rapid traction as observed by the widespread adoption into different organizational functions (Mariani & Dwivedi, 2024). In addition to its integration into functions, organizations are using it to drive organizational growth to facilitate new product development, value creation process and also business model innovation (Mariani et al., 2023). Unlike previous AI technologies, the generative capacity has enabled organizations to automate tasks and support decision making by transforming it from a tool to a collaborator in operations. This AI-human collaboration through GenAI does not replace humans but rather augments creative potential to enhance decision-making and drive organizational innovation (Nah et al., 2023).

Adoption of GenAI has also shifted the knowledge management process within organizations by extracting implicit information to support knowledge intensive task which were traditionally limited to humans (Böhm & Durst, 2025). This ability to generate new information by identifying learned patterns reshapes knowledge creation and provides a mechanism for knowledge-intensive organizations to enhance their intellectual capital (Silva, 2025). Furthermore, the ability to capture individual learnings from existing patterns helps organizations transform individual expertise into institutionalized strategic assets that drive organizational performance (Nakash & Bolisani, 2025).

An important conceptual distinction must be established between GenAI adoption as operationalized in this study and the related but theoretically distinct concept of AI capability. AI capability refers to the accumulated organizational competency to identify, assimilate, and deploy artificial intelligence technologies to create value; it is an embedded resource built incrementally over time through sustained investment in technical infrastructure, specialized human expertise, and managerial know-how for AI utilization (Mikalef & Gupta, 2021; Bharadwaj, 2000). As a resource-based construct, AI capability is characterized by path dependency and causal ambiguity, making it difficult for competitors to imitate or rapidly replicate (Barney, 1991). In contrast, GenAI adoption grounded in Davis's (1989) Technology Acceptance Model and Rogers' (1962) Diffusion of Innovation Theory refers to the behavioral and organizational decision-making process through which firms integrate specific GenAI tools and systems into their operational workflows. Adoption reflects the extent to which GenAI has been formally incorporated into organizational practice, shaped by individual and organizational perceptions of usefulness, ease of use, and compatibility with existing processes. Adoption is therefore a process variable that can occur at a discrete decision point, whereas capability is a stock variable that accumulates over time and cannot be readily acquired through a single adoption event (Teece et al., 1997).

This distinction carries important implications for the interpretation of this study's findings. Firms in the Ethiopian consulting sector may exhibit high levels of GenAI adoption integrating tools such as ChatGPT or Copilot into client deliverable workflows without necessarily having developed deep organizational AI capability in terms of in-house data infrastructure, proprietary AI development, or institutionalized AI governance practices. The performance and innovation benefits measured in this study are therefore appropriately attributed to the adoption process and its immediate organizational consequences, rather than to the depth of accumulated AI capability that may emerge only over longer time horizons and sustained investment cycles. This scope clarification also positions the study's findings as particularly relevant to organizations in emerging economies, where cloud-accessible GenAI tools have lowered the adoption barrier significantly, but where deep organizational AI capability remains nascent (Agrawal, 2024; Mariani & Dwivedi, 2024).

2.2 Future Organizational Performance

Organizational performance is defined as the ability of an organization to achieve its strategic objectives through a set of resources and decisions (Abubakar et al., 2019). The traditional approach of measuring organizational performance was focused on financial performance parameters, which are usually expressed quantitatively (Jović & Tomašević, 2021). This method has evolved into a modern approach where success is not only measured by financial output but also by a combination of internal process stability and subjective factors, such as reputation (Singh et al., 2016). Selvam et al. (2016) emphasize that organizational performance measures should extend beyond short-term profitability and incorporate a balanced measurement approach, which includes operational efficiency, employee satisfaction and sustainability.

In the context of management consulting firms or knowledge-based firms in general, performance measurement is assessed through an efficient knowledge management cycle (Jurgita et al., 2021). To capture this Ibatova et al. (2018) suggest the measurement of 4 key blocks of key performance indicators, namely finance, market, business processes, and employee. These indicators allow an objective measurement of organizational performance by creating the connection between operational parameters and strategic goals. Furthermore, identification of redundancies and automation for effective resource utilization have become a metric of organizational success (Olan, et al., 2022).

The advanced development of digital technologies has resulted in the adoption of digital business models by consulting firms to enhance services (Tavoletti et al., 2022). According to Mikalef et al. (2023), firms that successfully integrate digital technologies into their operations benefit from increased internal efficiency and enhanced market reputation, resulting in improved future organizational performance. This suggests that technology integration, such as GenAI, into core operations and services by firms has become a driver and determinant of organizational performance complementing the frequently used metrics (Tavoletti et al, 2022; Mikalef et al, 2023).

2.3 Innovation

Numerous definitions of innovation have been provided by different academic literature and scholars. According to Kahn (2018), innovation is a combination of outcome, procees and mindset

through which unique or new opportunities are identified and developed into outcomes. This perspective is supported by Gupta (2018), who defines innovation as a multistep creative process of generating new ideas by using existing resources and implementing them to ensure organizational success. Beyond the generation of new ideas and products, innovation can also be defined as a change to internal traditional organizational functions. This involves developing strategies to bring change to management practices and administrative structures within an organization, and this is referred to as managerial innovation (Damanpour & Aravind, 2012). Gomes & Wojahn (2017) further define innovation by relating it closely to a firm's learning ability, that result in a set of mechanisms towards improving organizational performance. These definitions collectively suggest that innovation is a multi-stage process that organizations conduct to remain competitive and sustain performance (Niu et al., 2023).

The primary motive for organizations to pursue innovation is for the purpose of gaining long-term strategic gains in the market by satisfying evolving needs and requirements (Nečadová & Scholleová, 2011). One major factor driving the evolving needs is the rapid advancement of technologies and digital transformations within the operating landscape, which has necessitated continuous organizational innovation (Niu et al., 2023). Technological advancements are recreating organizational boundaries and forcing firms to innovate their capabilities to effectively serve the needs of the market (Chen & Kim, 2023). Among the recent technological advancements is the introduction of AI, which has not only forced innovation but also reshaped the innovation process (Haefner et al., 2021).

According to O'Cass & Wetzels (2018), increased innovation is being observed in organizations providing professional and knowledge-intensive services. Among these are management consulting firms that have been highly involved in innovation in response to significant disruption caused by AI. Innovation within these firms is happening both in the form of exploitative and exploratory innovation. The exploratory innovation is happening through the adoption of new tools and technologies to streamline operations and improve productivity. On the other hand, the exploitative innovation has been focused on enhancing existing capabilities and practices (Goto, 2023).

2.3.1 Exploitative Innovation

Exploitative innovation is defined as a type of innovation that focuses on the improvement of a firm's products or services by utilizing existing knowledge and resources, such as technologies and tools. This approach to innovation is focused on refining the firm's offerings and processes by using existing capabilities (March, 1991). This definition is also supported by Manso (2011), who defines exploitative innovation as an incremental improvement on what is already within the capacity of an organization to enhance efficiency and ensure outcomes. In terms of market and customers, exploitative innovation aims to satisfy the needs of current customers and markets by improving offerings using existing organizational knowledge (Martini et al., 2013).

The choice of exploitative innovation often depends on the strategic needs of the organization in terms of risk tolerance and timeframe for result achievement. Organizations usually prioritize exploitative innovation when short-term payoffs are expected. In addition, this innovation approach is preferred by organizations when there is a need to avoid high uncertainty resulting from exploring new areas (Manso, 2011).

Organizations in different sectors have been observed using technology, such as GenAI, to improve existing operations. According to Johnson et al. (2022), organizations are utilizing technologies to innovate their process such as automating tasks and workflows. However, the study notes that there are challenges to integrating these technologies within the existing operations. Artificial intelligence is also observed to enhance exploratory innovation by creating a human and technology collaboration that ultimately results in efficiency maximization (Liu & Li, 2025). This enhanced collaboration has been beneficial in knowledge-intensive industries where organizations are using the technology to relieve existing resources from routine tasks and redirect them towards other productive processes (Fartash, et al., 2018).

Studies suggest that exploitative innovation is related to organizational performance. Exploitation helps organizations to perform in the existing market by leveraging existing experience and knowledge (Hou, Hong, & Zhu, 2019). Enhanced performance can be achieved in a competitive market when organisations improve their service offerings in alignment with those of customer needs (Jansen et al., 2006).

2.3.2 Exploratory Innovation

Exploratory innovation is a type of innovation that focuses on searching for knowledge and expertise to develop new products or services that are distinct from what the organization currently offers. This is achieved by activities such as searching, experimentation, risk-taking, and discovery (March, 1991). Compared to exploitative innovation, exploratory innovation is characterized by uncertainty as it involves exploring and coming up with new products or services whose outcomes are not immediately predictable. This type of innovation is closely linked with radical innovation that results in novel outputs and expansion towards new markets (Visser & Scheepers, 2022; Roth et al., 2024).

Organizations are motivated to engage in exploratory innovation when existing knowledge and services become insufficient to serve the market, making it necessary to expand the knowledge base and expertise (Mueller et al., 2013). According to Verwaal (2017), as competition within the market increases it becomes likely that organizations exhaust their existing knowledge and services. This results in a shift towards searching for new solutions. This is further amplified by the organization's risk tolerance and long-term orientation. Organizations with increased risk-apetite and long-term strategic output pursue exploratory innovation rather than focusing on incremental improvements (Braunerhjelm & Thulin, 2023).

Artificial intelligence technology is one of the most important tools that complements exploratory innovation. According to Johnson et al. (2022), AI is being used as a resource for exploratory innovation, especially for R&D activities, to help identify patterns and introduce new ideas. In addition, it is expanding the knowledge base for organizations by connecting them to global sources that were difficult to reach (Verwaal, 2017). From this, it can be understood that technology is acting as an enabler for innovation.

Findings from different studies indicate that exploratory innovation helps organizations improve performance and cope with competitive pressures. Braunerhjelm & Thulin (2023) claim that exploratory innovation is associated with long-term firm growth, such as employment expansion. This claim is consistent with March’s (1991) assertion that exploratory innovation is crucial for organizational performance and competitiveness despite the risk of uncertain and distant returns.

2.4 Organizational Agility

Organizational agility describes a firm's capability to sense and respond in time to unpredictable market changes and opportunities (Jayampathi, 2025). Another definition of it is the capacity to react swiftly and proactively to unforeseen changes in a dynamic environment through efficient resource restructuring and quick decision-making. According to Walter (2021) It can be broadly defined as an organization's capacity to flourish in a setting that changes quickly. Most people consider agility to be a dynamic ability. Agility capabilities like sensing, flexibility, responsiveness, and speed must be developed in response to shifting market or technological drivers. These capabilities are achieved through supporting enablers like processes, IT, and culture (Walter, 2021). Management's role in dynamic business environment is to monitor internal/external agility drivers and align resources to develop the necessary agility capabilities.

According to Walter (2021), responsiveness (quickly recognizing and responding to change), flexibility (planned adaptability), speed (completing tasks quickly), and innovative proactivity are frequently recognized agility capabilities. Yusuf et al., (1999), further define agility as the effective use of reconfigurable resources to explore competitive advantage through dimensions such as speed, flexibility, innovation, proactivity and profitability. In this regard, agile businesses reorganize their resources and procedures to quickly and creatively seize new opportunities.

Walter (2021) claims that agility and business results are positively correlated, and that agility is viewed as a differentiation strategy that strengthens competitiveness in volatile and complex markets. Budimana et al. (2023) further supports this arguing that managers rely on organizational agility and dynamic capabilities to accomplish project success in tumultuous and uncertain environments. Businesses with agility are able to swiftly adjust and seize new opportunities, maintaining future performance.

Innovation and agility are closely related. Organizations can more successfully engage in both exploration and exploitative innovation thanks to dynamic agility. According to Yusuf et al. (1999), innovation proactivity is specifically included in the definition of agility. Organizational agility is frequently seen as the result of incorporating cutting-edge IT and AI into daily operations in the context of digitalization. A recent study by Atienza-Barba et al. (2024) identifies an expanding field of study that connects AI and organizational agility. According to the research, businesses are primarily integrating AI into operations to increase agility. They characterize AI-enabled

transformation as the "genesis and overhaul of organizational routines." Put another way, successful AI adoption can itself generate new sources of agility by automating sense and respond processes

If rapid innovation is made possible by Gen AI, a company's ability to integrate those innovations would depend on its organizational agility. Strong agility capabilities, for instance, put businesses in a better position to participate in both exploratory and exploitative innovations without upsetting the company. Atienza-Barba et al. (2024) further proposes that by reorganizing routines, AI integration encourages agility.

It is necessary to explicitly distinguish organizational agility from the related but conceptually distinct construct of environmental dynamism, which has served as a moderating variable in related empirical frameworks (Singh et al., 2024; Jansen et al., 2006). Environmental dynamism refers to the rate of change and unpredictability in the external competitive and technological environment, capturing the external pressure on organizations to adapt (Jansen et al., 2006). Organizational agility, in contrast, is an internal dynamic capability; the organization's actual demonstrated capacity to sense environmental changes, reconfigure resources, and respond in a timely and effective manner (Walter, 2021; Eisenhardt & Martin, 2000). While environmental dynamism may motivate the development of agility, it does not guarantee it. Two organizations operating within the same dynamic external environment may exhibit vastly different levels of agility depending on their internal resource endowments, leadership orientation, and cultural openness to change. In the context of examining how GenAI adoption translates into innovation and performance outcomes, organizational agility is therefore a more proximal moderator than environmental dynamism, because it captures the internal organizational capacity through which GenAI resources are effectively deployed rather than the external conditions that necessitate deployment. This distinction is theoretically grounded in the Resource-Based View (Barney, 1991; Teece et al., 1997), where agility functions as a dynamic capability that enables value creation from technological investments such as GenAI adoption. As Sambamurthy et al. (2003) demonstrated in their foundational work on digital agility, it is the internal organizational capacity for rapid sensing and reconfiguration. It is not the external environment that determines whether technology investments yield competitive advantage. This distinction reinforces the conceptual

and empirical logic for examining organizational agility, rather than environmental dynamism, as the internal capability moderator in this study's framework.

2.5 Ethical Dilemmas

Ethical dilemmas are conflicts faced by decision makers between what needs to be done morally and organizational obligations. There are choices were deciding one standard may compromise another (Naamati-Schneider et al., 2024). In the context of generative AI, ethical dilemma is common from the tradeoffs introduced by innovation. One example of this is organizations struggle to balance between innovation against concerns for fairness, privacy, intellectual property or quality of service. Singh et al. (2024), note that GenAI can produce different content and therefore organizations must face ethical dilemmas as to where this technology is to be used. This is because companies don't want to compromise their ethical standards.

According to Singh et al. (2024), data privacy and security are major concerns. New AI tools may use sensitive data. Naamati-Schneider et al. (2024), report that digital transformation created dilemmas in balancing quality of care against efficiency and cost. One example is when allocating limited resources or using AI diagnostics which can affect patient welfare against financial constraints. In a similar manner, educational uses of GenAI bring dilemmas over authorship and originality. Muringa (2025), discusses students questioning the ethical justification of AI assisted essays considering academic integrity and autonomy.

The responsibility of ethical dilemma is mostly on employees and managers. Naamati-Schneider et al. (2024), discusses that continuous moral conflicts at the individual level can cause moral distress. This is because of knowing the right action and not being able to take it. This will lead to burnout and defensive behavior. This is an indicator that unresolved ethical tensions stress individuals and also act as barriers to change. In today's tech enabled environment, companies need to include ethics into culture and decision-making process to guide behavior (Martínez et al., 2021)

Rana et al. (2024), discusses that specific ethical principles such as fairness, accountability, transparency, accuracy and autonomy influence GenAI use. These principles affected managers' willingness to implement Gen AI. There is similar investigation by Salamzadeh et al. (2025) about the ethical side of GenAI driven innovation. They found that while technical features initially drive

adoption, ethical considerations become the primary focus as technology matures and faces stricter regulatory oversight. However, in their model the hypothesis of ethical dilemma as a moderator between exploitative innovation and organizational performance by AI adaptation was rejected. This indicates that there is a need for more research empirically.

From a theoretical standpoint, understanding how ethical dilemmas moderate the organizational outcomes of GenAI adoption requires grounding in individual-level moral decision-making theory. Jones' (1991) issue-contingent model of ethical decision-making argues that the moral intensity of an issue is defined by factors including the magnitude of consequences, the probability of harm, the immediacy of effects, and the degree of social consensus around the ethical issue determines the extent to which ethical considerations influence individual behavior and organizational decisions. In the context of GenAI, the potential for biased, incorrect, or privacy-violating AI-generated outputs carries significant moral intensity given the scale at which GenAI operates and the often-irreversible consequences of AI-generated errors in client-facing consulting work (Rana et al., 2024; Camilleri, 2024). High moral intensity is likely to trigger heightened ethical scrutiny among employees and managers, creating friction in GenAI-enabled activities and moderating both the innovation outcomes and performance benefits of adoption. Complementing this, Tenbrunsel and Messick's (2004) ethical fading theory suggests that when organizational competitive pressures such as client deadlines and billable hour targets are intense, ethical considerations can systematically fade from awareness, leading decision-makers to rationalize ethically questionable GenAI applications as organizationally necessary. This ethical fading is particularly relevant in high-pressure management consulting environments, where the urgency of client deliverables may override deliberate ethical reflection. Together, these theoretical frameworks provide the foundational logic for understanding why the salience and perceived severity of ethical dilemmas would moderate the effectiveness of GenAI adoption across its distinct innovation and performance pathways.

2.6 Theoretical Background

2.6.1 Diffusion of Innovation theory (DIT)

The diffusion of innovation theory provides an important explanation of how new techonolgies, such as GenAI, emerge and become integrated within organizations. This theory was first

introduced by Rogers (1962), and states how innovation is introduced and communicated over time among members. It explains that adoption is not instanteneous but rather happens through steps which are affected by perception (both individual and organizational perception), context and organizational readiness. Diffusion of innovation has been widely use in many organizational researches to understand the adoption and spread of digital technologies including Generative AI (Agrawal, 2024; Danson, 2025). Hence, it is important to apply this theory and examine the dynamics of GenAI adoption.

According to the theory, the basic factor which influences adoption decision is the perception of adopters on the attributes of the innovation which include compatability, complexity, trailability and observability. These attributes determine the likelihood, speed and rate of innovation adoption (Rogers, 1962). Emperical studies have tested this claim within the context of AI diffusion and found that the prceieved advantage plays a cruicial role in adoption with the findings indicating that organisations are more inclined to adopt AI systems when they percieve that it will bring performance improvements and enhanced efficiency (Agrawal, 2024; Mariani et al., 2023). In the context of GenAI, the percieved value is also associated with improved creativity, automation of routine tasks and improved decision support system for managers (AL-khatib & Wael, 2023).

Compatability is another factor that affects the diffusion of innovation. Innovations that allign with the organizations existing process and infrustructure are more likely to be adopted and develop further. Emperical literature on AI aided innovation indicate that compatability reduces resistance that could have resulted from integration costs (Reis & Junior, 2025). Opposite to this, perceived complexity of AI adoption can slow diffusion since it requires additional effort by organizations to improve technical skills and internal structures to sustain the diffusion (AL-khatib & Wael, 2023).

As stated above, diffusion of innovation is a step by step process which runs from initial discovery upto implemenation. This staged process indicate that the difffusion of innovation also applies to exploitative and exploratory innovation. During the initial stage of GenAI adoption organizations engage in exploratory innovation to understand the potential value this technology provides and its strategic relevance (Singh et al., 2024). The trailability attribute comes into action during this stage, as organizations engage in pilot experimentations to test the system, build capabilities while also understanding uncertainity in the technology (Johnson et al., 2022).

Once the advantage is percieved through the exploratory phase, the diffussion progresses and organizations engage in exploitative innovation to further refine and integrate GenAI into the existing system. During this stage, organizations use exploitative innovation to satisfy the observability and confirmation attributes of innovation to reinforce the percieved advantage and justify additional resource allocation (Jansen et al., 2006). From this it can be understood that diffusion of innovation theory can be extended to examine the variables of this study.

The diffusion created by GenAI may create value but it is improtant to cosider contextual factors such as ethical aspects that acompany AI adoption. Numerous studies suggest that ethical dilemmas related to data privacy and cybersecurity can pose a challenge to the adoption and persist along the diffusion process (Kiris & Gurul, 2025). This ethical factors can alter the adoption and diffusion process indicating a moderating effect in the relationship between GenAI adoption and innovation.

Additionally, it has been noted that organizational readiness affects the diffusion process. According to Noronha et al. (2022), Organization with higher degree of readiness and agility are in a better position to adapt and respond to feedback observed during the diffusion process. This agility also helps organizations to effectively balance exploratory and exploitative innovations (Fasnacht & Proba, 2024). Hence, the diffusion of innovation theory provides a strong theoretical framework for understanding how organizational agility moderates the relationship between GenAI adoption and innovation.

2.6.2 Resource-based View Theory (RBV)

The resource based view theory is an important theoertical framework which helps to understand how organizations achieve and sustain competitive advantage by using their unique internal resources. According to the theory, organizations can achieve improved performance and competetiveness by using valuable, rare, inimitable and non-substitutable internal resources and integrating them into organizational processess (Barney, 1991). The theory further explains that success of an organization is not dependent only on its external market positioning but also on how the firm owns unique internal resources and deploys them (Srivastava et al., 2001)

With the increasing digitalization, the resource based view has evolved to include digital assets like GenAI as key internal resources for achieving organizational success (Willi, 2025). According

to Chen et al. (2022), artificial intelligence has become an important intangible resource for organizations by providing them access to invaluable information that can potentially bring competitive advantage for the firm. This is also supported by Nayak (2023), indicating that firms with better GenAI capacity gain competitive advantage by using its unique capabilities. However, the GenAI should bundled with existing organizational assets such infrustructure and human capital to achieve improved organizational performance (Olan, et al., 2022). Based on this, the resource based view theoretical framework can be used to explore how GenAI, the organizatations unique resource, helps to gain competitive advantage and improved future organizational performance.

The transformation of GenAI resources is not only direct but also affected by exploratory and exploitative innovation. From a resource based view, organizational resources alone are not the determinants of competitive advantage but they should rather be mobilized through organizational process and innovations to create value (Mikalef & Gupta, 2021). Exploratory innovation thorugh GenAI supports this as it enables the organization to explore and enter into unexplored segments of the market by uncovering unique ideas and solutions (Rabitha & R, 2025). Similarly, exploitative innovation enables the organization to enhance and optimize existing resources by improving efficiency (Jackson & Sobrinho, 2025). Hence, the resource based view can also be used to explore how a firms resource like GenAI facilitates innovations towards achieving improved organizational performance.

While DIT and RBV are independently robust frameworks, their integration provides a more unified theoretical foundation for this study. DIT explains how GenAI spreads within organizations through staged adoption decisions shaped by internal factors, while RBV serves as the outcome theory, explaining how organizations that successfully bundle GenAI with existing resources to sustain competitive advantage and improve performance. This complementarity is further evident through exploratory and exploitative innovation, where the exploratory phase simultaneously reflects early diffusion and resource acquisition, and the exploitative phase reflects both diffusion confirmation and resource deployment for improved performance. Together, the two theories form a coherent and sequential logic that serves as the theoretical backbone of the conceptual model for this study.

2.7 Empirical Literature Review and Hypothesis Development

2.7.1 Generative AI Adoption and Exploratory Innovation

Different research on GenAI adoption have identified enablers that determine the successful integration of technology. At the individual level, Korzynski et al. (2023) argues that perceived usefulness, ease of use and performance expectancy shapes users' decisions to engage with GenAI tools and their satisfaction with its outputs which results in continued use. At the organizational level, AL-khatib & Wael (2023) applies the technology, organization and environment (TOE) framework to argue that technological readiness and the perceived compatibility of GenAI with existing workflows are the primary predictors of successful GenAI adoption. In addition, the researcher proposes that high perceived quality of the technology acts as an enabler for organizational change.

However, adoption of technology alone does not explain innovation outcomes. What matters for exploratory innovations is what GenAI enables and facilitates once it has been adopted. Korzynski et al. (2023) theorises that GenAI directly facilitates exploratory activities at both strategic and administrative levels by generating new ideas and facilitating knowledge creation through socialization, externalization, combination and internalization. Korzynski et al. (2023) further argues that GenAI enables prosumption whereby users actively create new value for themselves and the company indicating an exploratory behavior. AL-khatib & Wael (2023) further complements this suggesting that organizational support and technological readiness are positive predictors of exploratory innovation outcomes demonstrating that GenAI provides the exploratory capacity needed to discover innovative solutions that traditional AI can't achieve.

Abrokwah-Larbi (2023), further suggests that GenAI complements human decision-making and enables personalized content creation through deep learning and smart data capabilities that expand the organization's creativity and innovation capacity. Olan et al. (2022), also supports this by finding noting that AI-enabled knowledge sharing facilitates the transformation of existing data into new knowledge, which in turn enables the generation of innovative ideas and solutions.

While the studies reviewed above converge in establishing a positive relationship between GenAI adoption and exploratory innovation, closer examination reveals important theoretical and methodological tensions that require critical engagement. At the theoretical level, a fundamental

divergence exists between technology-push and capability-pull perspectives. Korzynski et al. (2023) take a predominantly technology-push stance, arguing that GenAI's inherent generative capacity autonomously stimulates exploratory behavior through presumption and knowledge socialization at the individual user level. In contrast, AL-khatib and Wael (2023) advance a capability-pull perspective, asserting that it is the organization's pre-existing readiness in terms of infrastructure, strategic intent, and technological compatibility that principally determines whether GenAI adoption leads to exploratory innovation outcomes. These two perspectives carry fundamentally different managerial implications: the former suggests that adoption alone is sufficient to trigger exploratory behavior, while the latter implies that adoption without organizational capability yields limited exploratory gains. This study aligns more closely with the capability-pull perspective, given that the Ethiopian consulting context is characterized by heterogeneous levels of technological infrastructure and varying GenAI adoption maturity, making organizational readiness a more decisive factor than the technology itself.

At the methodological level, several of the studies informing this relationship draw on single-country, single-industry, or largely conceptual designs (Abrokwah-Larbi, 2023; Olan et al., 2022), which limits the generalizability of their causal claims across diverse organizational settings such as knowledge-intensive consulting firms in developing economies. Moreover, extant research has largely examined the direct enabling effects of GenAI without adequately accounting for contextual boundary conditions such as competitive intensity, firm size, or the specific knowledge domain of the organization that may alter the strength of the adoption-exploration relationship (Mariani & Dwivedi, 2024). Furthermore, while most studies treat exploratory innovation as a unidimensional outcome, March's (1991) original conceptualization recognizes exploration as a multidimensional construct involving search, discovery, experimentation, and risk-taking, each of which may be differentially enabled or constrained by GenAI depending on the task and governance context. Future studies within this domain would benefit from disaggregating these dimensions of exploratory innovation to capture this conceptual complexity. Notwithstanding these limitations, the majority of available evidence supports a positive structural relationship between GenAI adoption and exploratory innovation.

Hence this study proposes the following hypothesis:

H1. GenAI adoption significantly and positively influences the outcomes of exploratory innovation in organizational settings.

2.7.2 Generative AI Adoption and Exploitative Innovation

Exploratory innovation relies on search and discovery whereas an exploitative innovation is driven by refinement, efficiency and implementation (Enkel, 2017).

Unlike exploratory innovation, which is slowed down by strict rules, exploitative innovation is positively influenced by formalization (Jansen, 2006). The same research defines formalization as the degree to which rules, procedures and instructions are written down and enforced. High quality GenAI adoption process provides structured templates, clear prompts and standard operating procedures. A company increases its efficiency and ability to refine current products and services by formalizing how AI is used for routine tasks.

Exploitative innovation depends on an individual's ability to understand existing knowledge and apply it to current problems. Enkel (2017) identified four dimensions of individual level absorption capacity. These are identification, assimilation, transformation and exploitation. They state that the exploitation dimension is clearly included as the fourth dimension because it focuses on incorporating transformed knowledge into the company's operations to achieve incremental innovation. The perceived quality of the AI adoption process specifically how well technology assists in transforming and applying data, supports individuals to perform exploitative tasks more effectively.

Long (2021) through the knowledge ecology theory discusses innovation as a continuous cycle of knowledge refinement within an industrial ecosystem. The research discusses the coordination of ambidextrous innovation through knowledge ecology spiral. Ambidextrous innovation is a business strategy where a company focuses on exploitation and exploration at the same time to achieve both short and long term goals (Waseel AH, 2024). Long (2021) argues that in order to get exploitative outcomes, the adoption of technology must encourage the internalization phase of knowledge. This is where individuals take AI generated insights and turn them into efficient practices.

Different research discusses process factors that contribute to successful exploitative outcomes. Galati (2021) indicates that leadership support is a moderator for technology adoption in SMEs.

This implies that leadership is essential for exploitative innovation to make sure GenAi is aligned with the company's strategic goals and existing resources. High quality adoption isn't about the software, instead it is about the governance and regulatory framework provided by the company (Sheshadri, 2019).

A critical appraisal of the literature on GenAI and exploitative innovation reveals important theoretical tensions that deserve explicit engagement. First, a conceptual ambiguity exists concerning whether GenAI is more naturally aligned with exploration or exploitation. March (1991) originally framed these as competing for organizational attention and resources, implying a structural trade-off. Several scholars argue that GenAI's capacity to generate novel and unpredictable outputs aligns it more naturally with exploratory rather than exploitative behavior, and that deploying GenAI for exploitation which requires structured, disciplined refinement of existing capabilities demands additional governance mechanisms that constrain GenAI's otherwise open-ended generative potential (Roberts & Candi, 2024; Johnson et al., 2022). From this perspective, the pathway between GenAI adoption and exploitative innovation may be more conditional and more dependent on organizational moderators such as leadership support (Galati, 2021), process formalization (Jansen et al., 2006), and employee absorption capacity (Enkel, 2017) than the pathway to exploratory innovation. This theoretical tension suggests that while a positive relationship is expected, its strength is likely context-sensitive and should not be assumed to operate uniformly across organizational settings.

Second, from a methodological standpoint, the empirical literature on GenAI and exploitative innovation remains comparatively thinner than the literature on exploration, with most studies drawing on conceptual frameworks or single-industry samples from manufacturing and IT sectors (Long, 2021; Enkel, 2017). The application of these frameworks to knowledge-intensive service firms such as management consulting where exploitation takes the form of refining client service methodologies and reusing accumulated consulting knowledge, rather than product-based iteration has received limited empirical attention. This gap reinforces the value of the present study, which examines this relationship within the specific operational context of Ethiopian consulting firms. Hence, this study proposed the following hypothesis.

H2. GenAI adoption significantly and positively influences the outcomes of exploitative innovation in organizational settings.

2.7.3 Generative AI Adoption and Future Organizational Performance

Generative AI is a relatively new technolgical development that is being widely used in different sectors. Its adoption and integration into organizational process can bring about a shift in the performance of organizations (Prado & Mantovani, 2025). Research indicates that GenAI have improved organizational performance by assisting in different tasks resulting in efficiency and competitiveness. To illustrate this, Kumar et al. (2025) studied how GenAI adoption affects firm performance and discovered that it enhances firm performance by enhancing business operations and improving efficiency. Moreover, it is also tranforming business in different industries by supporting the managers in decision making and also enhancing employee engagement through effective human-AI collaboration (Şahin & Karayel, 2024).

The mechanism through which GenAI improves future organizational performance has also been researched by numerous scholars and have found that it has the capability to transform knowledge creation and management. Olan et al. (2022) highlights that GenAI has the capacity to create new knowledge for organizations that can strategically improve performance. Kudryavtsev et al., (2024) further support this and argue that GenAI aids knowledge creation, access and capture which in return have a profound effect on firm performance. GenAI can also enhance organizations knowledge base through creative process that enable them to adopt strategies targeted at performance improvements (Mikalef & Gupta, 2021).

Emperical studies have also examined different dimensions of organizational performance resulting from GenAI adoption. From a financial performance perspective, improved performance has been observed as a result of automation, improved decision-making and enhanced financial planning (Antoniuk et al., 2025). Furthermore, GenAI's automation feature reduces routine task which results in reduced operational cost and enhanced resource allocation (Son, 2023). Interm of operational performance, GenAI streamlines internal process. For example, it allows an organization to strategically shift its resources, such as human capital, from extensive administrative tasks towards high-value roles which improves overall performance (Budhwar, et al., 2023; Prado & Mantovani, 2025).

Despite the weight of empirical evidence supporting a positive relationship between GenAI adoption and organizational performance, a critical reading of the literature reveals several unresolved tensions that this study must explicitly address. First, a fundamental measurement

inconsistency exists across studies. While Kumar et al. (2025) and Mikalef et al. (2023) operationalize performance improvement primarily in terms of operational efficiency and financial returns, studies such as Olan et al. (2022) and Kudryavtsev et al. (2024) conceptualize performance through a knowledge management lens, treating improved knowledge creation and knowledge capture as the primary performance outcome of GenAI adoption. These divergent operationalizations complicate cross-study comparisons and suggest that the relationship between GenAI adoption and performance is not uniform across performance dimensions. This study addresses this limitation by adopting a forward-looking, multi-dimensional measure of future organizational performance (Dubey et al., 2020) capturing both financial and market-facing dimensions which is particularly appropriate for the consulting sector where knowledge-intensive competitive advantages are the primary source of value creation.

Second, and more critically, the negative findings reported by Lui et al. (2022) and Rana et al. (2022) are not mere anomalies. They reflect a substantive and theoretically important argument about the governance conditions under which GenAI adoption generates value. Lui et al. (2022) found that AI investment carries a negative firm value effect when not accompanied by clearly communicated strategic alignment, suggesting that the performance benefit of adoption is conditional on how the technology is positioned within the organization's strategic narrative. Rana et al. (2022) identified inadequate oversight and governance failure as mechanisms through which AI adoption can degrade rather than enhance organizational performance creating operational inefficiencies and competitiveness erosion that offset the productivity gains. These findings collectively imply that the performance effect of GenAI adoption is conditional rather than universal: it is positive when organizations possess sufficient governance readiness and adaptive capability, and potentially negative in their absence. This conditioning logic provides additional theoretical grounding for the inclusion of organizational agility which includes governance agility as a moderating variable in the present study's model, and reinforces why the Ethiopian consulting sector context, where GenAI governance frameworks are still nascent, warrants specific empirical investigation.

The findings highlight the fundamental effect of GenAI adoption on future organizational performance; hence the following hypothesis has been proposed.

H3: GenAI adoption has a significant and positive impact on future organizational performance.

2.7.4 Exploratory Innovation and Future Organizational Performance

Organizational operating in today's rapidly changing environment are faced with the need to proactively innovate their businesses to adapt to ongoing changes, stay competitive and avoid obsolescence (Ioniţă, 2022). Ioniţă (2022) proposes the need for companies to transform themselves and improve their organization performance by engaging in innovative strategies that enables them to look into new opportunities. Hou et al. (2019) confirms that exploratory innovation has a significant and positive effect on firm performance, as it serves as source of absolute competitive advantage that is difficult for competitors to immitate.

Nyamekye et al. (2026) conducted a study on firm in Ghana and found that exploratory innovation enhances the flexiability of firms and creates dyanmic capacilities. According to the researchers, engaging in exploratory innovation not only creates dynamic capabilities but also helps the organiztions achieve improved performance. Wang D. S. (2019) further support this claim and argues that technology enabled exploratory innovation has a positive effect on firm performance, as it allows organizations adapt to new markets, enhance services and also swiftly respond to changing market demands.

Hou et al. (2019) discuss that some organizations tend to be wary of exploratory innovation due to its resource demand and uncertainity of outcomes. They contend that exploratory innovation has higher resource demand and is time consuming which makes organizations cautious from pursuing it. However, the study found that exploratory innovation has the potential to bring about distinct and unmatched advantages to organizations that facilitates sustained long term performance. Bogetoft et al. (2024) further confirmed this and found that organizations that have innovation oriented strategies, particularly those involving development of new capabilites, are better positioned to achieve performance improvements both in the short and long term.

Synthesing the result of these studies, the effect of exploratory innovation on future orgnaizational performance is evident. Hence, the following hypothesis has been proposed.

H4: Exploratory innovation has a significant and positive impact on future organizational performance.

2.7.5 Exploitative Innovation and Future Organizational Performance

Innovation remains as an important mechanism that companies use to develop new product, services or knowledge in order to achieve improved organizational performance. However, scholars contend that the innovation should not only focus on exploratory innovation but also exploitative innovation. Le et al. (2023) through their study on Vietnamese firms, found that organization engaging in exploitative innovation to expand and improve their existing products and service are better positioned to sustain their market position and achieve improved organizational performance. Exploitative innovation helps organizations achieve improved performance in the short run through efficency gains and optimization of existing capabilities to close the gap between their existing capabilities and market demands (Hou et al., 2019).

Marín-Idárraga et al. (2022) conducted a meta-analysis of how exploratory and exploitative innovation affects organizational performance. The finding of the study shows that, exploitative innovation enables organizations to achieve gradual but consistent performance improvements in efficiency and profitability as a result of contineous refinement of existing processes and deepening of knowledge capital.

Asiaei et al. (2022) also supports this and arguing that knowledge intensive organization that pursue exploitative innovation alongside exploratory innovation are more like to achieve enhanced performance through the delivery of knowledge based offerings that meet market demands.

The findings highlight the potential effect of exploitative innovation on future organizational performance; hence the following hypothesis has been proposed.

H5: Exploitative innovation has a significant and positive impact on future organizational performance.

2.7.6 Mediating Role of Exploitative and Exploratory Innovation

A study by Khan et al. (2025) examines the effect of GenAI adoption on organizational perfromance by adopting a technology-organization-environment paradigm. The finding of the study indicates that GenAI can bring about improved organizational performance by facilitating organizational innovativness. The innovation that results from this technology happens both in the form of exploratory and exploitative innovation. Based on this finding, the study argues that the

enhanced innovation as a result of GenAI adoption has the potential to improve organizational performance.

This claim has also been tested by Pokar's (2025) research which aims to understand the relationship between GenAI adoption and organizational performance by examining enablers. This study which is conducted across different types of organizations indicate the emergence of exploitative and exploratory innovation as a result of GenAI adoption. The innovations resulting from this process further enable the achievement of improved organizational performance. However, the researcher noted that the success of this process is dependent on the organizations readiness interms of resources and skills.

Roberts & Candi (2024) also studied how artificial intelligence is transforming innovation process within organizations. GenAI is changing how organizations innovate by providing advanced capabilities that helps organizations explore new ideas and radically innovate their business to stay ahead of competitors. Additionally, this technology is complementing employees creativity resulting in improved productivity and efficiency in task execution. This study suggest that organizations which are capable of adopting GenAI are better positioned to improve their innovativeness and this helps them stay ahead of competition and perform better in the market.

A critical reading of the mediation literature, however, surfaces important theoretical debates and methodological limitations that must be acknowledged. First, the studies reviewed including Khan et al. (2025), Pokar (2025), and Roberts and Candi (2024) treat exploratory and exploitative innovation as parallel mediators, implying that each independently channels a portion of GenAI adoption's effect on organizational performance. This parallel design, while testable, overlooks the possibility that exploratory and exploitative innovation operate sequentially rather than independently. Consistent with March's (1991) original argument that exploration provides the raw material from which exploitation subsequently extracts value, a serial mediation structure would suggest that GenAI adoption first stimulates exploratory innovation generating new ideas and opportunities which in turn informs and enables exploitative innovation through the refinement of those ideas into performance-enhancing outputs. If serial mediation is operative, parallel testing may underestimate the total indirect effect of GenAI adoption on organizational performance. This study adopts the parallel mediation design in alignment with Singh et al. (2024) as a conservative

and empirically tractable approach, but acknowledges this as a theoretical limitation and highlights it as a direction for future research.

Second, the available evidence consistently points toward partial rather than full mediation through innovation that is, GenAI adoption retains a significant direct effect on performance even after accounting for the innovation-mediated pathways (Singh et al., 2024). This is theoretically significant because it implies that GenAI contributes to organizational performance through mechanisms that bypass innovation entirely including direct efficiency gains from task automation, real-time decision support, and cost reduction (Kumar et al., 2025; Budhwar et al., 2023). Recognizing this partial mediation structure is important for the present study, as it positions exploratory and exploitative innovation as key but not exhaustive channels through which GenAI adoption shapes future organizational performance, and ensures that the direct adoption-performance relationship is not theoretically or empirically overlooked.

This findings emphasis the close relationship between between GenAI adoption and exploratory and exploitative innovation. It also suggests that this relationship also relates to change in future organizational performance. Hence, the following hypotheses have been proposed:

H6: Exploratory innovation positively mediates the relationship between GenAI adoption and future organizational performance

H7: Exploitative innovation positively mediates the relationship between GenAI adoption and future organizational performance

2.7.7 Moderating Role of Ethical Dilemmas and Organizational Agility

One important factor when considering the adoption of new technologies is organizational agility. Wahab & Radmehr (2024) propose that the potential benefit GenAI provides is dependent on the organizations agility towards emerging technologies. The research implies that organizations that are more agile easily adapt to new technologies and use them to improve performance. Organizations should also be flexiable and quickly provide the necessary resources needed for GenAI adoption and also facilitate organizational support to accletate its acceptance (AL-khatib & Wael, 2023).

Gong & Ribiere (2023) emphasis the significance of organizational agility in achieving and utilizing digital transformation within organizations. Organizational agility also affects innovation within organizations. Organizations with higher level of agility are better positioned to find innovative ways of operating by actively assessing developments and opportunities and take advantage of them to become industry leaders (Giacosa et al., 2022). Riyanto (2024) researched the interplay between ambidextrous leadership, agility, and innovation. The findings of this study indicate the importance of organizational agility in implementing both exploitative and exploratory innovations. The study suggests that organizational agility is required to respond and explore external changes in the operating landscape while also having the flexiablity to innovate existing operations.

Organizational agility has also been found to have a role in affecting organizational performance by numerous studies. A study conducted by Nafei (2016) across five companies found that organizational agility plays a significant role in affecting organizational performance. Hence, it suggests the importance of considering organizational agility when considering the key drivers of organizational performance. A study conducted by Atobishi et al. (2024) which examines the role organizational agility plays in the relationship between an organization's digital capabilities and organiztional performance further supports this. The study found that organization agility is a crucial enabler in translating digital capabilities, using technology to improve operations, into improved organizational performance. Arshad et al. (2024) also supports this findings claiming that the improved organizational performance to be achieved from the adoption of new technologies is amplified by agile organizational culture.

Based on the above argument it can understood that organizational agility could potentially affect the relationship between GenAI adoption, innovation and future organizational performance. Hence the following hypotheses have been proposed:

H8a: Organizational agility moderates the positive relationship between GenAI adoption and exploratory innovation.

H8b: Organizational agility moderates the positive relationship between GenAI adoption and future organizational performance.

H8c: Organizational agility moderates the positive relationship between GenAI adoption and exploitative innovation

Beyond organizational agility, the degree to which ethical dilemmas are perceived within organizations represents a critical condition for understanding how GenAI adoption shapes innovation and performance outcomes. In the context of GenAI, ethical dilemmas arise when organizations must navigate conflicting obligations between maximizing the operational benefits of GenAI and upholding ethical standards such as data privacy, fairness, intellectual property, accuracy, and quality of output (Tenbrunsel & Messick, 2004; Singh et al., 2024). Drawing on Jones' (1991) issue-contingent model of moral decision-making and Tenbrunsel and Messick's (2004) ethical fading theory introduced in Section 2.5, this study argues that ethical dilemma moderates each of the three pathways from GenAI adoption to its organizational outcomes through theoretically distinct mechanisms.

Ethical Dilemmas Moderating GenAI Adoption and Exploratory Innovation (H9a)

Exploratory innovation through GenAI involves generating new ideas, experimenting with novel service offerings, and engaging in knowledge-intensive discovery activities that extend beyond the organization's existing knowledge base (March, 1991). By its nature, GenAI-enabled exploration involves high levels of output novelty and uncertainty conditions under which ethical risks are most salient and least tractable. Employees and managers using GenAI for exploratory purposes encounter ethical concerns around the provenance of training data used by GenAI models, the intellectual property status of AI-generated ideas and content, and the risk of hallucinated or biased AI outputs corrupting new product or service development directions (Zada et al., 2024; Lin et al., 2025). Critically, because exploratory outputs are by definition new and unverified, the ethical risks of GenAI-generated exploration are harder to audit and correct than those arising from more structured exploitative tasks. According to Jones' (1991) moral intensity model, the high magnitude of potential consequences and the novelty of the ethical territory in GenAI-enabled exploration raise the perceived moral intensity of exploratory decisions, prompting employees to exercise greater ethical caution and to self-censor their engagement with GenAI for exploration purposes. Organizations in which ethical dilemmas are acutely perceived may thereby inadvertently constrain the creative freedom that GenAI enables, weakening its positive effect on exploratory innovation. Conversely, organizations where ethical dilemmas are managed through robust

governance frameworks and where ethical concerns are perceived as low allow employees to engage more freely with GenAI for exploratory innovation, amplifying its creative and generative capacity. This reasoning supports the hypothesis that ethical dilemmas moderate the positive relationship between GenAI adoption and exploratory innovation, weakening the relationship when ethical dilemma perceptions are high. This argument is consistent with Lin et al. (2025), who found that ethical concerns specifically around over-trust in GenAI outputs reduce employee engagement in exploratory innovation by suppressing the creative agency that effective exploration requires. (Freeman, 1984)

Ethical Dilemmas Moderating GenAI Adoption and Exploitative Innovation (H9c)

Although exploitative innovation is more structured and routinized than exploratory innovation, involving the incremental refinement of existing processes and the deepening of established knowledge (March, 1991; Jansen et al., 2006), it is not immune to the moderating influence of ethical dilemmas. When GenAI is used to refine existing organizational processes and improve current service offerings, ethical concerns manifest in distinct but consequential forms: the accuracy and reliability of AI-generated outputs embedded in client deliverables, the potential for algorithmic bias in process optimization recommendations, and the risk of inadvertent intellectual property infringement when GenAI draws on proprietary data patterns to generate incremental suggestions (Singh et al., 2024; AL-Kfairy, 2025). These concerns are especially consequential in the consulting context, where client trust in the accuracy and integrity of deliverables is a core competency and reputational asset. When ethical dilemmas are acutely perceived, organizations impose additional verification steps and governance layers on GenAI-assisted exploitative processes such as manual quality checks, output audits, and approval workflows that reduce the efficiency gains that would otherwise materialize from GenAI-enabled exploitation. Singh et al. (2024) note that organizational challenges arising from ethical considerations can impair firms' ability to innovate existing processes, while Lin et al. (2025) found that ethical concerns around AI reliance hinder employee creativity in incremental improvement tasks. The moderating effect of ethical dilemmas on the GenAI–exploitative innovation pathway is theoretically expected to be weaker than on the exploratory pathway, because exploitative tasks generate more verifiable and auditable outputs where ethical risks are more tractable and correctable (Singh et al., 2024). Nevertheless, where ethical dilemma perceptions are high, the governance friction introduced

constrains the exploitation gains from GenAI adoption, while low ethical dilemma perceptions allow exploitation benefits to materialize more fully.

Ethical Dilemmas Moderating GenAI Adoption and Future Organizational Performance (H9b)

At the organizational level, ethical dilemmas represent not merely individual decision-making challenges but systemic risks that can materially affect the aggregate performance outcomes realized from GenAI adoption. From a stakeholder theory perspective (Freeman, 1984), organizations are accountable to multiple bodies such as clients, employees, regulators, and professional bodies. These bodies hold distinct ethical expectations about the responsible use of AI in service delivery. When GenAI adoption generates ethical dilemmas that are unresolved or mismanaged, the consequences include reputational damage, regulatory penalties, erosion of client trust, and liability for substandard AI-generated outputs each of which directly undermines future organizational performance (Camilleri, 2024; AL-Kfairy, 2025). The empirical reality of these performance consequences is illustrated by cases such as Deloitte's 2025 repayment of service fees to the Australian government following the discovery of AI-generated errors in a commissioned report, a direct instance of how ethical failure in GenAI use translates into financial and reputational performance losses (Dhanji, 2025). More systematically, Rana et al. (2022) demonstrated that inadequate governance of AI outputs, a structural consequence of unresolved ethical dilemmas within organizations, leads to operational inefficiencies, competitiveness erosion, and degraded firm performance. Conversely, organizations that establish robust ethical governance frameworks for GenAI use, clear accountability structures, output verification protocols, and ethical training for employees, can neutralize these risks, allowing the performance benefits of GenAI adoption to materialize without the governance drag that ethical dilemmas impose. The moderating logic is therefore directional: organizations where ethical dilemmas are acutely perceived face compounded performance penalties from unresolved governance challenges, weakening the performance returns from GenAI adoption, while organizations where ethical dilemmas are effectively managed realize the full performance upside of adoption. This reasoning grounds the hypothesis that ethical dilemmas moderate the positive relationship between GenAI adoption and future organizational performance.

Hence the following hypothesis have been proposed:

H9a: Ethical Dilemma moderates the positive relationship between GenAI adoption and exploratoryinnovation.

H9b: Ethical Dilemma moderates the positive relationship between GenAI adoption and future organizational performance.

H9c: Ethical Dilemma moderates the positive relationship between GenAI adoption and exploitative innovation

2.8 Conceptual Model

Based on the discussion and the hypotheses above, the conceptual framework proposed for this study is shown in the following figure.

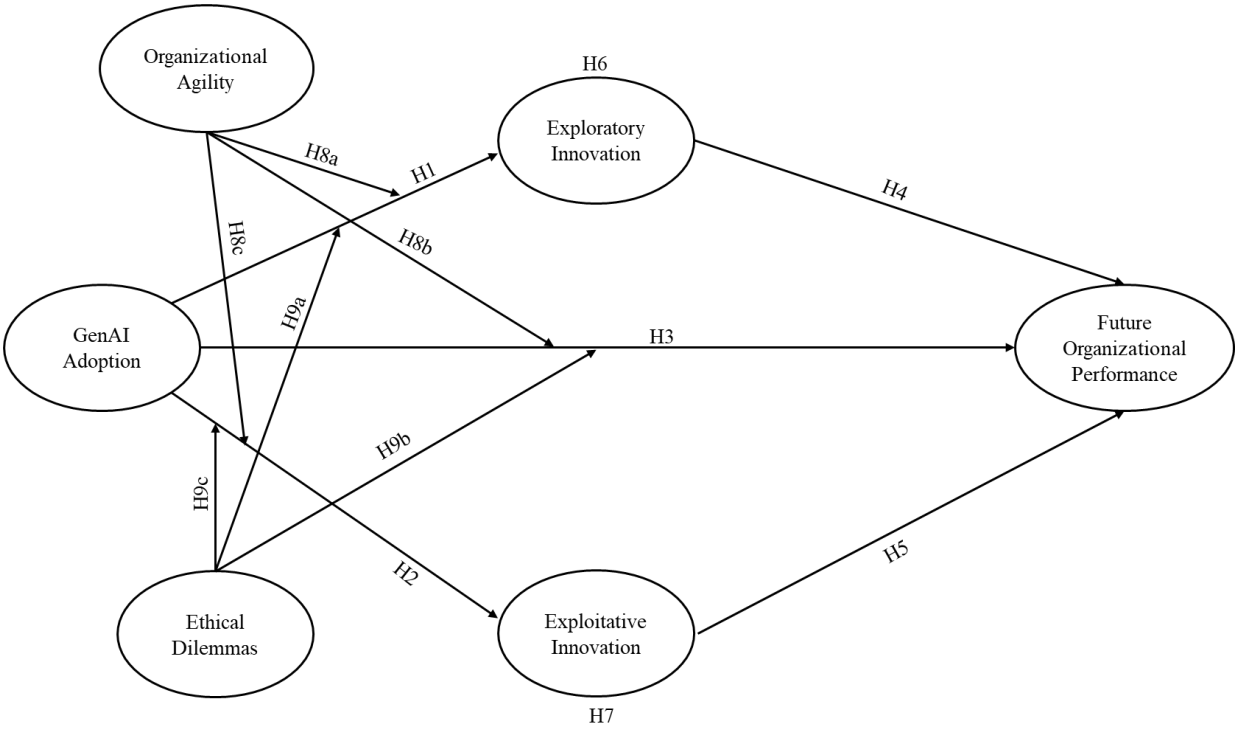


Figure 1: Conceptual framework developed for this study

The conceptual model for this study is adopted from Singh et al.(2024), who proposed a framework examining the relationship between GenAI adoption and organizational performance with exploratory and exploitative innovation as mediators and enviromental dynamism and ethical dilemmas as moderating variables. While this study maitains the proposed framework, environmental dynamism has been replaced by organizational agility as moderators. This

substitution of the moderating variable is justified by Wahab & Radmehr (2024), who found that organizational agility moderates the relationship between GenAI adoption and organizational performance. It is also further supported by Chen & Tajdini (2025), which propose to examine internal organization capbability factors as moderators in AI adoption and performance research.

CHAPTER THREE

3. RESEARCH METHODOLOGY

3.1 Introduction

The previous chapter identified the knowledge gap and reviewed existing studies on Generative Artificial Intelligence (GA) and Future Organizational Performance (OP), establishing the expected relationships among dependent, independent, mediating and moderating variables while outlining the conceptual framework for the study. This chapter presents the research design, sampling techniques, data collection instruments and analysis methods used for this study.

3.2 Research Methodology

The research used a quantitative research methodology to collect and analyze quantitative data using structured questionnaires. This type of research design is suitable for research which tries to describe, explain and predict the relationship between constructs that are being studied (Khalid et al. , 2012). It is also used to test objective theories by statistically analyzing hypotheses and the relationship between variables (Kandel, 2020).

This study is a cross-sectional study which examines the relationship between the constructs at a single point in time. A cross-sectional study is selected to enable the researcher to gather data on the variables and study the relationships within a limited timeframe. The research follows a deductive approach which will start by formulating the hypothesis, collecting primary data and analyzing results. The primary data will be collected using questionnaires from a sample of 242 employees from selected management consulting firms. This will include both managerial and non-managerial employees. Details of the target population and sampling technique are presented in the following section.

3.3 Research Design

Research design is the framework of the research methods used by the researcher and categorized into three broad types as exploratory, descriptive and explanatory (Kothari, 2004). An exploratory research is applied when the concept under study is relatively new and not sufficiently researched aiming to generate initial insights and identify key variables for further research (Sekaran &

Bougie, 2016). This type of research relies on qualitative approaches to examine patterns and theoretical directions (Saunders et al. , 2003).

Descriptive research seeks to systematically describe characteristics of a phenomenon, population or situation without manipulating variables (Bryman, 2016). This type of research design uses structured instruments such as surveys and questionnaires to identify patterns within the data. However, descriptive research is limited in its ability to establish causal relationships between variables (Kumar R. , 2018).

Explanatory research, also referred to as causal research, investigates the cause and effect relationship between variables using statistical models (Oppewal, 2010). This research design is suited for studies that develop and test hypotheses that are based on established theoretical frameworks (Creswell & Creswell, 2017).

Explanatory research is most appropriate for this study as the researcher developed hypotheses and investigated the relationship between GenAI (GA), Exploitative (EXPLT) and Exploratory (EXPLR) Innovation, Ethical Dilemma (ETH), Organizational Agility (AGI), and Future Organizational Performance (OP) by adopting a research framework established on existing empirical studies and theories.

3.4 Target Population and Sampling Technique

Based on a search of member organizations of the Ethiopian Business Advisory Service Providers Association (EBASPA), 55 qualified management consultancy firms have been identified. A LinkedIn search of management consulting firms filtered based on location and type of service has been used to further include additional consultancy firms that are not a member of the association. Based on this additional 167 management consulting firms have been identified raising the total population size to 222 firms.

The researcher adopts a multistage sampling technique, first to sample the organizations included in the study and second to select individual respondents from each participating company. In the first stage, 12 management consulting firms were selected from a total identified population of 222 firms using convenience sampling. Although the population comprised 222 firms, the application of deliberate inclusion criteria substantially reduced the eligible pool. Firms were required to operate exclusively in management consulting, thereby excluding hybrid consultancies that offer

combinations of IT, financial, or HR consulting services. Additional criteria included accessibility through the researcher's existing professional network and willingness to participate within the time and resource constraints of the study. The 12 firms that met these criteria vary in organizational size, spanning small, medium, and large firms, which strengthens the broader applicability of findings across different organizational contexts (Sekaran & Bougie, 2016). Furthermore, the unit of analysis for hypothesis testing operates at the level of individual respondents rather than firms, meaning the effective analytical sample is considerably larger than the number of participating organizations.

Convenience sampling is appropriate for this study given that the primary objective is to test hypothesized directional relationships among constructs rather than to estimate population parameters or achieve statistical representativeness (Bhattacherjee, 2012). The researcher acknowledges that the use of convenience sampling and the number of participating firms constitute a delimitation of this study, and that generalizability of findings beyond the sampled firms should be interpreted with appropriate caution.

The selected management consulting companies include: HST Consulting PLC, Deloitte Ethiopia, Grant Thornton Ethiopia, Melela Partners, Excel Consultrade, Precise, First Consult, Pragma Investment Advisory, Acasus Ethiopia, BDO Ethiopia, Mckinsey & Co. and Shega. The number of employees for these companies was identified from their respective websites, and LinkedIn was used as a supplementary source where website information was not available. However, it is important to note that LinkedIn is a self-reported platform and the accuracy of organizational information obtained from it is difficult to independently verify, which is acknowledged by the researcher as a potential limitation.

Table 1: Employee number of sampled organizations

S. N	Company Name	Number of employees
1	HST Consulting PLC	202
2	Deloitte Ethiopia	22
3	Grant Thornton Ethiopia	120
4	Melela Partners	10
5	Excel Consultrade	21

6	Precise	51
7	First Consult	125
8	BDO Ethiopia	33
9	Pragma Investment Advisory	13
10	Acasus Ethiopia	18
11	McKinsey & Co.	15
12	Shega	26

At the second stage of the sampling process, individual respondents were selected using simple random sampling from within the selected firms which have a combined employee population of 656 to yield a final sample of 242 respondents. The sample size for this study is calculated using Bukharis sample size formula for known poplulation and adopted from Daniel (1999).

The formula for a known population:

$$\text{Sample size} = \frac{\frac{z^2 \times p\,(1-p)}{e^2}}{1 + \left(\frac{z^2 \times p\,(1-p)}{e^2 N}\right)}$$

Table 2: Sample Size Calculation

Confidence Level	95%
Sample Proportion (p)	0.5
Margin of Error (e)	0.05
Population Size (N)	**656**
Alpha divide by 2	0.025
Z-Score (z)	1.96
Sample Size	**242**

This sample size is proportionally allocated to each organization based on the number of employees. This ensures proportional size to population representation of respondents. The formula used for this proportional allocation is:

$$n_i = \left(\frac{N_i}{N}\right) \times n$$

where Ni is the number of employees in one company, N is the total population of all 12 companies and n is total target sample size (242).

Table 3: Sample Size Allocation

S. N	Company Name	Number of employees	Sample Allocated
1	HST Consulting PLC	202	75
2	Deloitte Ethiopia	22	8
3	Grant Thornton Ethiopia	120	44
4	Melela Partners	10	4
5	Excel Consultrade	21	8
6	Precise	51	19
7	First Consult	125	46
8	BDO Ethiopia	33	12
9	Pragma Investment Advisory	13	5
10	Acasus Ethiopia	18	7
11	Mckinsey & Co.	15	6
12	Shega	26	10

3.5 Data Collection and Instrument

The researcher utilized existing questionnaires developed for similar studies by making contextual adjustments. The questionnaire has been structured into two sections where the first section focuses on demographic information of respondents, and the second section consists of questions measuring the six constructs of this study. GenAI was measured by a 5 item scale adapted from Davis (1989) by Singh et al. (2024), Future Organizational Performance has been measured using a 5 item scale by Dubey et al. (2020), Exploitative Innovation was measured by a 4 item scale by Jansen et al. (2009), Exploratory innovation was measured by a 5 item scale by Huang et al. (2014),

Ethical Dilemma was measured through a 4 item scale by Verma & Garg (2024) and organizational agility was measured using a 7 item scale adopted from Tallon & Pinsonneault (2011).

The questionnaires was mainly administered through digital tools such as googles forms and distrbuted to randomly selected employees of the organizations identified. Participation in the survey were voluntary and respondents did not receive financial compensation.

3.6 Data Measurement

All variables of this study have been measured using a 5-point Likert scale ranging from strongly disagree to strongly agree. According to Sachdev & Verma (2004), a 5-point Likert scale is appropriate for longer questionnaires as it reduces the burden on respondents which leads to increased response rate and quality. In addition to the ease of use, a 5-point Likert scale allows respondents to sufficiently express their feelings by reducing ambiguity (Preston & Colman, 2000). The 5-point scale also provides a variety of options ranging from extremes (strongly agree and strongly disagree) to moderate responses (Wyatt & Meyers, 1987).

3.7 Method of Data Analysis

SmartPLS 4.1.1.8 has been used to evaluate the conceptual model in this study as it is a widely recommended and increasingly used second generation analytical tool. PLS-SEM was applied to test the proposed hypothesis. A bootstrapping procedure with 5000 subsamples has been conducted to assess the significance of factor loadings and path coefficients, consistent with the recommendation of Hair et al. (2021) that a minimum of 5000 bootstrap subsamples be used to ensure stable estimates. When compared to other analytical methods, SmartPLS offers several advantages including the absence of strict requirements for data normality testing or multicollinearity assessment. PLS-SEM also provides stronger estimation capabilities than traditional regression techniques and is well suited for both simple and complex theoretical frameworks. PLS-SEM evaluates the measurement model and structural model. In this study, the measurement model has been assessed using indicatory reliability (outer loadings), convergent validity, internal consistency reliability and discriminant validity criteria.

3.8 Pilot Study or Pre-test

A pilot study is a preliminary study conducted to detect weaknesses in design and instrumentation. It is critical for refining the questionnaire and ensuring the reliability and validity of the data

collected in the main study (Saunders et al., 2019). The author conducted a pilot with 36 participants to evaluate the reliability and validity of the survey items.

3.8.1 Demographics Characteristics of Samples

Table 4: Demographics of Pilot Study Respondents

Characteristic	Category	Frequency	Percentage
Gender	Male	18	50%
	Female	18	50%
Age	18-25	12	33.3%
	26-35	22	61.1%
	36-45	2	5.6%
	46-55	0	0%
	55+	0	0%
Education	TVET	0	0%
	Bachelor's degree	19	52.8%
	Master's degree	17	47.2%
	Ph.D.	0	0%

3.8.2 Identification Measurement Model

The researcher identified the nature of the measurement models for all latent constructs based on criteria established by Hair et al. (2021).

Table 5: Model identification

Constructs	Typical Model	Reference
ETH	Reflective	Singh et al. (2024)
EXPLT	Reflective	He & Wong (2004), Le et al. (2023)
EXPLR	Reflective	He & Wong (2004), Ngoa et al. (2019)
GA	Reflective	Zada et al (2024), Manzoor & Malhotra (2025)
AGI	Reflective	Cegarra-Navarro et al. (2015)
OP	Reflective	Andrej et al. (2023)

Note: GA: Generative AI Adoption; EXPLR: Exploratory Innovation; EXPLT: Exploitative Innovation; OP: Future Organizational Performance; AGI: Organizational Agility; ETH: Ethical Dilemma

In line with the recommendation of Hair et al. (2021), all latent variables in this thesis were modeled using a reflective measurement model.

3.8.3 Pilot Test Analysis and Discussion

A pilot study was conducted with N= 36 participants to assess the feasibility and psychometric properties of the survey instrument. The data was analyzed using SmartPLS 4.1.1.8. Since the primary goal of the pilot was to validate the measurement model, structural path analysis was not performed. The researcher evaluated the reflective measurement model by using the following criteria:

3.8.3.1 Indicator Reliability/Outer Loading

Indicator reliability was assessed using outer loadings. It should exceed 0.708 to ensure that the construct explains more than 50% of the indicator variance (Hair et al., 2021). With most of the indicators in this analysis showing high loadings (ranging from 0.726 to 0.941), the reliability was high (Table 6). Despite this, AGI 2 (0.682), AGI3(0.561), AGI4(0.596) and ETH4(0.674) dropped below the threshold of 0.708. However, values between .40 and .70 can be justified if acceptable values are obtained on other construct reliability and discriminatory validity across indices (Hair et al., 2019).

Table 6: Pilot Test Outer Loading Results

	GA	OP	EXPLR	EXPLT	AGI	ETH
GA1	0.730					
GA2	0.876					
GA3	0.868					
GA4	0.941					
GA5	0.819					
OP1		0.919				
OP2		0.858				
OP3		0.832				
OP4		0.747				
OP5		0.826				
EXPLR1			0.784			
EXPLR2			0.829			
EXPLR3			0.780			
EXPLR4			0.818			
EXPLR5			0.802			

	GA	OP	EXPLR	EXPLT	AGI	ETH
EXPLT1				0.887		
EXPLT2				0.930		
EXPLT3				0.867		
EXPLT4				0.849		
AGI1					0.884	
AGI2					0.682	
AGI3					0.561	
AGI4					0.596	
AGI5					0.875	
AGI6					0.746	
AGI7					0.800	
ETH1						0.783
ETH2						0.726
ETH3						0.784
ETH4						0.674

Note: GA: Generative AI Adoption; EXPLR: Exploratory Innovation; EXPLT: Exploitative Innovation; OP: Future Organizational Performance; AGI: Organizational Agility; ETH: Ethical Dilemma

3.8.3.2 Internal Consistency and Convergent Validity

The Cronbach's Alpha, Composite Reliability, and Average Variance Extracted (AVE) results are presented in Table 7. The author assessed internal consistency reliability using the same data, which indicated that most constructs had high internal consistency. Cronbach's Alpha values range from 0.738 to 0.906, which is above the accepted limit of 0.70 (Hair et al., 2021). Similarly, Composite Reliability (CR) was generally strong, ranging from 0.759 to 0.918. Convergent validity was examined using AVE. All six constructs exceeded the minimum value of 0.50, with values ranging from 0.551 to 0.781. As a result, reliability and validity are ascertained for all the latent variables in the pilot study.

Table 7: Pilot Test Construct Reliability and Validity Results

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
GA	0.902	0.913	0.928	0.722
OP	0.895	0.918	0.922	0.703

EXPLR	0.862	0.868	0.900	0.644
EXPLT	0.906	0.907	0.934	0.781
AGI	0.862	0.899	0.893	0.551
ETH	0.738	0.759	0.831	0.552

Note: GA: Generative AI Adoption; EXPLR: Exploratory Innovation; EXPLT: Exploitative Innovation; OP: Future Organizational Performance; AGI: Organizational Agility; ETH: Ethical Dilemma

3.8.3.3 Discriminant Validity

Discriminant validity was checked using the Heterotrait-Monotrait ratio of correlations (HTMT) in order for the constructs of the model to be empirically distinct. Table 8 shows that all HTMT values were below the conservative threshold of 0.85 (Hair et al., 2021). The highest observed value was 0.772 (between AGI and EXPLR), indicating that the constructs were well understood as independent by respondents. As a result, discriminant validity is ascertained for all the latent variables in the pilot study.

Table 8: Pilot Test Discriminant Validity (HTMT) Result

	AGI	ETH	EXPLR	EXPLT	GA	OP
AGI						
ETH	0.464					
EXPLR	0.772	0.451				
EXPLT	0.608	0.430	0.487			
GA	0.538	0.286	0.580	0.451		
OP	0.667	0.344	0.601	0.730	0.452	

Note: GA: Generative AI Adoption; EXPLR: Exploratory Innovation; EXPLT: Exploitative Innovation; OP: Future Organizational Performance; AGI: Organizational Agility; ETH: Ethical Dilemma

3.9 Ethical Considerations

The researcher has adhered to ethical principles in the data collection process. Participation in the study was entirely voluntary, and participants were informed of this at the beginning of the questionnaire. In addition, the purpose of the study was explained to participants before completing the questionnaire to ensure informed consent. No personally identifiable information was collected, and all data was treated as anonymous and handled with the highest level of confidentiality.

CHAPTER FOUR

4. RESULT AND DISCUSSION

4.1. Introduction

This section discusses the findings of the study by analyzing and interpreting the data collected from respondents. As highlighted in chapter three, the data has been analyzed using SmartPLS 4.1.1.8 and PLS-SEM has been applied to test the proposed hypothesis. The chapter is organized into different sub-sections that present the data examination, response rate, demographic analysis and analysis of the measurement and structural model.

4.2. Data Examination

According to Hair et al. (2021), researchers are often challenged with missing data for self-administered questionnaires which raises the need for data examination. During data examination, there are two common types of missing data. These are missing responses from the entire survey and incomplete questionnaires with respondents leaving some items blank.

The research has used an online data collections tool, namely google forms. Hence, the issue of missing data has been eliminated by taking a precautionary step of making all items of the questionnaire as necessary. This prevents respondents from being able to submit the response where some items are missing, ultimately eliminating incomplete questionnaires. In addition, outlier detection was a preliminary step before PLS-SEM analysis and was handled in a separate software environment.

4.3. Response Rate

The questionnaire for this study has been distributed to 242 respondents to address the sample size determined. Accordingly, 219 questionnaires have been filled out and submitted by respondents resulting in a response rate of 90.5%. Hence, the analysis of the study data is based on 219 respondents.

4.4. Respondents Demographic Characteristics

As presented in Table 9 below, 219 employees working in different management consulting firms participated in this survey. Out of the 219 survey respondents, 121 were female accounting for 55.3% of the total survey respondent whereas 98 were male, representing 44.7% of the total.

Regarding the age distribution, the majority of respondents fell within the 26-35 years age group with 112 (51.1%) individuals. This is followed by those within 36-45 age group with 69(31.5%) respondents. 32(14.6%) respondents were within 18-25 age group, and the remaining 6(2.7%) respondents were within 46-55 age group.

In terms of educational background, most respondents held a master's degree accounting for 141 (64.4%) individuals. This is followed by those with a bachelor's degree with 76 respondents accounting for 34.7% of the total. Only two respondents reported having a doctorate (Ph.D.) accounting for less than 1% of the total.

Table 9: Demographics of respondents

Demographic Variable	Groups	Frequency	Percent
Gender	Male	98	44.7%
	Female	121	55.3%
Educational level	Bachelor's Degree	76	34.7%
	Master's degree	141	64.4%
	PhD	2	0.9%
	Others	0	0.0%
Age	18-25 years	32	14.6%
	26-35 years	112	51.1%
	36-45 years	69	31.5%
	46-55 years	6	2.7%
	55+ years	0	0.0%

4.5. Descriptive Statistics

Table 10 below shows the descriptive statistics of the study variable based on the 5-point Likert scale. Generally, the results indicate that the respondents showed a moderate to high level of

agreement with most items with an average score greater than 3 except for Ethical Dilemma. For the GenAI adoption construct (GA) the mean score ranges from 3.909 to 4.219 and median value equal to 4. This suggests that the respondents generally agreed with the statements used to measure this construct.

Contrary to the results of GA, the items used to measure Future Organizational Performance (OP) and Exploratory Innovation (EXPLR) have a mean ranging from 3.037 to 3.507 and median of 3.000 and 4.000. These values are close to neutral, suggesting that the respondents neither agree nor disagree with the claim and some are inclined towards slight agreement. The items used for measuring Organizational Agility (AGI) have a moderate mean value ranging from 3.215 to 3.986 and median of 3.000 and 4.000, indicating a moderate positive perception by respondents. Ethical Dilemma (ETH) has a moderate mean value ranging from 2.014 to 2.562 and median of 2.000 indicating that respondents disagree or are inclined toward slight disagreement with the presence of ethical dilemmas. These low mean and median values of ETH suggest that the sampled respondents do not perceive themselves to be faced with ethical dilemma in their work. This may also help explain why ethical dilemma's moderating role hypothesized under H9a, H9b and H9c yield non-significant results. This is further explained in the moderation analysis section of the study.

As indicated in the table the median value for most items is either 3.000 and 4.000 which indicates that the responses are concentrated around neutral and agree rather than strongly agree or disagree. This finding is consistent with the findings indicated by the mean values. However, the items measuring Ethical Dilemma (ETH) have a median value of 2.000 indicating inclination towards disagreement among respondents.

The standard deviation values for all items are close to 1, ranging from 0.935 to 1.207, which signifies an acceptable level of variation in the response of participants and their perceptions.

The skewness values for most items are negative, indicating that the data is left skewed. This result implies that the large proportion of responses are concentrated towards higher values on the scale indicating the positive perception of respondents. Contrary to this, ethical dilemma items show positive skewness which implies that responses are concentrated towards lower values.

Additionally, the excess kurtosis results range from -0.959 to 0.791, which are close to zero, indicating a normal distribution.

Table 10: Descriptive statistics

	Mean	Median	MIN	MAX	N	SD	Excess kurtosis	Skewness	P value
GA1	4.055	4.000	1.000	5.000	219.000	1.010	0.316	-0.968	0.000
GA2	4.219	4.000	1.000	5.000	219.000	0.935	0.791	-1.160	0.000
GA3	3.909	4.000	1.000	5.000	219.000	1.021	0.087	-0.801	0.000
GA4	3.995	4.000	1.000	5.000	219.000	1.009	0.379	-0.931	0.000
GA5	3.900	4.000	1.000	5.000	219.000	1.042	-0.358	-0.651	0.000
OP1	3.493	4.000	1.000	5.000	219.000	1.104	-0.584	-0.414	0.000
OP2	3.324	3.000	1.000	5.000	219.000	1.119	-0.743	-0.213	0.000
OP3	3.402	4.000	1.000	5.000	219.000	1.061	-0.585	-0.329	0.000
OP4	3.507	4.000	1.000	5.000	219.000	1.091	-0.497	-0.432	0.000
OP5	3.338	3.000	1.000	5.000	219.000	1.079	-0.708	-0.289	0.000
EXP LR1	3.502	4.000	1.000	5.000	219.000	1.120	-0.653	-0.379	0.000
EXP LR2	3.333	3.000	1.000	5.000	219.000	1.124	-0.769	-0.239	0.000
EXP LR3	3.037	3.000	1.000	5.000	219.000	1.093	-0.678	-0.157	0.000
EXP LR4	3.452	4.000	1.000	5.000	219.000	1.082	-0.616	-0.388	0.000
EXP LR5	3.288	4.000	1.000	5.000	219.000	1.207	-0.896	-0.365	0.000
EXP LT1	3.813	4.000	1.000	5.000	219.000	1.063	-0.009	-0.792	0.000
EXP LT2	3.717	4.000	1.000	5.000	219.000	1.107	-0.511	-0.579	0.000

	Mean	Median	MIN	MAX	N	SD	Excess kurtosis	Skewness	P value
EXPLT3	3.712	4.000	1.000	5.000	219.000	1.116	-0.244	-0.702	0.000
EXPLT4	3.813	4.000	1.000	5.000	219.000	1.054	-0.188	-0.679	0.000
AGI1	3.726	4.000	1.000	5.000	219.000	1.084	-0.322	-0.670	0.000
AGI2	3.580	4.000	1.000	5.000	219.000	1.121	-0.795	-0.348	0.000
AGI3	3.361	3.000	1.000	5.000	219.000	1.086	-0.627	-0.305	0.000
AGI4	3.215	3.000	1.000	5.000	219.000	1.195	-0.805	-0.179	0.000
AGI5	3.553	4.000	1.000	5.000	219.000	1.131	-0.320	-0.656	0.000
AGI6	3.712	4.000	1.000	5.000	219.000	1.075	0.076	-0.806	0.000
AGI7	3.840	4.000	1.000	5.000	219.000	1.076	-0.040	-0.808	0.000
ETH1	2.438	2.000	1.000	5.000	219.000	1.170	-0.749	0.399	0.000
ETH2	2.562	2.000	1.000	5.000	219.000	1.158	-0.959	0.239	0.000
ETH3	2.014	2.000	1.000	5.000	219.000	1.027	0.443	1.017	0.000
ETH4	2.493	2.000	1.000	5.000	219.000	1.148	-0.844	0.336	0.000

Note: GA: Generative AI Adoption; EXPLR: Exploratory Innovation; EXPLT: Exploitative Innovation; OP: Future Organizational Performance; AGI: Organizational Agility; ETH: Ethical Dilemma

4.6 PLS-SEM Algorithm and Bootstrapping

The Partial List Square structural equation model (PLS-SEM) has been used to analyze the study data. The PLS-SEM has been used to conduct a regression analysis to model and examine the relationship between the latent variables. The selection of this model is appropriate due to the sample size consideration. The PLS-SEM has less strict sample size requirements compared to other models making it suitable for studies with relatively moderate or smaller sample. This is achieved without compromising statistical power (Hair et al., 2019). In addition to the sample size requirement, the PLS-SEM allows the simultaneous estimation of both the measurement and structural models despite the complexity of constructs and the number of indicators used to measure the construct. This enables the estimation of the construct relationships with a single analytical procedure (Sarstedt et al., 2021).

The structural equation has been assessed by bootstrapping the original set of data and creating subsamples of 5,000. The bootstrapping technique has been used to assess the statistical significance of both the structural and the measurement model components of the structural equation (Hair et al. 2021).

The first component of the structural equation is the measurement model, also referred to as the outer model. This model focuses on the relationship between a construct and its indicators (Hair et al. 2021). The measurement model can either be reflective or formative depending on the relationship between the construct and its variables. The measurement model for this study is reflective as the indicators are affected by the latent variable. The bootstrapping technique has been applied to measurement models to examine the statistical significance of the outer loadings which are the coefficients for the relationship between the construct and its indicators (Hair et al., 2019).

The second component of the structural equations is the structural model, also referred to as the inner model. The structural model is focused on examining the interrelationship between the constructs or latent variables ultimately testing the hypothesis (Sarstedt et al., 2021). The structural model consists of both endogenous (dependent) and exogenous (independent) variables that are linked with structural path relationships. The endogenous variables are those which are explained by other constructs in the model whereas the exogeneous variables are those which are not affected by other variables in the model (Hair et al. 2021). The bootstrapping technique has been used to test the statistical significance of the path coefficients in the structural model.

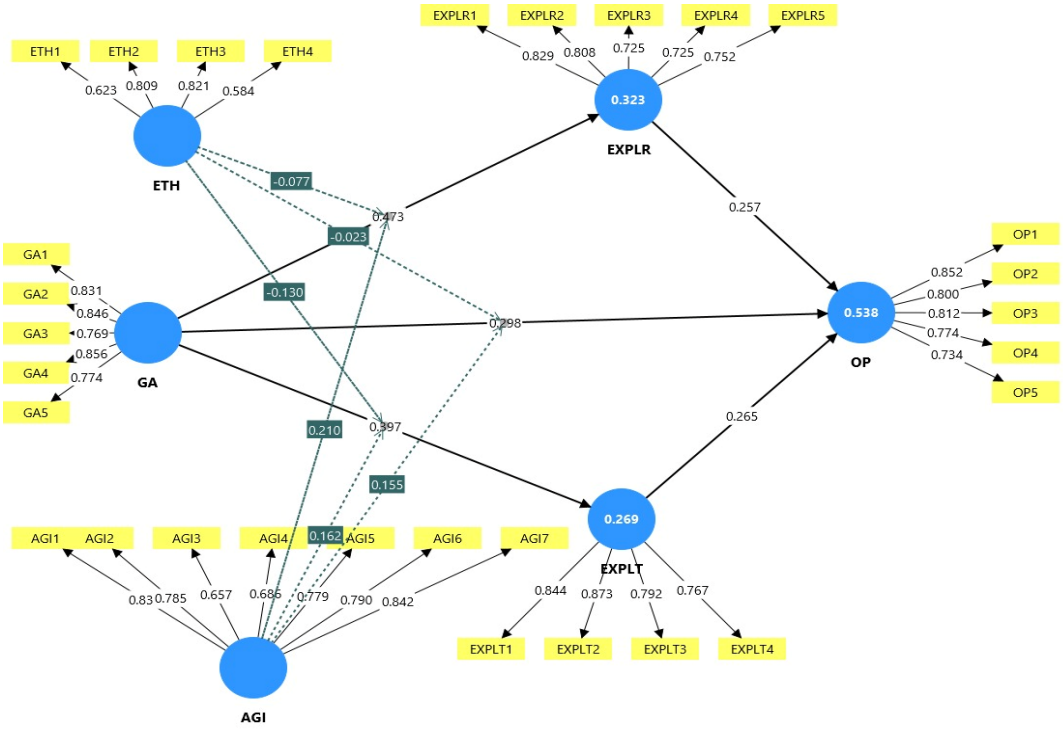


Figure 2: PLS-SEM Model

Note: GA: Generative AI Adoption; EXPLR: Exploratory Innovation; EXPLT: Exploitative Innovation; OP: Future Organizational Performance; AGI: Organizational Agility; ETH: Ethical Dilemma

4.7. Measurement Model Analysis

A measurement model analysis has been conducted to ensure the validity and reliability of the constructs in the study before proceeding to hypothesis testing. The analysis focuses on examining the strength of the relationships between the construct and its indicators. According to Hair & Alamer (2022), the assessment of a measurement model is dependent on the type of model. The study suggests five steps to test validity and reliability for reflective models. Given that this study adopts a reflective model, the following steps are applied:

1. Estimating the loading of indicators along with the p-values
2. Estimate indicator reliability
3. Examine construct internal consistency reliability
4. Assessing convergent validity
5. Testing for discriminant validity

4.7.1 Indicator Loadings and Reliability

The first step in the measurement model analysis involves examining the outer loading of indicators for each construct to test their reliability. According to Hair et al. (2021), a standardized outer loading of 0.70 is considered desirable as it indicates that a significant portion of the indicator's variance is explained by the construct. However, indicators with an outer loading of 0.40 and 0.70 may be considered desirable and justifiable given that acceptable results are obtained from other tests such as consistency reliability and convergent validity. Indicators with outer loadings that fall below the threshold should not automatically be removed but rather their retention or removal should be based on their impact on overall construct reliability and validity. They may be eliminated if their removal improves the results of construct validity and reliability. Contrary to this, the indicator shall be maintained if its removal weakness the results of the construct validity and reliability measures.

As shown in Table 11, all of the indicators for Generative AI adoption (GA), Future Organizational Performance (OP), Exploratory Innovation (EXPLR) and Exploitative Innovation (EXPLT) exhibit desirable outer loading values that are greater than the 0.70 threshold, indicating strong indicator reliability. For Organizational Agility (OA) and Ethical Dilemma (ETH), two indicators fall below the 0.70 threshold while all remaining indicators meet the criteria. Despite this these indicators are retained as their values are close to the acceptable range and their removal does not result in significant improvement in the results of construct validity and reliability.

Table 11: Indicator Loadings

Construct	Indicator	Loading	P values
Generative AI Adoption	GA1	0.831	0.000
	GA2	0.846	0.000
	GA3	0.769	0.000
	GA4	0.856	0.000
	GA5	0.774	0.000
Future Organizational Performance	OP1	0.852	0.000
	OP2	0.800	0.000
	OP3	0.812	0.000
	OP4	0.774	0.000

Construct	Indicator	Loading	P values
	OP5	0.734	0.000
Exploratory Innovation	EXPLR1	0.829	0.000
	EXPLR2	0.808	0.000
	EXPLR3	0.725	0.000
	EXPLR4	0.725	0.000
	EXPLR5	0.752	0.000
Exploitative Innovation	EXPLT1	0.844	0.000
	EXPLT2	0.873	0.000
	EXPLT3	0.792	0.000
	EXPLT4	0.767	0.000
Organizational Agility	AGI1	0.830	0.000
	AGI2	0.785	0.000
	AGI3	0.657	0.000
	AGI4	0.686	0.000
	AGI5	0.779	0.000
	AGI6	0.790	0.000
	AGI7	0.842	0.000
Ethical Dilemma	ETH1	0.623	0.004
	ETH2	0.809	0.000
	ETH3	0.821	0.000
	ETH4	0.584	0.008

Note: GA: Generative AI Adoption; EXPLR: Exploratory Innovation; EXPLT: Exploitative Innovation; OP: Future Organizational Performance; AGI: Organizational Agility; ETH: Ethical Dilemma

4.7.2 Internal Consistency Reliability

The next step in the measurement model analysis is evaluating internal consistency reliability. Internal consistency reliability measures the degree to which indicators of the same construct are consistent with each other. In other words, it explains whether indicators of the same construct are correlated with each other and jointly represent the construct.

The statistical measures used to assess internal consistency reliability are Cronbach's alpha (α) and composite reliability (CR). Cronbach's alpha is considered a traditional measure of the correlation between indicators of a construct. This measure is usually considered a conservative measure and assumes that all indicators contribute equally to a construct without considering their outer loadings. On the other hand, composite reliability is less restrictive and measures the correlation between indicators by considering the varying contribution each has based on the outer loading. Composite reliability can be assessed using both composite reliability (rho_a) and Composite reliability (rho_c). Both are acceptable measures with the only difference being the measurement error considerations. rho_a accounts for measurement error hence provides a more precise estimate. The acceptable threshold for both Cronbach's alpha and composite reliability is a value that exceeds 0.7 indicating that the construct is reliably measured by the indicators. However, a result exceeding 0.95 is deemed unsatisfactory as it signals redundancy of indicators and a possible unwanted response pattern (Purwanto & Sudargini, 2021).

As shown in Table 12, all the constructs for this study exceed the acceptable threshold of 0.7 for each measure of internal consistency. In addition, the results are also below 0.95. These results indicate that the indicators of each construct are correlated and jointly represent the same construct without redundancy.

Table 12: Constructs Reliability and Convergent Validity

Constructs	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Generative AI Adoption (GA)	0.875	0.888	0.909	0.666
Future Organizational Performance (OP)	0.854	0.857	0.896	0.632
Exploratory Innovation (EXPLR)	0.827	0.835	0.878	0.592
Exploitative Innovation (EXPLT)	0.837	0.847	0.891	0.672
Organizational Agility (AGI)	0.885	0.907	0.910	0.592

Constructs	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Ethical Dilemma (ETH)	0.751	0.730	0.806	0.514

4.7.3 Convergent Validity

The next step following the internal consistency analysis is the convergent validity test. The convergent validity test measures the extent to which indicators of the same construct share a high proportion of variance. It tests whether indicators that are expected to be correlated are related and that they collectively represent the same underlying concept.

In PLS-SEM analysis convergent validity is captured by the Average Variance Extracted (AVE) for each construct. As a rule of thumb, the minimum acceptable value of AVE is 0.50. An AVE value of 0.50 or higher indicates the construct explains more than 50% of the variance in its indicators. An AVE less than 0.50 indicates the variance is due to measurement errors in the indicators rather than the construct (Hair et al. 2021).

In table 12 above, it can be observed that the AVE for all six constructs of this study exceed 0.5. This indicates that each construct sufficiently explains more than 50% of the variance in its respective indicators thereby indicating an adequate convergent validity. From this result it can be understood that the indicators of the same construct have a high degree of variance and strongly represent the latent variables. This result, considered together with the outputs of the internal consistency reliability tests, show that all the constructs exceed the recommended thresholds in the respective categories, suggesting that the measurement model is both valid and reliable.

4.7.4 Discriminant Validity

The last step in the measurement model analysis is the discriminant validity test. The discriminant validity tests the extent to which a construct is conceptually distinct from the other constructs in the study. It helps to ensure that each construct is unidimensional and captures a unique concept with minimal overlap. The fundamental measure of discriminant validity is the heterotrait-monotrait ratio (HTMT) test. In addition to HTMT, Fornell-Larcker criterion and cross loadings can be used to test discriminant validity for reflective constructs (Hair et al. 2021; Rasoolimanesh, 2022).

4.7.4.1 Heterotrait-Monotraint Ratio (HTMT)

The HTMT ratio matrix is used in PLS-SEM analysis to assess a measurement model's discriminant validity. It evaluates the distinctness of a construct from other constructs, ensuring that it measures a unique concept rather than overlapping with other variables. It is calculated by dividing the average correlations between indicators across different constructs (heterotrait-heteromethod correlations) to the average correlations of indicators within the same construct (monotrait-heteromethod correlations).

The recommended threshold for HTMT values is less than 0.85 and indicates good discriminatory validity. This threshold is considered to be conservative, and the threshold could be elevated to 0.90 depending on the context of the research. HTMT of < 0.90 is considered acceptable when the constructs are conceptually similar or derived from overlapping theories (Hair et al. 2021).

The results presented in table 13 below show that the HTMT values for all constructs are below the conservative threshold of 0.85 with the highest value being 0.675 between future organizational performance and exploratory innovation. These results indicate that the constructs for this study capture distinct concepts with minimal overlap.

Table 13: Heterotrait-monotrait ratio (HTMT) – Matrix

Constructs	AGI	ETH	EXPLR	EXPLT	GA	OP
Organizational Agility (AGI)						
Ethical Dilemma (ETH)	0.163					
Exploratory Innovation (EXPLR)	0.367	0.085				
Exploitative Innovation (EXPLT)	0.349	0.132	0.471			
Generative AI Adoption (GA)	0.408	0.088	0.564	0.485		
Future Organizational Performance (OP)	0.424	0.137	0.675	0.651	0.618	

4.7.4.2 Fornell-Larcker Criterion

Fornell-Larcker criterion is one of the first method used to assess discriminatory validity in PLS-SEM. According to Fornell & Larcker (1981), a construct is considered to have acceptable discriminatory validity when it shares more variance with its indicators rather than other constructs. It is calculated by obtainining the square root of the Average Variance Extracted (AVE)

of each construct. After obtaining the square root of the AVE for each construct is is compared with all other constructs in the model.

A construct is assumed to have a desirable discriminatory validity when each latent variable's square root of the AVE is higher than the correlation between that construct and any other construct in the model. If latent variable's square root of the AVE is smaller than any of the corresponding variables it signals a compromise in discriminant validity and implies that the construct may not be sufficiently unique.

The results presented in Table 14 show that square root of the Average Variance Extracted (AVE) of each construct is greater than the construct's correlations with all other constructs in the model. These results demonstrate that the constructs are conceptually distinct. The findings are consistent with that of the HTMT test and indicate the successful establishment of discriminant validity within the measurement model.

Table 14: Fornell-Larcker criterion for discriminant validity

Constructs	AGI	ETH	EXPLR	EXPLT	GA	OP
Organizational Agility (AGI)	0.770					
Ethical Dilemma (ETH)	-0.135	0.717				
Exploratory Innovation (EXPLR)	0.326	-0.012	0.769			
Exploitative Innovation (EXPLT)	0.302	-0.145	0.395	0.820		
Generative AI Adoption (GA)	0.374	-0.061	0.488	0.428	0.816	
Organizational Performance (OP)	0.388	-0.139	0.568	0.558	0.547	0.795

4.7.4.3 Cross-Loading

Another measure of discriminant validity is assessing the cross-loading of indicators. Cross loading is the correlation of an indicator with all other constructs in the model in addition to its respective construct. A measurement model exhibits strong discriminant validity when the indicator has the highest loading on its own construct compared to its loading (cross-loading) on other constructs. If the construct has a higher loading on another construct, it indicates a compromise in discriminatory validity and that it is not uniquely measuring its own construct (Rasoolimanesh, 2022).

Table 15 presents the loading of each indicator across all constructs. As highlighted in bold, it can be observed that the loading of each indicator is highest for its respective latent variable. This shows that the indicators are strongly related to their constructs hence the establishment of discriminant validity within the model. This result further supports the results obtained from the HTMT and Fornell-Larcker criterion tests.

Table 15: Cross-loading

Indicators	GA	OP	EXPLR	EXPLT	AGI	ETH
GA1	**0.831**	0.496	0.396	0.455	0.303	-0.017
GA2	**0.846**	0.449	0.445	0.342	0.311	-0.024
GA3	**0.769**	0.371	0.362	0.295	0.281	-0.086
GA4	**0.856**	0.529	0.441	0.379	0.357	-0.085
GA5	**0.774**	0.350	0.329	0.236	0.263	-0.039
OP1	0.429	**0.852**	0.438	0.476	0.378	-0.157
OP2	0.520	**0.800**	0.432	0.493	0.247	-0.078
OP3	0.469	**0.812**	0.495	0.435	0.324	-0.056
OP4	0.408	**0.774**	0.444	0.443	0.287	-0.128
OP5	0.336	**0.734**	0.451	0.361	0.306	-0.139
EXPLR1	0.461	0.470	**0.829**	0.398	0.286	-0.010
EXPLR2	0.376	0.468	**0.808**	0.252	0.345	-0.015
EXPLR3	0.365	0.352	**0.725**	0.280	0.251	0.049
EXPLR4	0.306	0.443	**0.725**	0.257	0.128	-0.071
EXPLR5	0.356	0.443	**0.752**	0.321	0.223	0.003
EXPLT1	0.352	0.517	0.385	**0.844**	0.201	-0.166
EXPLT2	0.398	0.497	0.307	**0.873**	0.265	-0.110
EXPLT3	0.356	0.431	0.295	**0.792**	0.226	-0.121
EXPLT4	0.288	0.367	0.306	**0.767**	0.315	-0.069
AGI1	0.410	0.380	0.310	0.315	**0.830**	-0.149
AGI2	0.217	0.343	0.253	0.193	**0.785**	-0.096
AGI3	0.243	0.145	0.200	0.187	**0.657**	-0.069
AGI4	0.179	0.178	0.197	0.181	**0.686**	-0.056

Indicators	GA	OP	EXPLR	EXPLT	AGI	ETH
AGI5	0.296	0.315	0.225	0.247	**0.779**	-0.130
AGI6	0.277	0.242	0.231	0.210	**0.790**	-0.075
AGI7	0.331	0.379	0.303	0.257	**0.842**	-0.114
ETH1	0.003	-0.044	0.029	-0.019	-0.129	**0.623**
ETH2	-0.064	-0.129	-0.003	-0.110	-0.161	**0.809**
ETH3	-0.041	-0.113	-0.031	-0.149	-0.057	**0.821**
ETH4	-0.092	-0.027	0.066	-0.001	-0.036	**0.584**

Note: GA: Generative AI Adoption; EXPLR: Exploratory Innovation; EXPLT: Exploitative Innovation; OP: Future Organizational Performance; AGI: Organizational Agility; ETH: Ethical Dilemma

4.8 Structural Model Analysis

Following the evaluation of the measurement model, the second step is evaluation of the structural model. This analysis is conducted to evaluate the interrelationship between the constructs or latent variables. The structural model for this study has GenAI adoption (GA) as an exogenous variable, exploratory (EXPLR) and exploitative innovation (EXPLT) as mediator variables, organizational agility (AGI) and ethical dilemma (ETH) as moderators and future organizational performance (OP) as an endogenous variable (See Figure 3).

Hair et al. (2021) suggests that the structural model analysis should consist of model collinearity test, evaluation of the significance and relevance of the structural relationships, assessing the coefficient of determination and examination of out-of-sample predictive power. The collinearity test is conducted by evaluating the Variance Inflation Factor (VIF) values to ensure that predictor constructs are not highly correlated. The significance and relevance of structural relationships is assessed by evaluating the path coefficients (β) between variables. In addition to the path coefficient, t-values, p-values and confidence intervals are obtained by bootstrapping to further test the significance of the structural model. The coefficient of determination (R^2) is then used to evaluate the explanatory power of exogenous variables. Lastly, the model's predictive capability is assessed through the out-of-sample prediction measure (Q^2).

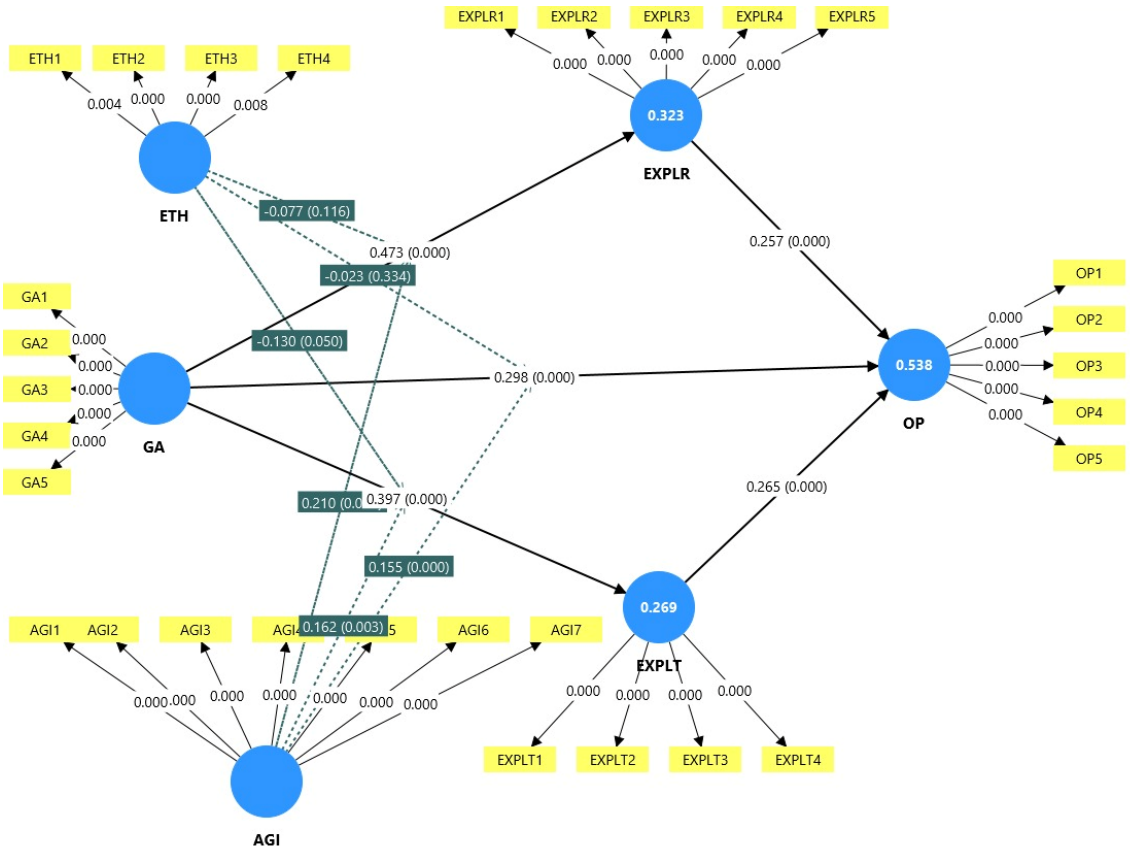


Figure 3: Bootstrapped Structural Model Results

Note: GA: Generative AI Adoption; EXPLR: Exploratory Innovation; EXPLT: Exploitative Innovation; OP: Organizational Performance; AGI: Organizational Agility; ETH: Ethical Dilemma

4.8.1 Assessment of Collinearity Issues Between Constructs

Correlation is the extent to which predictors of a constructs in the model overlap in explaining the same variance. Assessment of the collinearity issues between constructs is an initial step in the structural model analysis to ensure the absence of high correlations between constructs. The VIF value is used to examine collinearity among constructs in the model, where values above 5 indicate problematic collinearity while values below 3 are ideal(Hair et al., 2021; Purwanto & Sudargini, 2021). The VIF values for the study's latent constructs are displayed in Table 16.

The VIF values indicate that all constructs including the mediators, moderators and interaction terms are below the threshold of 3. This implies the absence of any collinearity issues between the constructs and that they are sufficiently independent.

Table 16: Collinearity Statistics (VIF)-Inner model

	VIF
AGI -> EXPLR	1.254
AGI -> EXPLT	1.254
AGI -> OP	1.371
AGI x GA -> EXPLR	1.190
AGI x GA -> EXPLT	1.190
AGI x GA -> OP	1.300
ETH -> EXPLR	1.051
ETH -> EXPLT	1.051
ETH -> OP	1.073
ETH x GA -> EXPLR	1.090
ETH x GA -> EXPLT	1.090
ETH x GA -> OP	1.117
EXPLR -> OP	1.516
EXPLT -> OP	1.404
GA -> EXPLR	1.233
GA -> EXPLT	1.233
GA -> OP	1.707

Note: GA: Generative AI Adoption; EXPLR: Exploratory Innovation; EXPLT: Exploitative Innovation; OP: Future Organizational Performance; AGI: Organizational Agility; ETH: Ethical Dilemma

4.8.2 Assessment of the Significance and Relevance of Structural Relationships

PLS-SEM is used to generate estimates for the relationships in the structural model, such as path coefficients that show the correlations between the constructs. The path coefficients describe the strength of the relationships between the constructs, and the value range from -1 to +1. The sign and direction of the path should be similar with the hypothesized relations with a path coefficient of +1 indicating a significant positive correlation, whereas values close to -1 indicating a significant negative correlation. Values of path coefficients close to 0 are considered insignificant (Purwanto & Sudargini, 2021; Hair et al., 2021). The magnitude of path coefficients can be evaluated by examining the direct and indirect effects, as well as the total effect which represents the sum of both. According to Nitzl et al. (2016) examining the direct, indirect and total effect

offers a wide range of testing options for a study with multiple mediators and enables researchers to discuss findings in a more accurate way.

Hypothesis testing has been done to examine the direction, sign of predicted path coefficients connecting the constructs' and tested for statistical significance.

4.8.2.1 Direct Hypothesis Test Results

The hypothesized relationships of this study have been examined by assessing the coefficients of each path and by measuring the significance of p values for each path. The results of hypothesis testing are shown in Table 17.

The table shows that the first hypothesis (H1) supported a positive significant relationship between GenAI adoption (GA) and exploratory innovation (EXPLR), with a path coefficient of $\beta = 0.473$ ($t = 7.864$, $p < 0.05$). The magnitude of this coefficient reflects a moderate to strong association, suggesting that GenAI adoption plays a meaningful role in shaping exploratory innovation outcomes in organizational settings. This finding is consistent with past studies which suggest that the adoption of GenAI enhances exploratory innovation (AL-khatib & Wael, 2023; Korzynski et al., 2023; Olan et al., 2022). Organizations adopting GenAI have enhanced capability for exploratory innovation as its use enables organizations to access new opportunities by leveraging the novel and unprecedented contexts created by the technology (AL-khatib & Wael, 2023). However, the findings of Hoelzemann et al. (2024) contend this claim by finding that this data driving exploration provided by AI tend to direct organizational search efforts towards well-explored and familiar knowledge domains rather than genuinely novel ones suggesting that rather than facilitating exploratory innovation, AI adoption may inadvertently bias organizations towards exploitation of existing knowledge. The positive relationship observed in the present study may reflect the specific organizational context of the sampled consulting firms, where GenAI is deployed as a complementary tool that augments human creativity rather than operating as an autonomous mechanism for exploration.

This finding is further consistent with the Diffusion of Innovation theory, which provides context into the dynamics of technology adoption and its potential impact on innovation within organizations. The ability of technology such as GenAI to generate new solutions and insights creates an enabling factor for organizations to experiment with new ideas and enhances creativity, which in return promotes exploratory innovation by supporting organizations in the development

of new knowledge. Therefore, GenAI adoption enhances exploratory innovation within organizations.

The second hypothesis (H2) tested the relationship between GenAI adoption (GA) and exploitative innovation (EXPLT). The result indicates a positive significant relationship with a path coefficient of $\beta = 0.397$ ($t = 5.215$, $p < 0.05$), reflecting a moderate association between the two constructs. This finding is consistent with that of Khan et al. (2025), Zhu et al. (2026) and AL-khatib & Wael (2023). Khan et al. (2025) through a technology-organization-environment (TOE) framework found that GenAI adoption has the potential to improve both exploitative and exploratory innovation. Liu & Li (2025) proposed that GenAI adoption promotes exploitative innovation by improving operational efficiencies that ultimately help firms refine existing processes and capabilities, while also enabling the reallocation of skilled labor and managerial attention towards utilizing existing knowledge for improving organizational processes. Zhu et al. (2026) further claims that GenAI enhances exploitative innovation by assisting employees in matching the technology with their tasks, making it easier for them to improve existing processes and outputs, an effect that is further strengthened by employees' awareness of the technology which encourages greater use and a positive attitude towards it. However, conflicting perspectives exist in literature. Wang & Long (2025) found that the widespread adoption of AI technologies creates a sense of job insecurity among employees, which can deter engagement in both creative and process-oriented innovation activities, including the incremental refinements associated with exploitative innovation. Based on this contradictory finding, a possible explanation for the positive relationship observed in the present study may be due to the specific organizational climate of the sampled consulting firms, where GenAI maybe be perceived by employees as a tool that complements and enhances their existing capabilities rather than one that threatens their roles. From this, it can be understood that GenAI adoption has the potential to enhance exploitative innovation within organizations. This finding is also aligned with the Diffusion of Innovation theory in such a way that technological adoption facilitates the enhancement of existing organizational capabilities.

The third hypothesis (H3) tested the relationship between GenAI adoption (GA) and future organizational performance (OP). The path coefficient of $\beta = 0.298$ ($t = 5.038$, $p < 0.05$) indicates a moderate association between the two constructs. This finding is consistent with existing literature such as Prado & Mantovani (2025), Kumar et al. (2025), Şahin & Karayel (2024),

Kudryavtsev et al. (2024) and Budhwar et al. (2023). The findings of Kumar et al. (2025) indicate that the adoption of GenAI positively impacts organizational performance by reducing operational costs, automating routine tasks, and enabling better resource allocation. Şahin & Karayel (2024) further support this by claiming that GenAI adoption has a transformative potential to improve efficiency within organizations through enhanced problem-solving capacity and improved managerial decision making. GenAI adoption also improves organizational performance by positively influencing key performance indicators such as the ability to achieve and sustain competitive advantage through enhanced knowledge and improved innovation processes (Mikalef & Gupta, 2021). Nonetheless, Rana et al. (2022) debates this claim and cautions that inadequate governance in AI-integrated systems can introduce operational risks that lead to poor business decisions, ultimately undermining firm efficiency and competitive advantage. This suggests that the direct effect of GenAI adoption on organizational performance may be influenced by several contingent factors, and that its influence may operate more strongly through its effect on innovation capabilities, with exploratory and exploitative innovation serving as important conduits through which GenAI adoption ultimately shapes organizational performance outcomes.

The findings of H3 are further consistent with the resource-based view theory, which proposes that organizations achieve and sustain competitive advantage through the possession and deployment of unique, valuable, and difficult to imitate internal resources. Within this theoretical lens, the adoption of GenAI positions the technology as a distinctive organizational resource that enhances internal capabilities in ways that competitors cannot easily replicate. By augmenting the knowledge base of the organization, streamlining decision making processes, and enabling more efficient utilization of existing resources, GenAI functions as a strategic asset that drives superior organizational performance. The resource-based view further suggests that the value of such a resource is not derived from its adoption alone but from the extent to which it is embedded within and complementary to the organization's existing capabilities, implying that firms that effectively integrate GenAI into their core operations are better positioned to realize sustained performance gains. Hence, GenAI adoption enhances future organizational performance.

The fourth hypothesis (H4) tested the relationship between exploratory innovation (EXPLR) and future organizational performance (OP). The result indicates a positive significant relationship with a path coefficient of $\beta = 0.257$ ($t = 4.383$, $p < 0.05$), representing a small to moderate practical

effect. This finding is aligned with the findings of existent literature (Hou et al., 2019; Jansen J. , 2005). Organziations with higher level of exploratory innovation have the ability to achieve improved performance by developing new products and services targeted towards new customers and markets (Jansen J. , 2005). This is also suggested by Jansen et al. (2006) claiming that exploratory innovation helps firms establish new markets during intense competitive rivalry by enabling the development of new products and services to serve new customers. The relatively modest coefficient suggests that while exploratory innovation contributes positively to performance, its effect may be contingent on the organization's ability to scale new ideas, which is a process that extends beyond the scope of innovation activity alone. However, this finding is not without contradiction. Voss et al. (2008) found that exploratory innovation had no direct positive effect on performance and could in fact harm short-term performance due to the high costs and uncertainty associated with pursuing radically new products and markets, arguing that the returns from exploration are significantly delayed and often fail to materialize. Similarly, Laureiro-Martínez et al. (2015) notees that excessive exploratory innovation leads to a "failure trap," whereby firms continuously search for new ideas without consolidating gains, resulting in resource dissipation and diminished performance particularly in organizations that lack the routines necessary to commercialize innovations effectively. These contradictory findings may be explained by contextual differences. The positive relationship observed in the present study may reflect the characteristics of the sampled organizations, which may possess sufficient absorptive capacity to translate exploratory activities into tangible performance outcomes.

The fifth hypothesis (H5) tested the relationship between exploitative innovation (EXPLT) and future organizational performance (OP). The result shows a positive significant relationship with a path coefficient of $\beta = 0.265$ ($t = 5.200$, $p < 0.000$), reflecting a small to moderate practical effect. This finding is in line with the findings of (Ioniţă, 2022; Le et al., 2023; Hou et al., 2019). According to Le et al., (2023), organizations that engage in exploitative innovation refine their existing products and services while maintaining existing markets positions. This improves their ability to successfully compete and enhance their performance. Similarly, Ioniţă (2022) emphasizes that an organization’s performance measured through competitive advantage and firm value is affected by exploitative innovation. By implementing exploitative innovation, organizations are able to introduce services that are new to the firm but already exist in the market enabling them to perform better and remain competitive. However, some studies suggest that the

relationship between exploitative innovation and organizational performance may not always be straightforward. Gupta et al. (2006) found that exploitative innovation, while beneficial in stable environments, may produce diminishing returns when market conditions shift, as firms that focus predominantly on refining existing services may find it increasingly difficult to respond to emerging competitive pressures. Similarly, Ngo and O'Cass (2012) found that exploitative activities alone are insufficient to drive superior performance without being complemented by strong market orientation and marketing capabilities, suggesting that the performance benefits of exploitative innovation are conditional rather than universal. These findings do not necessarily contradict the positive relationship observed in the present study but rather highlight that the magnitude of exploitative innovation's effect on performance may vary depending on the broader organizational and environmental context.

From the results of H4 and H5, both exploratory and exploitative innovation demonstrate positive and significant effects on future organizational performance. The similarity in the magnitude of their respective path coefficients ($\beta = 0.257$ and $\beta = 0.265$) further underscores the importance of pursuing both innovation types in a balanced manner, consistent with the organizational ambidexterity literature. Jansen J. (2005) claims that organizations should strike a balance between exploratory and exploitative innovation. According to the research, organizations that are able to stike this balance (also refered to as Ambidextrous organizations) are better positioned to adapt to the operating environment and perform better. A well managed balance between exploratory and exploitatory activities facilites a synergistic combination of operational effectiveness and strategic flexibility, allowing organizations to achieve superior performance (Martini et al., 2013). From this it can be understood that despite the positive effect both exploratory and exploitative innovation has on future organizational performance, it is important to consider the optimal balance when pursuing both innovation types simeltenously.

In conclusion, the direct hypothesis test results show that all of the hypotheses listed in table 17 exhibit a positive path coefficient and p-values below 0.05 indicating a statistically significant and positive relationship between the construct items.

Table 17: Hypothesis testing results (Direct effects)

	Path coefficient (β)	**Standard deviation**	**T statistics**	**P values**
H1. GA -> EXPLR	0.473	0.060	7.864	0.000

H2. GA -> EXPLT	0.397	0.076	5.215	0.000
H3. GA -> OP	0.298	0.059	5.038	0.000
H4. EXPLR -> OP	0.257	0.059	4.383	0.000
H5. EXPLT -> OP	0.265	0.051	5.200	0.000

Note: GA: Generative AI Adoption; EXPLR: Exploratory Innovation; EXPLT: Exploitative Innovation; OP: Future Organizational Performance

4.8.2.2 Mediation Analysis Results (Indirect Effects)

Mediation analysis focuses on examining how a third variable affects the relationship between two variables (dependent and independent variables). For the context of this research, mediation analysis assesses the role of exploratory and exploitative innovations in the relationship between GenAI adoption (GA) and future organizational performance (OP). The results are presented in table 18 below.

From the table it can observed that the direct effect (β= 0.298, p= 0.000) of GenAI adoption on future organizational performance and indirect effect (β= 0.121, p= 0.000) of GenAI adoption on future organizational performance through exploratory innovation are both significant and positive effects. Variance Accounted For (VAF), which determines the extent to which the indirect effect explains the total effect of the relations, has been calculated to further confirm the type of mediation. Based on this, exploratory innovation has a VAF of 28.88% which is between 20% and 80% confirming partial mediation. Partial meditation can also be considered complementary meditation when both the indirect effect and the direct effect are significant and point in the same direction (Hair et al., 2021). The result infers that GenAI adoption improves future organizational performance both directly and indirectly through exploratory innovation. This means that exploratory innovation parially explains but does not fully account for the relationship.

Similarly, the direct effect (β= 0.298, p= 0.000) of GenAI adoption on future organizational performance and indirect effect (β= 0.105, p= 0.000) of GenAI adoption on future organizational performance through exploitative innovation are both significant positive effects indicating a mediating effect. The VAF result for exploitative innovation is 26.05%, which also falls between 20% and 80%, confirming partial mediation. In addition, the mediation is considered complementary as both effects are significant and in the same direction. The result infers that GenAI adoption improves organizational performance both directly and indirectly through exploitative innovation. This findings are consistent with similar researchs that have simuleneously examined the mediation effect of both exploratory and exploitative innovations

such as Singh et al., (2024), Khan et al. (2025) and Shahid et al., (2026). Organziations that have utilized the unique capacity of GenAI to generate new ideas for exploration and to optimize current operations through exploitative process tend to gain significant competitive edge and improved performance (Singh et al., 2024). However, these mediation findings are not consistent across all organizational contexts. Khan et al. (2025) found that the mediating role of exploratory and exploitative innovation between GenAI adoption and organizational performance is contingent on the stage of the technology adoption rather than having a similar outcome at different stages. The finding of the study indicates that the effect is more pronounced in firms with higher levels of AI maturity and less evident in early-stage adopters. This suggests that the mediation pathway between GenAI adoption and performance through innovation activities may not be uniformly replicable and is conditional on the organization's underlying digital infrastructure, governance structures, and human capital readiness. The significant mediation effects observed in the present study may therefore reflect a relatively favorable level of organizational readiness among the sampled firms, which enabled exploratory and exploitative innovation to serve as effective mediating mechanisms in translating GenAI adoption into improved performance outcomes.

Based on this, it can be concluded that both exploratory and exploitative innovation serve as complementary partial mediators in the positive relationship between GenAI adoption and future organizational performance.

Table 18: Mediation Analysis Results

	Direct effect		**Specific indirect effect**			***VAF***	***Results***
Hypotheses	***β***	***P***	***β***	***T***	***P***		
H6: GA -> EXPLR -> OP	0.298	0.000	0.121	3.898	0.000	28.88%	Partial
H7: GA -> EXPLT -> OP	0.298	0.000	0.105	3.648	0.000	26.05%	Partial

Note: GA: Generative AI Adoption; EXPLR: Exploratory Innovation; EXPLT: Exploitative Innovation; OP: Future Organizational Performance

4.8.2.3 Moderation Analysis Results

Moderation occurs when the effect of an independent variable on a dependent variable depends on a third variable known as the moderator variable (Hair et al., 2021). The moderation analysis is conducted to examine the moderating effect of the third variable by assessing whether it changes the strength or direction of the relationship between the independent and dependent variables. In the context of this research, the moderation analysis examines the moderating effect of ethical dilemmas (ETH) and organizational agility (AGI) on the relationship between GenAI adoption

(GA) and exploratory innovation (EXPLR), GenAI adoption (GA) and future organizational performance(OP), and GenAI adoption(GA) and exploitative innovation (EXPLT). The results are presented in table 19 below.

According to Hair et al. (2021), a moderating variable is considered to be significant if its p-value is less than 0.05. Based on this, the result of the moderation analysis for organizational agility (AGI) indicates that it significant as all p-values are below the acceptable threshold. The positive path coefficient for all three paths suggests the that organizational agility positively moderates the relationship between GenAI adoption and the outcome variables, namely exploratory innovation, exploitative innovation and future organizational performance. To determine whether the moderation effects are partial or full, it is necessary to examine whether the direct relationships between GenAI adoption and the three outcome variables remain significant after the inclusion of organizational agility as a moderator. In this study, the direct paths from GenAI adoption to exploratory innovation, exploitative innovation, and future organizational performance remain statistically significant even after incorporating the interaction terms with organizational agility. This indicates that organizational agility functions as a partial moderator across all three relationships.

To further analyze the moderating effect of organizational agility, interaction plots were drawn and basic slope analyses were conducted based on high (1 standard deviation above the mean), mean, and low (1 standard deviation below the mean) levels of organizational agility. As illustrated in Figure 4, the slope at high levels of organizational agility is the steepest, indicating that GenAI adoption has the strongest positive effect on exploratory innovation when organizational agility is high, while the slope at low levels is less steep, suggesting a negligible effect. Similarly, Figure 5 reveals that the slope at high levels of organizational agility is comparably steeper compared to the mean and low levels, indicating that the positive effect of GenAI adoption on future organizational performance is strongest when organizational agility is high, while the slope at low levels is the flattest, suggesting that firms with low agility gain comparatively less performance benefit from GenAI adoption. Lastly, Figure 6 shows that the slope at high levels of organizational agility has the steepest slope compared to the mean and low levels. This suggests that the positive effect of GenAI adoption on exploitative innovation is higher when organizational agility is high, while the

flattest slope at low agility levels indicates a considerably weaker effect. Therefore, H8a, H8b, and H8c are supported.

This finding is consistent with that of similar studies which have examined the effect of technology adoption on innnovation and organization performance through organizational agility (Arshad et al., 2024; Wahab & Radmehr, 2024; Nina Röder, 2014; Wamba, 2022). Organization with agile methodologies achieve the maximized benefit of new technology adoptions as it helps them become more efficient and responsive to changing environment which ultimately results in organizational success (Arshad et al., 2024). Wahab & Radmehr (2024) further confirmed the moderating role of organizational agility in the postive relationship between AI adoption and firm performance. They concluded that agile organizations are better able to translate technological capabilities into improved performance. In addition, organizations with technnology enabled agility have been observed to better manage innovation (Nina Röder, 2014). However, the moderating role of organizational agility is contended by some literature. Vaculík et al. (2018), found that under disruptive organizational changes, firms are required to trade off short-term benefits for long-term performance, and that higher levels of agility can lead organizations to abandon existing innovation projects, increasing the likelihood of innovation project termination rather than enhancing it. Furthermore, when competitive intensity is too high, the moderating effect of organizational agility on the relationship between operational activities and performance outcomes can turn negative, suggesting that the benefits of agility are contingent on the environmental context in which organizations operate. These contradictory findings highlight that organizational agility does not unconditionally strengthen the relationship between technology adoption and innovation or performance outcomes. Based on the findings of this study, it can be concluded that organizational agility partially moderates the positive relationship between GenAI adoption and exploratory innovation, future organizational performance and exploitative innovation.

The results for the second moderating variable, Ethical Dilemma (ETH), all have a p-value equal to and greater than 0.05. This p-values are above the threshold indicating that ethical dilemma does not have a significant moderating effect on the relationship between GenAI adoption and the outcome variables, namely exploratory innovation, future organizational performance, and exploitative innovation at 5% significance level. Simple slope analysis has not been conducted for

the ethical dilemma moderation hypotheses (H9a, H9b, and H9c) as the interaction terms were not statistically significant.

This finding is consistent with that Salamzadeh et al. (2025), which also studied the moderating effect of ethical dilemmas on the relationship between GenAI and exploitative innovation and organizational performance. However, the result different from that of other studies like Singh et al. (2024) and Wang & Zhang (2025) which found a significant moderating effect of ethical dilemma. For instance, Singh et al. (2024) found that the adoption of GenAI improves exploratory innovation, future organizational performance and exploitative innovation under the moderating effects of ethical dilemmas.

The differences in the results may be attributed to differences in the contextual setting of the studies including organizational type, country context and stage of GenAI adoption all of which may influence how ethical dilemmas are precieved within organizations. Additionally, the low ethical dilemma mean scores observed in this study suggests that the social desirability bias identified in Chapter 1 may have materialized for this constuct. This means that respondents may have been inclined to underreport their experiences of ethical dilemmas since acknowledging such issues could be perceived as unfavorable. Hence, this clusters responses to the lower end and has resulted in the observed low mean scores and potentially masking the moderating effect of ethical dilemma.

It is important, however, not to interpret this non-significant result as evidence that ethical considerations are irrelevant to GenAI-driven innovation and improved future organizational performance. A better observation of this finding is that ethical concerns surrounding GenAI may not yet have reached a level of organizational visibility sufficient to influence innovation and performance outcomes in the sampled context. This aligns with a broader pattern observed in the literature, wherein organizations tend to prioritize the immediate performance benefits of AI adoption while the governance of its associated ethical risks remains underdeveloped (Floridi, et al., 2018). It is therefore possible that as GenAI adoption matures and becomes more deeply embedded in organizational decision-making, ethical tensions will rise and may begin to exert a more detectable moderating influence on innovation outcomes than was observed in the present study.

Based on the findings of this study, the hypotheses proposing that ethical dilemmas moderates the positive relationship between GenAI adoption and exploratory innovation, future organizational performance and exploitative innovation are rejected.

Table 19: Moderation Analysis Results

	Path coefficient (β)	Standard deviation	T statistics	P values
H8a: AGI x GA -> EXPLR	0.210	0.059	3.535	0.000
H8b: AGI x GA -> OP	0.155	0.045	3.420	0.000
H8c: AGI x GA -> EXPLT	0.162	0.059	2.764	0.003
H9a: ETH x GA -> EXPLR	-0.077	0.065	1.193	0.116
H9b: ETH x GA -> OP	-0.023	0.053	0.428	0.334
H9c: ETH x GA -> EXPLT	-0.130	0.079	1.650	0.050

Note: GA: Generative AI Adoption; EXPLR: Exploratory Innovation; EXPLT: Exploitative Innovation; OP: Future Organizational Performance; AGI: Organizational Agility; ETH: Ethical Dilemma

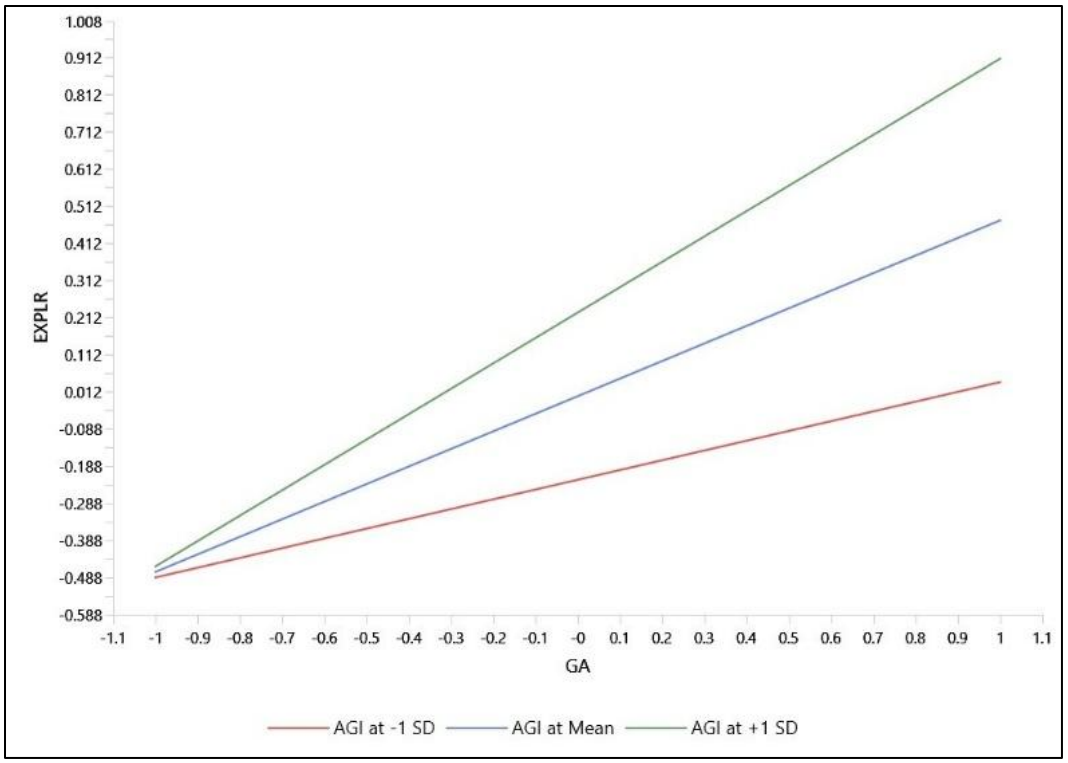


Figure 4: The moderating effect of Organizational Agility (AGI) on GenAI Adoption (GA) and Exploratory Innovation (EXPLR)

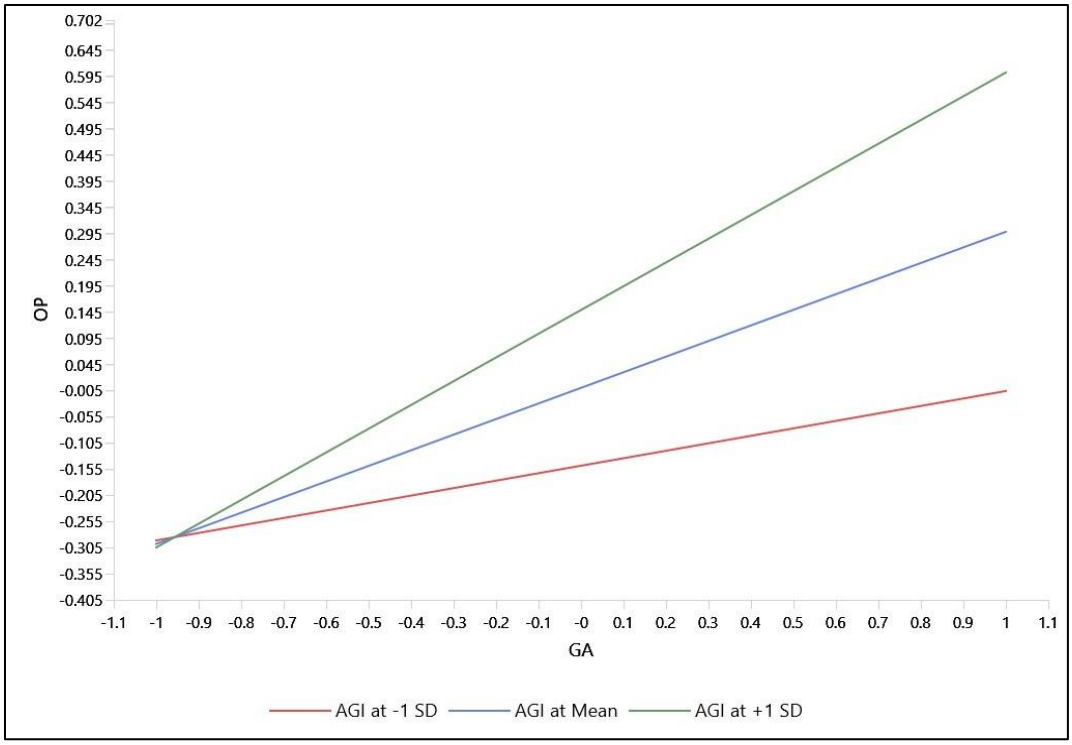


Figure 5: The moderating effect of Organizational Agility (AGI) on GenAI Adoption (GA) and Future Organizational Performance (OP)

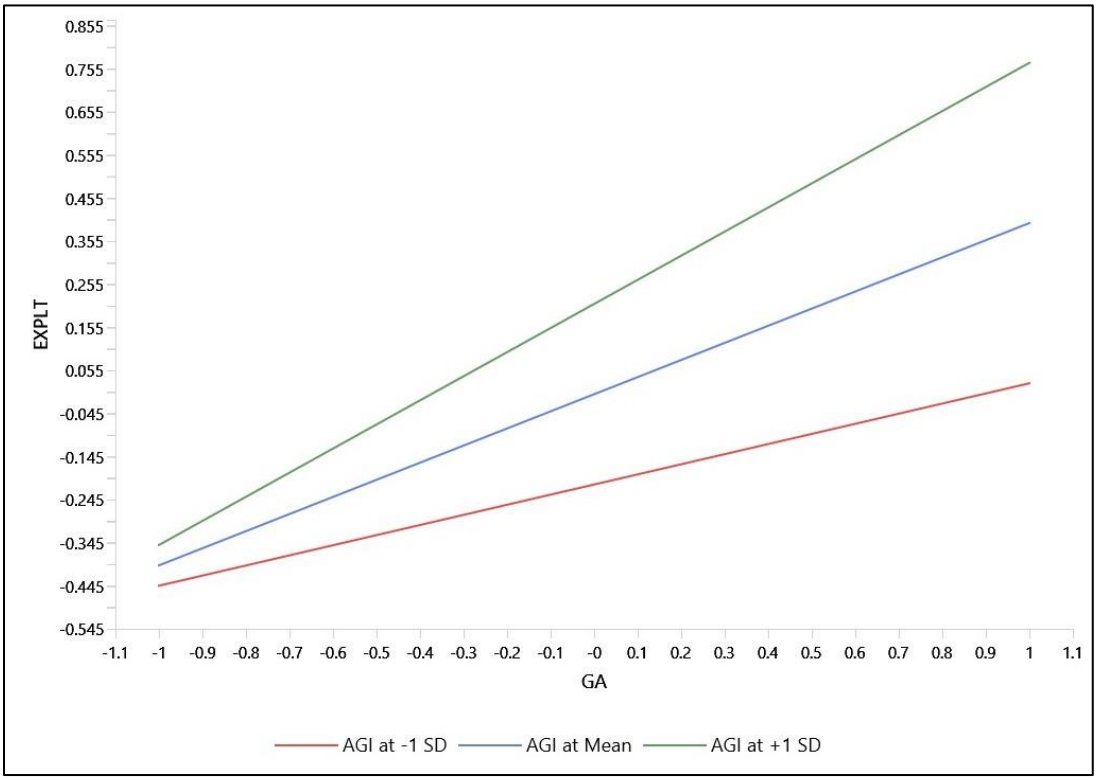


Figure 6: The moderating effect of Organizational Agility (AGI) on GenAI Adoption (GA) and Exploitative Innovation (EXPLT)

4.8.3 Coefficient of Determination (R^2)

The next step in the structural model analysis is assessing the coefficient of determination (R^2). R^2 measures variance in the outcome variables explained by the predictor variables. Hair & Alamer (2022) propose that R^2 values between 0 to 0.10 as weak, 0.11 to 0.30 as modest, 0.30 to 0.50 as moderate and above 0.50 as strong explanatory power. However, the researchers suggest that the R^2 are evaluated relative to the research context. The R^2 results for this study are presented in table 20.

The findings show that the predictor variable, GenAI adoption, explains 0.323 exploratory innovation, indicating moderate explanatory power. In the case of exploitative innovation, GenAI adoption explains 26.9% the variance in exploitative innovation. This indicates modest explanatory power. A R-squared that is between 0.10 and 0.50 is acceptable in social science research when some or most of the explanatory variables are statistically significant (Ozili, 2023). Based on this the R-squared results for exploratory and exploitative innovation are acceptable since the explanatory variable (GenAI adoption) has statistically significant relationship with both constructs.

The R-squared result for future organizational performance is 0.538. This means that the three explanatory variables, GenAI adoption, exploitative innovation and exploratory innovation collectively explain 53.8% of the variance in organizational performance. Based on this, the R-square is above 0.5 which signals that the model has good explanatory capability in accounting for variations in organizational performance.

Table 20: Coefficient of Determination

	R-square	R-square adjusted
EXPLR	0.323	0.307
EXPLT	0.269	0.252
OP	0.538	0.523

Note: EXPLR: Exploratory Innovation; EXPLT: Exploitative Innovation; OP: Future Organizational Performance

In addition to R2, changes in the value of R2 are used to see whether the effect of the predictor variable on the dependent variable has a substantive effect which is measured by the effect size (f2) (Purwanto & Sudargini, 2021). As a rule of thumb, an effect size of 0.02 indicates a small effect, 0.15 signals moderate effect and 0.35 represents a large effect. The f2 results presented in

table 21 show that f2 ranges from 0.000 (ETH → EXPLR) to 0.268 (GA → EXPLR) indicating that GenAI adoption has the highest effect on endogenous variables.

4.8.4 Predictive Relevance (Q^2)

The last step in the structural model analysis is assessing the predictive power of the model. This analysis examines whether the findings not only apply to the data used for estimation but also other data sets to ensure generalizability of findings (Hair et al., 2021). Q^2 value greater than zero indicates predictive relevance whereas a value equal to or less than zero indicates absence of predictive relevance. The Q^2 results presented in table 21 are all above zero which leads to the conclusion that the model has predictive relevance for all endogenous constructs. In other words, the structural model is capable of accurately predicting exploratory innovation, exploitative innovation and future organizational performance.

Table 21: f-square and Q-square results

	f square			**Q square**		
	EXPLR	**EXPLT**	**OP**	**EXPLR**	**EXPLT**	**OP**
GA	0.268	0.175	0.113	0.277	0.216	0.384
AGI	0.060	0.048	0.035			
ETH	0.000	0.020	0.017			
AGI x GA	0.069	0.038	0.050			
ETH x GA	0.008	0.021	0.001			
EXPLR	-	-	0.094			
EXPLT	-	-	0.108			
OP	-	-				

Note: GA: Generative AI Adoption; EXPLR: Exploratory Innovation; EXPLT: Exploitative Innovation; OP: Future Organizational Performance; AGI: Organizational Agility; ETH: Ethical Dilemma

CHAPTER FIVE

5. CONCLUSION, RECOMMENDATION, AND FUTURE RESEARCH DIRECTION

5.1 Conclusion

The objective of this study was to examine the effect of GenAI adoption on future organizational performance by considering the mediating role of exploratory and exploitative innovation and moderating effect of organizational agility and ethical dilemmas in the context of management consulting firms in Ethiopia. The findings indicate that GenAI adoption facilitates improved future organizational performance both directly and indirectly through different innovation types.

Regarding the first research question, the findings of this study confirm the significant and positive effect of GenAI adoption on exploratory innovation of management consulting firms enabling companies to generate new ideas and explore new opportunities. Looking at the second research questions, GenAI adoption has been found to have positive impact on exploitative innovation by creating the capability to improve organizational processes, enhance efficiency and facilitate effective resource allocation. The study's hypothesis testing outcomes has also addressed the third research question of this study, confirming that GenAI adoption has a significant positive effect on future organizational performance.

With respect to the fourth research question, the findings of this study confirmed that exploratory innovation has a significant positive effect on future organizational performance. Organizations with higher levels of exploratory innovation are better positioned to improve future organizational performance by developing new products and services targeting new customers and markets. In addition, exploitative innovation was also confirmed to have a significant positive effect on future organizational performance, addressing the fifth research question. This indicates that organizations engaging in exploitative innovation enhance performance by improving existing services and strengthening their competitive position.

Regarding the sixth research question, both exploratory and exploitative innovation were found to have a complementary partial mediating effect on the positive relationship between GenAI adoption and future organizational performance. This suggests that GenAI adoption not only

indirectly influences future organizational performance through exploitative and exploratory innovation but also has a direct effect on future performance.

With regard to the seventh research question, the results for the moderating effect of organizational agility have been found to be significant in strengthening the positive relationship between GenAI adoption and exploitative innovation, exploratory innovation and future organizational performance. This suggests that organizations with higher levels of agility are better positioned to leverage GenAI tools towards improving exploitative and exploratory innovations as well as future organizational performance.

Conversely, the moderating effect of ethical dilemma on the relationship between GenAI adoption and exploratory innovation, exploitative innovation and future organizational performance was found to be statistically insignificant. This shows that ethical dilemmas do not significantly affect the relationship between GenAI adoption, exploratory innovation, exploitative innovation and future organizational performance within the context of this study. This finding diverges from similar studies which found a significant moderating effect in their respective contexts. The divergence can be attributed to differences of the organizational type, country context and stage of GenAI adoption, which influences how ethical dilemmas are perceived within organizations.

5.2 Recommendation

Based on the research findings, the researcher proposes the following recommendations for management consulting firms and other similar knowledge intensive organizations that have adopted or are considering GenAI adoption.

First and foremost, given that GenAI adoption has been found to significantly drive exploratory innovation, exploitative innovation and future organizational performance, management consulting firms should make strategic investments in GenAI tools that are specifically tailored to the needs of the consulting industry. This includes investing in GenAI tools that support key consulting activities such as data analytics, market research, report write up and knowledge management.

Second, it has been found that GenAI adoption facilitates both exploratory and exploitative innovation which in return results in improved future organizational performance. One key consideration is the need for balancing between these two types of innovations to achieve

ambidextrous innovation. This means that management consulting firms adopting GenAI should have a strategy that does not limit its uses towards improving existing operations through exploitative innovation but also balance its usage towards generating new ideas and service offerings through exploratory innovation.

Third, given that H3 confirmed a significant and positive effect of GenAI adoption on future organizational performance, and that exploratory and exploitative innovation were found to partially mediate this relationship, management consulting firms should leverage GenAI beyond innovation driven activities. Specifically, firms should also apply GenAI to support core business functions such as decision making and strategic planning. This ensures that the benefits of GenAI adoption are realized across multiple aspects of organizational performance in addition to innovation.

Fourth, the confirmed moderating effect of organizational agility on the relationship between GenAI adoption and exploratory innovation, future organizational performance and exploitative innovation indicate the importance of creating an organizational culture that is agile and responsive to changes. This includes adopting organizational strategies that facilitate agility and creating a culture that encourages experimental learning and embraces change. By being agile, management consulting firms will be better positioned to sense the changes and advancements in GenAI technology and better adapt to them to improve the organization’s performance.

Fifth, despite the moderating effect of ethical dilemma being found to be insignificant in this study, organizations should not interpret it as an indication that ethical considerations are irrelevant to GenAI adoption. Rather, this finding may be context-specific to Ethiopia's consulting sector and warrants further investigation of the role of ethical dilemmas in GenAI adoption.

Sixth, as a general best practice consideration, management consulting firms integrating GenAI into core business functions should provide training to employees to ensure effective utilization of the technology. Without the appropriate training, the performance and innovation benefits identified by this study may not be fully realized.

From a broader managerial implication perspective, decision-makers in management consulting firms should consider GenAI adoption as a strategic organizational priority rather than treating it as a purely operational tool. Given that this study empirically confirmed that GenAI adoption

directly and indirectly improves organizational performance through both exploratory and exploitative innovation, its consideration should be elevated to the strategic level. This means that consulting firm leadership should establish clear organizational objectives for GenAI utilization and regularly evaluate the extent to which GenAI uses and investments are delivering the expected innovation and performance outcomes.

Lastly, at the policy level, industry regulators and professional consulting associations in Ethiopia should recognize the empirically demonstrated performance and innovation benefits of GenAI adoption and translate this evidence into actionable policy support. These include formulating policies that facilitate adoption in the sector and those which lower the barriers to GenAI adoption for smaller consulting firms. In addition, sector-specific ethical governance guidelines should be developed to ensure that GenAI is adopted responsibly and in a manner that protects client confidentiality and professional accountability.

5.3 Future Research Direction

Future research could examine how the relationship between GenAI adoption and organizational performance varies when applied to the context of other industries. Testing the relationship across different industries and organizational contexts might provide holistic understanding of how adopting GenAI affects the future organizational performance in different sectors. For example, future studies could conduct a similar study in technology firms which actively use GenAI for software development, as well as financial institutions which use it for tasks such as credit scoring.

Future studies could also adopt longitudinal research design to examine how the relationship between GenAI and future organizational performance evolves as the organization progresses towards different stages beyond initial adoption. This could reveal whether the strength or direction of the relationship changes over time.

Another avenue for future research is exploring the mediating and moderating role of other variables in the relationship between GenAI adoption and future organizational performance. From the resource-based view perspective, variables such as absorptive capacity and knowledge management capability are theoretically relevant as they determine an organization’s ability to acquire and integrate new technological knowledge such as GenAI. Additional variables such as organizational learning, which are relevant from the Diffusion of Innovation Theory (DIT) perspective, may also affect the adoption of GenAI in an organization which in turn affects the

performance outcome. Beyond these, future studies could further enhance the model by examining variables such as organizational culture, leadership support, digital maturity, and employee AI competency, all of which are theoretically relevant factors that may either enable or constrain the extent to which GenAI adoption translates into meaningful innovation and performance outcomes. Examining the model with additional variables may help to better understand underlying factors that could potentially affect the relationship.

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ANNEX

Data Collection Instrument

Addis Ababa University

College of Business and Economics

Department of Management

MSc in International Business

Dear Participant,

My name is Natnael Kebede and I am a graduate student at Addis Ababa University, College of Business and Economics, Department of Management. I am currently conducting research for my master's thesis in International Business.

The objective of this study is to assess the effect of Generative AI adoption on future organizational performance in management consulting firms through the mediating role of exploratory and exploitative innovations, and the moderating role ethical dilemmas and organizational agility. As a professional working within the management consulting sector, your insights are essential for the success of this study.

The survey is designed to be straightforward and will take approximately 5 minutes of your time to complete. Your participation is entirely voluntary. All responses are strictly anonymous and will be handled with the highest level of confidentiality. The data collected will be used exclusively for academic purposes. Most questions use a 5-point scale; please select the option that best reflects your level of agreement with each statement.

Thank you very much for your time, effort, and valuable contribution. Feel free to reach out via WhatsApp or Telegram for any questions through this number +251923670291.

Section 1: Demographic information
Gender: ☐ Male ☐ Female
Age group: ☐ 18-25 ☐ 26-35 ☐ 36-45 ☐ 46-55 ☐ 55+

Educational Background:

☐ TVET/Level 4 Diploma ☐ Bachelor's degree ☐ Master's Degree ☐ Ph.D. ☐ Other

Section 2: Survey Questions

Instruction: Please answer the following section based on the following scale:

5. Strongly Agree
4. Agree
3. Neutral
2. Disagree
1. Strongly Disagree

Questions	**5**	**4**	**3**	**2**	**1**	**Source**	**Found in**
Generative AI adoption:						Davis (1989)	(Singh, Chatterjee, & Mariani, 2024)
1. Generative AI adoption in my role would lead to a substantial improvement in organizational productivity.							
2. The utilization of generative AI tools would enable me to accomplish complex tasks more efficiently.							
3. I would find it easy to instruct generative AI to perform specific tasks.							
4. Generative AI would make it easier for me to perform my organizational responsibilities.							
5. Becoming proficient at using generative AI would be a straightforward and manageable endeavor.							
Organizational Future Performance						Dubey et al. (2020)	(Singh, Chatterjee, & Mariani, 2024)
1. Our organization will experience significant growth in revenue in the upcoming future.							
2. Our organization will achieve notable growth in market share in the upcoming future.							
3. The return on investment for our organization will be commendable in the upcoming future.							

4. Our organization will successfully develop and introduce new products or services							
5. The return on capital employed by our organization will be satisfactory in the upcoming future							
Exploratory Innovation							
1. Our organization accepts demands that go beyond existing products and services.							
2. We pioneer the development of new products and services.						Huang et al. (2014)	(Singh, Chatterjee, & Mariani, 2024)
3. Experimentation with novel products and services is common in our local market.							
4. We successfully bring to market products and services entirely novel to our organization.							
5. Seizing new opportunities in untapped markets is a frequent practice.							
Exploitative Innovation							
1. Our organization consistently refines the provision of existing products and services.							
2. Our organization regularly introduces enhancements to existing products and services specifically for our local market.						Jansen et al. (2009)	(Singh, Chatterjee, & Mariani, 2024)
3. Our organization actively pursues strategies to increase economies of scale in existing markets.							
4. Our organization continuously strives to expand services for existing clients.							
Ethical dilemmas							
1. I am likely to prefer using unauthorized versions of software or technology.						Verma & Garg (2024)	(Singh, Chatterjee, & Mariani, 2024)
2. I am inclined to use organizational hardware and software resources for personal needs.							

3. I am likely to share organizational resources with entities outside the organization.							
4. I am likely to take undue advantage of unencrypted VPN services available within the organization							
Organizational agility							
1. The firm responds to changes in aggregate consumer demand							
2. The firm customizes a product or service to suit an individual customer.							
3. The firm reacts to new products or service launches by competitors.						(Tallon & Pinsonneault, 2011)	(Wahab & Radmehr, 2024)
4. The firm introduces new pricing schedules in response to changes in competitors' prices.							
5. The firm expands into new regional or international markets.							
6. The firm Changes (i.e., expand or reduce) the variety of products/services available for sale.							
7. The firm adopts new technologies to produce better, faster, and cheaper products and services.							