RESPONSIBLE AI IN THE US: STRATEGIC RESPONSES OF SMALL- AND MEDIUM-SIZED ENTERPRISES TO INSTITUTIONAL PRESSURES

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Responsible AI in the US: Strategic Responses of Small- and Medium-Sized Enterprises to Institutional Pressures

by

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Abstract

The rapid advancement and adoption of artificial intelligence (AI) technologies have created unprecedented challenges for organizations implementing responsible AI practices. While extensive research exists on AI implementation in large corporations, limited attention has been paid to how small- and medium-sized enterprises (SMEs) navigate institutional pressures while pursuing responsible AI development. This study will investigate the strategic responses of U.S.-based SMEs to institutional pressures in implementing responsible AI technologies, examining how these organizations balance ethical considerations with innovation imperatives and legitimacy. Drawing on Oliver's (1991) theoretical framework of strategic responses to institutional pressures, this research will employ a qualitative methodology to analyze how AI practitioners within SMEs interpret and respond to institutional demands. This research intends to extend Oliver's framework by revealing how resource constraints and organizational size influence strategic responses to institutional pressures in the context of emerging technologies. Additionally, it will address a critical gap in understanding how SMEs navigate the complex landscape of responsible AI implementation while maintaining competitiveness. The findings will have significant implications for organizational theory, particularly in understanding how smaller organizations adapt to institutional pressures in technology-intensive industries.

Keywords: responsible artificial intelligence, small- and medium-sized enterprises (SMEs), organizational theory, business ethics

ACKNOWLEDGMENTS

Because the chair, committee member, and methodological reader are already acknowledged on the title page, avoid adding them here. This section should be reserved for those who made a direct or particularly meaningful contribution to your doctoral journey. Be sure to recognize anyone who provided tangible support. Typically, names are not included, and professional acknowledgments precede personal acknowledgments. This section is optional and should be less than one page.

Examples:

- I would like to thank my classmates, professors, librarians, university staff, and the doctoral advising team for their incredible support during the doctoral journey.
- I especially appreciated the support of my work colleagues, who encouraged me to pursue this degree and provided valuable insight along the way.
- I would like to extend my sincere appreciation to the participants, who made this research possible.
- I am forever grateful to my friends and family, who provided emotional support and encouragement along the way.

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CHAPTER I: INTRODUCTION

A new age of technological innovation has disrupted various sectors of the global economy driven by rapid advancements in artificial intelligence (AI), machine learning, and deep learning. In the U.S., growth in AI has produced a significant rise in AI-focused businesses, particularly in small and medium-sized enterprises (SMEs). Since 2017, the number of U.S.-based AI SMEs has doubled, playing an essential role in furthering AI innovation and technological development (Tracxn Technologies, 2024; Tricot, 2021; Winecoff & Watkins, 2022). As SMEs advance to the forefront of innovative development, they are encouraged to move AI initiatives from experimental to production as quickly as possible. However, they experience unique challenges that mature organizations do not face; larger enterprises tend to create industry standards, while SMEs tend to adjust to them (Hopkins & Booth, 2021; DiMaggio & Powell, 1983). These challenges SMEs face affect how AI practitioners are expected to respond (Goodstein, 1994). If AI practitioners in these SMEs lack the autonomy to make ethical decisions when developing and deploying these systems, they may perpetuate the status quo (Batool et al., 2023; Constantinescu et al., 2021). Therefore, SMEs must develop AI responsibly while navigating institutional pressures. The purpose of this qualitative study is to understand how U.S.-based SMEs strategically respond to institutional pressures faced when implementing responsible AI.

By examining the strategic responses of AI SMEs, which often operate with fewer resources than larger organizations, the proposed study is designed to reveal what influences organizations to react to institutional pressures and how they adapt to external pressures (Hopkins & Booth, 2021; Winecoff & Watkins, 2022). The findings of the proposed research will contribute to understanding how SMEs maintain legitimacy, competitiveness, and sustainability as they seek to adopt responsible AI. This research could provide valuable insights for developing effective strategies and inform both practices and policies for responsible AI innovation in SMEs.

This chapter provides an overview of the proposed study and outlines its context, significance, and structure. It discusses the AI landscape and gradually narrows the focus to specific research problems and questions. This chapter is organized as follows: background of the proposed study, problem statement, purpose of the study, importance of the study, theoretical framework, and research questions. The chapter concludes with definitions of the terms and identifies any assumptions, limitations, and delimitations. The following section explores how the evolving landscape of AI development presents unique challenges and opportunities to SMEs.

Background of Study

Artificial intelligence (AI) technologies have become increasingly prevalent in driving promises of efficiency, innovation, and competitive advantage across various sectors. However, alongside these potential benefits, there is a growing recognition of significant negative social consequences associated with AI, including racial and gender biases (Bender et al., 2021; Bolukbasi et al., 2016; Buolamwini & Gebru, 2018; Noble, 2018; Rekabsaz & Schedl, 2020; Sweeney, 2013), environmental injustice (Li et al., 2023; Urzedo et al., 2024), and human right injustices (Mattu, 2023; Miragoli, 2024; Raso et al., 2018). Larger organizations have responded by establishing councils dedicated to ensuring responsible development and deployment of AI systems (Walker, 2020). Conversely, SMEs are often disadvantaged due to limited resources and personnel and an urgent need to achieve profitability (Hopkins & Booth, 2021). SMEs represent a substantial segment of the global economy and are characterized as a substantial influencer in the AI industry (Tracxn Technologies, 2024; Tricot, 2021; Winecoff & Watkins, 2022). However, SMEs tend to lack the proper resources to operate and provide optimal service. For instance, many SMEs lack dedicated ethical AI leads or psychologists due to financial constraints or a belief that such roles are unnecessary (Miller, 2022). In addition, they have an increased dependence on external funding, which can be competitive (Poderys, 2015). These limitations leave AI systems vulnerable to risk since the moral and ethical agents of these systems are left to those who create them. As a result, the ethical agency of AI systems in SMEs often rests with the practitioners themselves, further complicating efforts to ensure fairness, transparency, and accountability in AI algorithms (Miller, 2022).

Practitioners in the field increasingly struggle to transition from theoretical discussions to practical implementations (Morley et al., 2023; Rakova et al., 2021). Despite the availability of tools to aid responsible AI creation, institutional pressures heavily influence decision-making processes, affecting the ethical development of AI technologies (Rakova et al., 2021; Winecoff & Watkins, 2022). Institutional pressures stem from social and political norms and expectations that pervade organizational culture (DiMaggio & Powell, 1983). For instance, practitioners may face conflicting pressures, such as the temptation to prioritize financial gains over fairness (Hopkins & Booth, 2021) or the need to comply with regulatory requirements, such as the European Union's General Data Protection Regulation (GDPR), which mandates strict data protection measures (Data Protection in the EU, 2023). To grow and survive, organizations dependent on resources must align themselves with their external environment.

A central tenet of institutional theory is that aligning with societal norms and expectations grants legitimacy. This legitimacy, in turn, attracts resources to organizations that are perceived as legitimate (Dowling & Pfeffer, 1975). “Legitimacy is a generalized perception or assumption that the actions of an entity are desirable, proper, or appropriate within some socially constructed systems of norms, values, beliefs, and definitions” (Suchman, 1995, p. 574). It is argued that legitimacy serves as a social endorsement that can significantly influence an organization's survival and success (De Paula et al., 2023; Ferreira et al., 2021). To maintain legitimacy, organizations must adapt to the norms and expectations of their environment.

As more organizations adapt to societal norms, they tend to become increasingly similar over time due to institutional isomorphism (DiMaggio & Powell, 1983). DiMaggio & Powell (1983) outlined three primary factors that lead organizations to become increasingly similar: (1) coercive pressures, which are formal and informal expectations imposed by regulatory bodies; (2) normative pressures, which arise from professional norms, industry standards, and shared values within a field; and (3) mimetic pressures, which involves emulating successful or leading organizations’ practices. As a result, these pressures contribute to a convergence of organizational structures, strategies, and practices across industries, regardless of their unique contexts. Over time, institutional isomorphism not only shapes the behaviors of individual organizations but also reinforces the homogenization of entire fields and sectors.

Oliver (1991) argued that organizations use different strategic behaviors based on the social and/or economic reward that yield the most fruitful allocation of resources for the organization. It is claimed that the lower the perceived reward (i.e., social legitimacy) for conforming, the less likely the organization will conform. Oliver's work contends that there are five factors to consider when determining the likelihood of an organization conforming or resisting: cause, constituents, content, control, and context. Understanding these five factors is particularly crucial in the AI industry, where SMEs must carefully weigh the benefits of conformity against their resource limitations when implementing responsible AI practices.

The study intends to leverage Oliver's (1991) framework, which provides the setting for exploring strategic responses to institutional pressures. This conceptual framework presents a systematic classification of strategic responses to institutional pressures, identifying both the multifaceted nature of potential actions and the contextual antecedents that give rise to them. It allows for an exploration of strategic options beyond compliance or resistance, providing a nuanced understanding of not only how but also why and under what circumstances specific responses are chosen. By examining these responses through Oliver's lens, the research can systematically analyze how AI practitioners in SMEs navigate institutional demands, considering their unique resource constraints and operational contexts.

Statement of the Problem

Artificial intelligence has undergone advancements in many areas, including machine learning and deep learning, expanding adoption at an increasing rate (De Fátima Soares Borges et al., 2021; Haleem, 2023). The proliferation of AI technologies has catalyzed a notable increase in the number of SMEs specializing in AI within the U.S. These organizations serve as key drivers in advancing AI research, innovation, and technological progress (Tracxn Technologies, 2024; Tricot, 2021). However, AI SMEs face unique challenges that more established organizations do not have, such as limited resources, personnel, and an urgent need to achieve profitability (Hopkins & Booth, 2021; Winecoff &

Watkins, 2022). SMEs face mounting institutional pressures as they attempt to integrate AI technologies into their operations while maintaining legitimacy and sustainability (Chaudhuri et al., 2022). Despite the transformative potential of AI, SMEs struggle to balance innovation with compliance and ethical considerations (Celsi, 2023). The general problem is that SMEs face institutional pressures while implementing AI technologies, resulting in challenges to maintain legitimacy and sustainability in their AI initiatives. SMEs are challenged to navigate multiple stakeholders' demands while attempting to remain competitive and responsible in their AI adoption.

Current research has covered AI adoption in large organizations; however, less effort has been made to study the multiple ways in which companies can respond to institutional pressures for responsible AI. In an era of rapidly growing AI technology, it is exceedingly important to understand the motivation behind the decisions that influence specific strategic responses when implementing AI technologies. The specific problem is that there is limited insight into how AI SMEs strategically respond to institutional pressures, resulting in unclear motivations for adopting responsible AI practices. This gap leaves unanswered questions about the specific strategies SMEs employ to align with institutional demands while upholding ethical standards. By exploring these responses, the study proposes to contribute to research on responsible AI by focusing on how SMEs' unique approaches could inform broader practices in the AI industry. Understanding these strategic responses could help develop frameworks that enable SMEs to balance innovation with ethical implementation while maintaining organizational legitimacy.

Purpose of the Study

The purpose of this qualitative study is to understand how U.S.-based SMEs strategically respond to institutional pressures faced when implementing responsible AI. By examining how SMEs identify and react to different institutional pressures, this research will explore the specific challenges these organizations face and the factors that influence their strategic responses when implementing responsible AI technologies. Through an in-depth analysis of practitioners' experiences and decision-making processes, this study will uncover the key institutional pressures affecting AI SMEs and identify the predictors that shape their strategic responses to these pressures. The findings will address the current knowledge gap regarding SMEs' strategic behaviors in the AI industry. This qualitative approach will enable a rich understanding of the complex dynamics between institutional pressures and organizational responses, contributing to both theoretical frameworks and practical applications in the field of responsible AI adoption among SMEs.

Importance of the Study

The overarching focus of this study is to understand how SMEs in the AI industry strategically respond to institutional pressures through the lens of Oliver's (1991) Framework. While prior research has explored institutional dynamics in large enterprises, what is worth investigating is how external institutions influence the environment and eventually shape and determine strategic actions. This study will advance organizational leadership theory by extending Oliver's strategic response framework to the context of AI adoption in SMEs, potentially revealing unique patterns and adaptations specific to smaller organizations. Additionally, the findings will provide SME leaders with evidence-based strategies for responding to institutional pressures while maintaining organizational legitimacy and sustainability. The findings of this research are particularly relevant for organizational diversity, as they will elucidate how SMEs can successfully adopt responsible AI practices, creating a more ethically sound AI adoption across diverse organizational contexts.

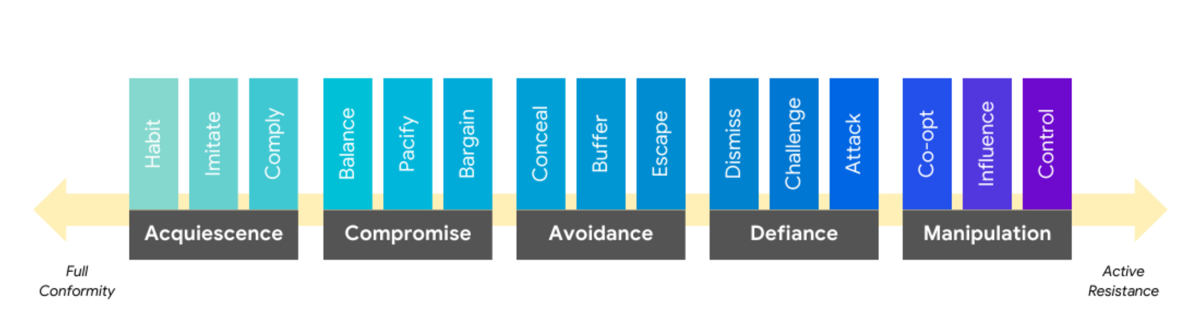
Conceptual Framework

The proposed research will be grounded in Oliver's (1991) seminal work on strategic responses to institutional processes, which integrates insights from both institutional theory and resource dependence theory (RDT). Institutional theory explores how organizational structures and practices are shaped by institutional rules and norms (Selznick, 1949, 1957). Their work was extended to discuss how those processes influence organizational practices to become increasingly homogenized as organizations conform to institutional expectations (DiMaggio & Powell, 1983; Meyer & Rowan, 1977). Organizations that conform to socially accepted norms and values are regarded as legitimate (Meyer & Scott, 1983). Resource dependence theory complements institutional theory by examining how organizations interact with external entities to secure resources, focusing on the power dynamics within the relationship (Pfeffer & Salancik, 1978). These foundational theories laid the groundwork for understanding how organizations respond to external pressures. However, both theories have their limitations. While institutional theory posits that organizations passively conform to institutional pressures, RDT highlights their active pursuit of resources and power.

Oliver's (1991) framework integrated both theories to outline five core strategic responses ranging from passive to active: acquiescence, compromise, avoidance, defiance, and manipulation, and three respective tactics; these are illustrated in Figure 1. These strategic responses address how organizations respond to institutional pressures to achieve stability and legitimacy. Oliver positioned acquiescence on the passive end of the spectrum in conformity to institutional pressures. Acquiescence can take three forms: following unconscious norms (habit), mimicking successful organizations (imitate), or consciously obeying rules or requirements (comply). For example, SMEs may adopt industry best practices or adhere to regulatory requirements to avoid social scrutiny or gain legitimacy.

Figure 1

Strategic Responses to Institutional Pressures and Their Respective Tactics Based on Oliver's Framework (1991)



The second strategy, compromise, involves partial conformity that attempts to equalize conflicting demands (Oliver, 1991). The tactics involved include accommodating multiple stakeholders' expectations (balance), partially complying with expectations (pacify), and negotiating with stakeholders (bargain). For instance, SMEs may need to balance rapid innovation with ethical implementation or may implement a partial ethical practice that accommodates rapid innovation.

Avoidance, the third strategy, involves attempting to evade conforming to institutional pressures through concealment, buffering, or escape (Oliver, 1991). Organizations that conceal their true intentions give the appearance of conformity. Buffering means reducing or decoupling technical activities from oversight. Escaping is the most dramatic avoidance strategy, involving a complete change of goals, activities, or domains to avoid institutional constraints.

The fourth strategic response is defiance, which challenges or rejects institutional pressures. To increase active resistance, the three tactics of defiance are dismissal, challenge, and attack (Oliver, 1991). Dismissal refers to ignoring the rules, typically exercised when the perceived consequences are low. Organizations that challenge institutional pressures take a more active role in defiance, contesting the validity of the rules, norms, or expectations. Attacking represents another form of active opposition to institutional pressures; however, this tactic attempts to invalidate the institutional value and the external stakeholders expressing it.

Oliver's fifth strategic response, manipulation, is the most proactive strategy, where organizations seek to change or exert power over institutional pressures and expectations (Oliver, 1991). Organizations actively alter, re-create, or control the pressures or stakeholders that impose them through tactics such as bringing influential stakeholders (co-opt), shaping institutional values (influence), or establishing dominance over those applying pressure (control). This approach shifts the balance of power in the organization's favor, ensuring that institutional norms and expectations align more closely with their strategic objectives. By doing so, they not only mitigate external constraints but also create opportunities to establish competitive advantages within their institutional environment.

By applying Oliver's framework, the study aims to bridge the existing literature on responsible AI adoption and SME adaptation to institutional pressures. While prior research has been constrained to large enterprises, little work has systematically examined how SMEs balance these pressures with the resource constraints and competitive dynamics inherent to their size and industry. This study contributes to the literature by examining the predictors and specific tactics that drive SMEs' strategic responses to institutional pressures within the AI industry. It leverages Oliver's strategic response framework to provide comprehensive insight into how SMEs navigate the ethical challenges of responsible AI, situating the study at the intersection of institutional theory, resource dependence theory, and emerging literature on responsible AI. A more in-depth examination of the conceptual framework is presented in Chapter II.

Research Questions

Qualitative research studies are structured to gain a deeper understanding of human experiences, feelings, and perspectives behind a phenomenon (Leedy & Ormrod, 2015). Such methods are particularly well-suited for exploring complex, context-dependent processes that involve dynamic interactions between individuals and their environments (Creswell & Poth, 2018). The purpose of this qualitative study is to understand how U.S.-based SMEs strategically respond to institutional pressures faced when implementing responsible AI. The following research question (RQ) and sub-questions (SQ) will guide the study:

RQ: How do AI practitioners at SMEs strategically respond to institutional pressures when implementing responsible AI technologies?

SQ1: What are the institutional pressures SMEs face when implementing responsible AI technologies?

SQ2: What are the predictors of the strategic responses when implementing responsible AI technologies?

The research question, *RQ*, is intended to gain insight into how SMEs manage institutional pressures while developing responsible AI technologies despite resource limitations. By focusing on AI practitioners' strategies, the research can identify successful patterns and approaches that enable SMEs to maintain operations and sustainability in the face of institutional pressures. Moreover, examining these strategies can uncover how SMEs balance ethical concerns with business objectives, particularly when institutional demands may conflict with operational goals (DiMaggio & Powell, 1983). Understanding these dynamics could contribute to the broader field of institutional theory and provide actionable insights.

To fully understand these strategic responses, the research must first identify the institutional pressures themselves, *SQ1*. Understanding these forces provides context for analyzing how SMEs navigate their implementation of responsible AI technologies, directly supporting the research objective by illuminating the specific challenges that can impact SMEs. Institutional pressures may include regulatory compliance requirements, ethical mandates from industry bodies, and social expectations for transparency and fairness in AI systems (DiMaggio & Powell, 1983). These pressures often interact in complex ways, and identifying their specific nature is crucial for developing practical interventions to support SMEs in achieving responsible AI implementation.

Finally, the second sub-question, *SQ2*, is intended to examine the predictors of strategic responses, helping reveal why specific approaches are chosen over others. These predictors can give insight into how AI SMEs' resource constraints influence strategic decisions. For instance, variables such as societal fitness, who and how many external forces are applied, and agency over application may significantly shape how SMEs adapt to institutional demands (Oliver, 1991). By identifying these predictors, the research aims to provide a framework for understanding the internal and external factors that drive strategic variation among SMEs when implementing responsible AI.

Overview of Research Design

The proposed qualitative study examines how AI practitioners in U.S.-based SMEs strategically respond to institutional pressures when implementing responsible AI technologies. A qualitative study is suitable for this study because it explores how individuals interpret and make sense of their lived experiences, which aligns with the study's objective of analyzing complex, context-dependent experiences and perspectives of AI practitioners in SMEs (Merriam & Tisdell, 2015; Tomaszewski et al., 2020; Ryan et al., 2007). Additionally, the qualitative approach allows for a pragmatic and flexible approach to data collection and analysis while maintaining methodological rigor.

Semi-structured interviews will serve as the primary data collection instrument. A semi-structured approach provides flexibility to respond to the situation at hand, which will allow for an in-depth exploration of participants' experiences and perspectives (Merriam & Tisdell, 2015). It is well-suited to uncover nuanced insights and themes relevant to the research questions (Creswell & Poth, 2016). An interview protocol will be developed and validated through pilot testing to ensure relevance and clarity.

The targeted population will be AI practitioners from U.S.-based SMEs that incorporate AI, machine learning, or predictive analytics. A purposive sampling method will be used to recruit participants through online AI and tech-related communities, company emails, LinkedIn, and professional networks. To account for attrition and data saturation, approximately 15 – 20 individuals will be selected based on criteria such as interview length, saturation, and homogeneity to ensure comprehensive and representative analysis (Bekele & Ago, 2022; Salmons, 2014).

Interviews will be conducted virtually through password-protected Microsoft Teams meetings to accommodate geographical distribution and schedules. Each interview is expected to last approximately 30-90 minutes, providing ample time for a thorough discussion of the research topics. They will consist of open-ended questions to encourage detailed responses, and follow-up inquiries will be used to delve deeper into emerging themes. Interviews will be transcribed verbatim using Microsoft Teams' Live Transcription feature, member-checking to ensure accuracy. The interview data will be coded and analyzed thematically. Thematic analysis will be used to identify key themes and patterns that reveal how AI practitioners in SMEs respond to institutional pressures. Further details about the study method, procedures, and analysis will be outlined in Chapter III.

Definition of Terms

Within the context of this research, several terms require clear and specific definitions to ensure a shared understanding of their meaning and their relationship to one another. Defining these terms is critical to maintaining consistency and clarity throughout the study, as it establishes a common framework for interpreting key concepts and ideas. Moreover, precise definitions help delineate the scope of the research, prevent potential misinterpretations, and align the study with established literature in the field (Creswell & Poth, 2018). By providing clear explanations of these terms, this section aims to enhance the rigor of the research and provide a foundation for analyzing the findings in alignment with the study's objectives and theoretical framework.

Artificial intelligence (AI) is machine-simulated human intelligence that can perfect some cognitive functions such as decision-making and predictions or implement algorithms using technologies such as machine learning, deep learning, natural language processing, and image recognition (Badghish & Soomro, 2024; Copeland, 2024; McKinsey & Company, 2024).

AI ethics / ethical AI is a systematic framework based on a set of values and principles that guide societies in dealing with the known and unknown impacts of AI on humanity, society, and the environment (UNESCO, 2022).

AI governance encompasses the systematic policies, procedures, and practices that ensure AI development is responsible and ethical (Agarwal, 2023).

AI models are computational systems that utilize algorithms to learn patterns from existing datasets, enabling them to make predictions or decisions based on new, unseen data (Bhattacharya et al., 2022; Yousefzadeh & Cao, 2022).

AI practitioners are professionals who design, implement, and manage AI systems, ensuring their ethical application and effectiveness across various domains while navigating the complexities of AI governance and fairness (Terry et al., 2022; Mäntymäki et al., 2022; Möllmann et al., 2021; Morley et al., 2021).

Financial pressures are the forces that impact an organization's decision-making, resource allocation, and overall strategy, such as limited budgets, market competition, debt obligations, or stakeholder expectations for profitability and growth (DiMaggio & Powell, 1983; Winecoff & Watkins, 2022).

Institutional isomorphism is organizational homogenization, the tendency for organizations within the same industry to become increasingly similar in structure, culture, and output (DiMaggio & Powell, 1983; Sakib, 2020; Winecoff & Watkins, 2022).

Institutional pressures represent the formal and informal forces, such as regulatory bodies, market forces, societal expectations, and technological changes, external to the organization that can influence its behavior and decisions (DiMaggio & Powell, 1983; He et al., 2019; Oliver, 1991).

Normative pressures are the conscious and unconscious cultural influences exerted on an organization, shaping organizational behaviors to align with shared definitions of rational and appropriate conduct, often leading to structural homogeneity among organizations. These pressures enforce the adoption of systems deemed legitimate by relevant professional groups to gain, maintain, and defend organizational legitimacy (DiMaggio & Powell, 1983; Durand et al., 2019; Munir & Baird, 2016; Suchman, 1995).

Regulatory pressures encompass the formal rules, policies, and practices that impact how SMEs' structure, operations, and decision-making processes. These constraints are placed on organizations by government bodies, industry standards, and legal frameworks (Oliver, 1991; Winecoff & Watkins, 2022).

Responsible AI (rAI) is the development and use of AI systems that respect human rights and democratic values while minimizing the risk of adverse consequences (Lu et al., 2023, p. 14; OECD, 2024b).

Small and medium enterprise (SME) is typically an organization with either 500 employees or fewer or less than $7.5 million in average annual receipts, excluding large multinationals, state-owned enterprises, and conglomerates (Lin et al., 2022; U.S. Small Business Administration, 2023).

Assumptions, Limitations, and Delimitations

Assumptions, limitations, and delimitations are integral to framing this research and contextualizing its findings. Assumptions outline the foundational premises accepted as true without direct verification, shaping the research design and methodology. Limitations acknowledge potential weaknesses beyond the researcher's control that may affect the study's outcomes (Theofanidis & Fountouki, 2018). Delimitations, on the other hand, define the intentional boundaries set by the researcher to narrow the focus and ensure the manageability of the study (Theofanidis & Fountouki, 2018). Acknowledging these elements not only strengthens the credibility of the research by promoting transparency but also offers valuable context for future researchers to interpret findings, replicate studies, or address the identified gaps (Ellis & Levy, 2009). Together, these considerations provide a comprehensive framework for understanding the study's scope and positioning within the broader academic discourse.

Assumptions

The primary assumptions are that participants are familiar with AI technologies and their organization's institutional pressures. It is also assumed that participants will respond honestly and accurately during virtual interviews with relevant experiences. Another assumption is that SMEs are subject to the same regulatory standards as larger organizations. Lastly, it is assumed that the selected sample size of 15-20 participants will be sufficient to reach data saturation. These assumptions underpin the study's methodology and influence how the research questions can be effectively addressed.

Limitations

Limitations influence the results and generalizability or transferability of the study (Leedy & Ormrod, 2015). Several limitations affect the generalizability and results. For example, only one researcher will be reviewing and interpreting the data, which can inadvertently introduce personal biases, running the risk of skewed findings (Patton, 2015). It is also important to note that the qualitative research is focused on U.S.-based SMEs, limiting the transferability of findings to other geographical contexts or organizational sizes (Leedy & Ormrod, 2015). Additionally, virtual interviews may constrain the capture of non-verbal cues during data collection, potentially affecting the richness of insights into practitioners' experiences. Due to the evolving nature of AI, this study may not account for evolving practices and perspectives. Lastly, the researcher is a data and security professional as well as an ethical AI consultant to organizations. The researcher is considered a subject matter expert in the security and ethical AI field, which could contribute to bias in this study.

Delimitations

Specific delimitations have been established to maintain focus and methodological rigor. Delimitations are the boundaries set by the researcher to ensure the research is focused (Leedy & Ormrod, 2015). This research will not cover any non-AI SMEs and organizations outside the U.S. Moreover, AI governance frameworks can vary significantly between countries; therefore, limiting the study to U.S. SMEs allows for a consistent regulatory and cultural context (Dixon, 2022). (However, due to emerging regulations in each state, it is important to note any regional regulations that affect organizations.) Focusing on AI-involved SMEs ensures that all participants have direct experience with the challenges of responsible AI implementation, providing relevant data for the study. The use of a single industry allows for a controlled examination of institutional pressures (SQ1) and strategic response predictors (SQ2) within a consistent regulatory and cultural context. The target sample size of 15-20 participants is a deliberate choice to achieve depth rather than breadth in understanding how AI practitioners strategically respond to institutional pressures (RQ). While these delimitations may limit the generalizability of the findings, they enhance the study's ability to provide deep, context-specific insights into how AI practitioners in U.S. SMEs respond to institutional pressures in responsible AI implementation. Future research could expand on these findings by exploring different geographical contexts or larger sample sizes.

Summary

The proposed study aims to explore how SMEs in the U.S. strategically respond to institutional pressures when implementing responsible AI technologies. As SMEs continue to drive AI innovation, they face unique challenges such as limited resources and rapid profitability, which contrasts with the capabilities and structures of larger organizations. These challenges influence SMEs' ethical decision-making processes, potentially affecting the societal impact of their AI systems. The research will be based on Oliver's (1991) framework, which outlines five key strategies for how organizations respond to institutional pressures. By using a qualitative approach with semi-structured interviews, the study is designed to uncover nuanced insights into how AI practitioners within SMEs manage these pressures to promote ethical AI practices. This research seeks to contribute valuable insights for enhancing responsible AI development in SMEs, informing both practice and policy in the AI industry.

Chapter II presents a comprehensive review of the literature, focusing on key concepts relevant to the study, including responsible AI, SMEs, institutional theory, resource dependency theory, and Oliver's Framework. This review critically examines the related theoretical foundations and empirical studies, highlighting their significance in understanding the dynamics of AI adoption within SMEs and the broader institutional and resource-related challenges they face. Chapter III delves into the qualitative methodology that will be used in the research, providing a detailed discussion of the research design, including the formulation of research questions, the participant selection process, and the approach to data analysis. Additionally, the chapter addresses the trustworthiness of the study and ethical considerations. This structure lays the foundation for a holistic examination of f how responsible AI can be effectively applied in SMEs while navigating the complexities of institutional and resource dependencies.

CHAPTER II: REVIEW OF THE LITERATURE

The proposed qualitative study's purpose is to investigate how AI practitioners in U.S.-based SMEs strategically respond to institutional pressures faced in the AI industry when implementing responsible AI technologies. A comprehensive review of the scholarly literature is essential to identify knowledge gaps and inform strategies for SMEs to address institutional pressures in responsible AI implementation effectively. The literature review not only describes the theoretical perspectives and previous research findings related to the problem but also provides a way to synthesize and gain a new perspective based on what has been done (Leedy & Ormrod, 2015; Randolph, 2009). It is a systemic approach to identifying relationships between ideas and practices, establishing context, and relating ideas and theory to application (Randolph, 2009).

As AI continues to transform business operations, understanding how SMEs navigate institutional demands while implementing responsible AI technologies may help them adopt strategies to mitigate ethical issues arising from AI (Stahl et al., 2021). The proposed study employs Oliver's (1991) framework to examine strategic responses to institutional pressures, contributing to both theoretical understanding and practical applications in the field. Through a comprehensive literature review, the proposed research explores the intersection of institutional theory, AI implementation, and SME operations, addressing the central research question and supporting questions:

RQ*:* How do AI practitioners at SMEs strategically respond to institutional pressures when implementing responsible AI technologies?

SQ1*:* What are the institutional pressures SMEs face when implementing responsible AI technologies?

SQ2: What are the predictors of the strategic responses when implementing responsible AI technologies?

This chapter presents a review of the most pertinent knowledge related to the proposed study. It presents an analysis of the existing literature emphasizing key constructs to support the proposed research and the conceptual framework used to explore this phenomenon. The chapter concludes with an illustration of how the proposed study fits into the existing body of knowledge.

Search Strategy

This section describes the search process used to locate the literature related to the proposed study. The search strategy used for this paper is unorthodox yet innovative in that AI was leveraged to search for relevant research papers. The AI tools used to discover scholarly, peer-reviewed articles were Elicit, Connected Papers, and Scite. Elicit and Connected Papers source academic articles from Semantic Scholar Paper Corpus, an open-access dataset for academic articles (Connected Papers, 2024; Elicit, 2024). Scite also includes open-access articles, but it also contains articles through agreements with publishers, such as Sage, Pubmed, and Wiley (Scite, 2024). All tools suggested pertinent papers that were then located, verified, and reviewed.

To ensure a comprehensive search, in addition to the AI tools, content searches were conducted in several search engines for peer-reviewed journals, scholarly books, conference papers, and doctoral dissertations. The University of Arizona Global Campus's library databases, where the literature was primarily sourced from EBSCOhost, Emerald, Ebook Central, IEEE Explore, JSTOR Journals, Leadership Quarterly, ProQuest Central, Research Gate, SAGE Journals Online, Science Direct, and Wiley Online Library. In addition, Google

Scholar provided information for relevant research on the topic. Research topics included seminal work on institutional theory, resource dependence theory, organizational theory, legitimacy, and strategic responses. The general search and subsequent refined searches were limited to whole phrases found in English-only peer-reviewed sources. The results of the general search were refined using Boolean (AND/OR) searches to find studies. The primary keywords initiating the search were *SMEs, small and medium enterprises, artificial intelligence, responsible AI, ethical AI, strategic responses,* and *AI in SMEs*.

The literature discussed in this chapter is broad and deep. It contains seminal works primarily from Turing (1950), McCarthy et al. (1955), Dowling & Pfeffer (1975), Meyer & Rowan (1977), Pfeffer and Salancik (1978), DiMaggio & Powell (1983), and Oliver (1991). To keep the scholarship current, approximately 80% of the sources selected for the research were published after 2019. Earlier sources have been included in the review to provide readers with an inclusive perspective on responsible AI.

Responsible Artificial Intelligence (AI)

Artificial intelligence, a term often bandied about in both academic and professional discourse, has captured the imagination of researchers and the public alike. While the concept of machines exhibiting intelligence has been explored for centuries, from ancient philosophers pondering the possibilities of systematizing thought to machines performing tasks traditionally done by humans, its modern incarnation has witnessed a surge of interest and development in recent decades (Ponomarenko et al., 2024). Despite the ubiquity of AI, its precise definition remains elusive. However, the most adopted definition comes from the Organisation for Economic Co-operation and Development (OECD), an intergovernmental organization committed to shaping the policies that govern AI (Grobelnik et al., 2024):

> An AI system is a machine-based system that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments. Different AI systems vary in their levels of autonomy and adaptiveness after deployment. (OECD, 2024a, p. 4)

This rapid advancement in AI technologies has not only transformed industries and reshaped our daily lives but also raised profound ethical and societal questions. For instance, as AI systems become increasingly integrated into sectors such as healthcare, there are growing concerns regarding biases in algorithms and the potential for discrimination, which can adversely affect patient care and outcomes (Elendu et al., 2023; Secinaro et al., 2021). Moreover, the ethical implications of AI extend beyond healthcare, affecting areas like marketing and finance, where issues of transparency and accountability are paramount (Olatoye et al., 2024; Rahman et al., 2024). The history of artificial intelligence underscores the critical need for responsible AI development. Several scholars contend that comprehending this evolutionary process is essential to appreciating the paramount significance of ensuring AI systems are responsible and aligned with human values (Han et al., 2021; Patel & Fan, 2024; J. Wang et al., 2023).

Overview of Artificial Intelligence

The concept of artificial intelligence can be traced back to the 17th century when Gottfried Leibniz, Thomas Hobbes, and René Descartes pondered the possibility of systematizing all rational thought (Russell & Norvig, 2020). It was not until two centuries later that John McCarthy coined artificial intelligence at the Dartmouth Summer Research Project on Artificial Intelligence (DSRPAI). DSRPAI was a two-month-long workshop conducted in 1956 at Dartmouth College that attempted to simulate human intelligence. The researchers built on 17th century philosophers' theory and explored the conjecture that a machine could precisely replicate any aspect of human intelligence (McCarthy et al., 1955). This workshop complemented Alan Turing's work, which aimed to identify intelligence through a machine's ability to mimic human-like conversation (Turing, 1950). Although no significant discoveries emerged from the workshop, it was a pivotal event that helped solidify AI as a distinct field of research.

Given the limited technology, significant progress was made towards AI in the 1950s and 1960s. Foundational AI concepts emerged, such as neural networks and the perceptron, an interconnected network of neurons that could computer and implement logic (Russell & Norvig, 2020). These discoveries led to early contributions to the field. For instance, ELIZA was developed by Joseph Weizenbaum in January 1966 as one of the first natural language processing programs able to attempt the Turing Test (Haenlein & Kaplan, 2019; Landsteiner, 2005; Weizenbaum, 1966). ELIZA was just one of many landmark AI programs, including SHRDLU (Winograd, 1971) and the General Problem Solver (Newell & Simon, 1961), that aimed to demonstrate how machines could mimic human intelligence. However, limitations of the technologies led to the first AI winter in 1970.

The cycles of optimism and disappointment in AI are known as AI springs and AI winters, respectively. AI winters were periods where funding and interest in AI decreased primarily due to the limitations of early systems and the lack of technology to handle the challenges of truly intelligent systems. The First AI Winter struck in the 1970s when the technology was expected to provide translations during the Cold War (Haenlein & Kaplan, 2019; Jiang et al., 2022). Early efforts failed to deliver, leading to a decline in funding. The early 1980s saw a renewed interest in AI, but this optimism was short-lived. Researchers underestimated the inherent complexity of achieving true AI (Jiang et al., 2022; Russell & Norvig, 2020). Primarily, early AI technologies were limited in how they handled real-world complexities and lacked scalability (Bravo et al., 2013; Haenlein & Kaplan, 2019; Jiang et al., 2022). This led to overhyped promises and underdelivered results, contributing to a subsequent downturn and the second AI winter (Jiang et al., 2022). Each AI winter emphasized the importance of realistic expectations, interdisciplinary collaboration, and ethical considerations.

The lessons learned from the AI winters underscored the resurgence of AI in the 1990s. Computing and data limitations presented significant obstacles when developing and training AI systems. Nevertheless, a combination of algorithmic advancements, increased computing power and data availability, and a focus on practical applications contributed to the revival and subsequent growth of the field. Machine learning, which involves the design and development of algorithms enabling computers to learn, began making significant strides in the late 1980s. This progress laid the groundwork for algorithms such as decision trees (1986), support vector machines (1995), AdaBoost (1997), and random forests (2001) to tackle complex problems effectively (Jiang et al., 2022).

Similarly, the rediscovery of backpropagation for training multilayer neural networks marked a turning point, eventually leading to the deep learning revolution of the 21st century (Russell & Norvig, 2020). In addition, the continual advancement in computing power enabled researchers to run the complex algorithms necessary to develop and deploy successful AI applications (Jiang et al., 2022; Martinez et al., 2019). Lastly, the abundance of data generated by the Internet and digitization in the late 1990s and early 2000s proved crucial for training more powerful AI models (Martinez et al., 2019; Russell & Norvig, 2020). The abundance of data and datasets, coupled with increased computing power to implement complex algorithms, transformed the capabilities of AI systems, enabling them to expand from theoretical to practical application.

The journey of AI has matured from rudimentary calculations to its current state. As technology grows more powerful and integrates into various aspects of daily life, not only does it have the potential to solve complex problems, but it also introduces risks associated with its misuse or unintended consequences. This shift underscores an approach that ensures AI technologies are developed and utilized in a way that is ethical, fair, transparent, and aligns with societal values. The following section explores the evolution of responsible AI, examining the factors that have driven this shift, making it imperative to address these concerns in AI development.

Importance of Responsible AI

As AI becomes increasingly prevalent across various industries and integrated into daily life, ensuring these technologies operate in a manner that upholds ethical standards becomes imperative to its development and deployment (Almpani et al., 2023; Husna et al., 2024). The growing complexity of AI applications, coupled with their potential for far-reaching consequences, demands a critical examination of the ethical implications and societal risks associated with their development and use. These technological advancements, while undeniably propelling the progress of AI, have also highlighted a pressing concern: the need for responsible AI (rAI).

Responsible AI refers to the ethical and transparent development, deployment, and utilization of AI technologies designed to prioritize human values, rights, and well-being

(Arrieta et al., 2020; Díaz-Rodríguez et al., 2023; Göllner et al., 2024; Herrmann, 2023; Lancaster et al., 2024). Responsible AI advocates for a human-centered approach to AI that aims to reduce biases and promote fairness (Trocin et al., 2021). It also necessitates a concerted effort to foster transparency, accountability, governance, and robustness (Arrieta et al., 2020; Göllner et al., 2024; Herrmann, 2023). Finally, a rAI system protects an individual's privacy and data security by ensuring there is data governance, secure development, and safeguarding against data breaches and misuse (Arrieta et al., 2020; Göllner et al., 2024). The goal of building rAI systems is to reduce the adverse effects on human and societal outcomes.

Trust is not simply given to AI systems; it must be earned through consistent performance and ethical behavior (Badhurunnisa & Dass, 2023; Eitel-Porter, 2020; Göllner et al., 2024; Herrmann, 2023). Building trustworthy systems becomes imperative as they become increasingly ingrained in society, influencing critical decisions. In healthcare, AI has been used to identify patterns for early disease detection and assist in diagnosis (Rathore & Rathore, 2023). In education, AI is transforming teaching practices and student learning (Dave & Patel, 2023). For example, through data analysis, educators can tailor instruction to individual student needs and enhance assessment methodologies to enable a personalized learning experience (Rashmi, 2023). AI systems are being applied in investment decisions, risk management, portfolio optimization, and stock market analysis (James, 2023; Weber et al., 2023). AI's influence on decision-making processes underscores the importance of earning societal trust through transparency, accountability, explainability, robustness, and fairness.

Transparency and explainability often are used interchangeably. However, transparency allows for informed oversight by disclosing information about the data used to train the models, while explainability focuses on providing information about the system's decision-making process (Akbarighatar, 2024; Arrieta et al., 2020; Bano et al., 2023; Díaz-Rodríguez et al., 2023; Eitel-Porter, 2020; Göllner et al., 2024). Both are leveraged to establish trust, as they enable stakeholders to scrutinize the system for fairness, errors, or potential ethical issues. To address these concerns, recent studies have proposed frameworks to examine the intersection of fairness and robustness in AI algorithms (Baharlouei et al., 2023; Baharlouei & Razaviyayn, 2023; Whang et al., 2021). These frameworks highlight the importance of balancing both fairness and robustness, as focusing solely on one may adversely affect the other (Roh et al., 2021). When issues with AI systems arise, individuals or groups demand accountability, urging that an individual or organization be held responsible (Dignum, 2022). To determine accountability, who is responsible must be identified at every stage of the AI lifecycle, from design to development to deployment to use (Lu et al., 2022). A clear delineation of responsibility builds trust and necessitates a mechanism for appeal and recourse (Jakesch et al., 2022). Strong governance controls, including managed processes and audit trials, are a necessary precondition for rAI (Eitel-Porter, 2020). With the rapid evolution of AI and its potential impact on society, transparency, explainability, accountability, and fairness are fundamental for establishing trust in AI systems (Göllner et al., 2024; Merhi, 2022).

Responsible AI does not just consider ethical preferences; it also ensures that the system is beneficial to society and does not cause intentional or unintentional harm. Transparency, accountability, explainability, robustness, and fairness form the foundation of a rAI system, where each element reinforces the others. By integrating these factors, a rAI system earns societal trust. The following sections will delve into the advantages and challenges of implementing rAI in an organization.

Advantages Adopting RAI

The building blocks of rAI practices offer benefits for individuals, organizations, and society. By prioritizing transparency, fairness, and accountability in AI development and deployment, entities can harness AI's potential while reducing associated risks. This approach not only fosters trust and acceptance but also leads to systems that drive innovation responsibly and ethically (Choung et al., 2022).

Adopting and implementing rAI practices offer practical advantages, including the mitigation of adverse consequences such as legal, ethical, and operational risks (Wang et al., 2020). As countries develop more AI regulations, companies slow to adopt rAI principles risk legal penalties (D. Kumar & Suthar, 2024; Samuel-Okon et al., 2024) and falling left behind (Singh, 2023), potentially struggling to retrofit their technology to comply with new standards or risk losing the ability to use it. Adhering to rAI guidelines not only safeguards businesses from financial and reputational harm but also helps to ensure that AI systems are aligned with broader societal values (De Laat, 2021; Eitel-Porter, 2020; Lancaster et al., 2024). Companies known for corporate social responsibility (CSR) and corporate digital responsibility (CDR) gain a competitive edge (Wang et al., 2020; Baskentli et al., 2019; Kunz & Wirtz, 2023). Embracing rAI practices can significantly enhance a company's CSR efforts. Cheng et al. (2021) proposed a framework categorizing AI responsibilities into functional, legal, ethical, and philanthropic components, aiming to build long-lasting trust between AI systems and humans beyond mere algorithmic fairness. Earning and sustaining trust among users, stakeholders, and the public is paramount to AI adoption (Bedué & Fritzsche, 2021; Choung et al., 2022). Public confidence will develop if the system is perceived as beneficial and its risks are minimized; otherwise, AI systems are likely to face resistance (Choung et al., 2022; Floridi et al., 2018). Particularly in high-stake sectors like criminal justice and healthcare, transparent decision-making processes can build trust and reduce suspicion (Von Eschenbach, 2021). When consumers trust a company perceived as ethical and responsible, the firm benefits from an increased market share and profitability. In addition, when rAI is prioritized, organizations are more likely to avoid costly mistakes and rework associated with addressing ethical issues (Eitel-Porter, 2020; Rakova et al., 2021).

Other added benefits of rAI are improved scalability, value extraction, job creation, and skill development. Having a few AI systems can be manageable; however, scaling them up can lead to complexities such as data bias and loss of original intent (Eitel-Porter, 2020). RAI advocates for resilient governance frameworks, which make it easier for businesses to scale their AI tools and extract their full value (Eitel-Porter, 2020). While rAI can transform how organizations scale, it also can transform the workforce. As more AI systems are implemented and alter how repetitive tasks are performed, it frees up humans to focus on more strategic tasks requiring creativity, critical thinking, and emotional intelligence, specifically in AI-related jobs that require a combination of technical, ethical, and regulatory expertise, such as governance, auditing, system maintenance, and policy development (Badet, 2021). However, there is a need for specialized skills in these positions. According to the World Economic Forum (2023), by 2028, 44% of workers’ skills will be disrupted. To adapt to the changing job market shaped by rAI, organizations will need to collaborate with educational institutions and policymakers to address existing skill gaps and develop a workforce prepared for the ethical challenges posed by AI (Badet, 2021; Hugosson et al., 2019).

Challenges Adopting RAI

While the adoption of rAI offers substantial benefits, ensuring that AI systems are developed and deployed in ethical and socially beneficial ways presents a complex array of challenges. These challenges span technical, organizational, and regulatory domains, each posing significant barriers to adoption. From a technical perspective, practitioners are confronted with the daunting task of building and deploying AI systems that are not only effective but also transparent, explainable, and reduce bias. Organizationally, integrating rAI practices affect organizational culture (Heger et al., 2022; Rakova et al., 2021), human and physical resources (Akbarighatar, 2024; Bujold et al., 2023; A. Kumar, 2024), and top management engagement (Heger et al., 2022; Herrmann, 2023). Furthermore, regulatory frameworks introduce additional layers of complexity, as AI practitioners must navigate a cornucopia of national and international guidelines, often with ambiguities or inconsistencies (Akbarighatar, 2024; Alexander et al., 2023). Balancing innovation with risk mitigation becomes challenging when tasked with enforcing regulation and ensuring accountability (Sadek et al., 2024). These challenges are amplified as AI practitioners attempt to translate rAI principles to practical implementation across different teams. In the subsequent sections, a more in-depth examination of each set of challenges will be undertaken.

Technical Challenges

Parthasarathy et al. (2024) identified technical concerns as the most significant barrier to AI adoption. Adopting rAI presents numerous technical challenges that require ongoing research and development to establish guidelines and practices that make implementing rAI principles possible. The technical complexity of rAI implementation presents a formidable barrier that demands continuous adaptation and expertise that many organizations may not possess (Merhi, 2022; Oliveira, 2023). For instance, deep learning models often function as a 'black box,' making it challenging to implement transparency (Ahmad, 2024; Badhurunnisa & Dass, 2023). Lack of transparency and explainability in complex AI models impedes practitioners' comprehension of the underlying logic that drives its decision-making (Ahmad, 2024). This opacity creates a barrier to evaluating whether the AI model is making unbiased and fair decisions. Researchers have attempted to mitigate this issue by creating simpler AI models to allow for easier identification of potential biases or errors. However, these models may not achieve the same level of predictive accuracy as a complex model (Arrieta et al., 2020).

The quality of the training data significantly affects the fairness of an AI system. When trained on poor quality or biased data, the system will not only perpetuate those biases but also amplify them (Mayson, 2018; Ntoutsi et al., 2020). Studies have shown that facial recognition systems perform poorly on darker skin tones and women due to the skewed dataset in which it was trained (Buolamwini & Gebru, 2018). One approach to mitigate biases in datasets is to create a datasheet that provides detailed information about the data in the dataset (Gebru et al., 2021). It serves as a resource for data creators and data consumers, allowing data consumers to make informed decisions about the dataset. Explainability and data quality are hallmark qualities of a rAI system, ensuring fairness and ethical compliance.

One of the most significant challenges is the gap between translating rAI principles into actionable steps. Not only is there a lack of standardization of terminology and metrics for evaluating AI systems, but also practitioners are often left with an ethical framework with no defined methods or guidance on how to engage with these stakeholders (Conklin et al., 2024). Without standardized measurements, it becomes challenging to operationalize rAI principles. This ambiguity can cause misalignment between organizational goals and system outcomes. Several sources stressed the importance of developing clear, measurable metrics for rAI principles and having practical tools that assist practitioners in implementing them (Akbarighatar, 2024; Heger et al., 2022; Sadek et al., 2024; Wang et al., 2020). These recommendations can help organizations move beyond the principles and towards more context-specific guidelines to provide actionable steps (Ibáñez & Olmeda, 2021; Rakova et al., 2021; Sadek et al., 2024).

Organizational Challenges

Adopting rAI within organizations forces a cultural transformation that extends beyond technological advancements and often clashes with organizational culture and structure. Many companies prioritize rapid AI deployment to gain immediate business benefits, which may undermine the extensive ethical assessments and risk mitigation efforts required for rAI implementation (Alexander et al., 2023). For example, the demand for speed and efficiency typically outweighs ethical considerations, leading to decisions that might increase short-term gains but compromise long-term societal impacts (Sjøberg, 2022). Misaligned organizational incentives further compound this issue, creating an environment where ethical AI initiatives are deprioritized in favor of faster, more profitable solutions (Rakova et al., 2021). This misalignment demonstrates how deeply ingrained cultural values and structural limitations can impede the successful integration of rAI principles into a company’s operational framework.

One of the most critical structural challenges in rAI adoption is the lack of clear ownership and accountability, as responsibilities are often dispersed across multiple departments, leading to reactive rather than proactive approaches to ethical issues (Alexander et al., 2023; Coeckelbergh, 2019; Díaz-Rodríguez et al., 2023; Schiff et al., 2020). This diffusion of responsibility, where no single entity is held accountable for AI implementation outcomes, hampers effective risk mitigation and exacerbates internal resistance to rAI adoption. Employees may resist rAI changes due to fear of job displacement or changes to existing processes and workflows (Badhurunnisa & Dass, 2023; Merhi, 2022).

Responsible AI requires a workforce that is equipped with both technical and ethical competencies; finding or training employees with the necessary skills to develop, deploy, and govern AI systems responsibly puts employees and the organization in jeopardy (Merhi, 2022; Oliveira, 2023). Furthermore, the absence of cross-functional collaboration, often due to siloed organizational structures, prevents the effective exchange of knowledge needed to develop holistic and ethically sound AI systems (Conklin et al., 2024; Schiff et al., 2020).

Overcoming organizational challenges in adopting responsible AI requires a comprehensive approach that integrates cultural shifts, skills development, and practical implementation strategies. A key factor is fostering a data-driven culture that prioritizes ethical considerations, transparency, and accountability alongside the development of AI-specific codes of ethics and the distribution of ethical responsibilities across the organization (Conklin et al., 2024; Ibáñez & Olmeda, 2021). Aligning organizational incentives with rAI goals ensures employees are motivated to engage with ethical AI initiatives while addressing the skills gap through targeted training programs and establishing dedicated support can aid in bridging technical and ethical competencies (Ibáñez & Olmeda, 2021; Merhi, 2022).

Breaking down disciplinary silos by promoting collaboration between technical and non-technical teams and employing cross-functional efforts like red team exercises enhances communication and fosters an inclusive approach to rAI (Gill et al., 2022; Ibáñez & Olmeda, 2021; Merhi, 2022; Rakova et al., 2021; Schiff et al., 2020). To translate high-level principles into actionable practices, organizations must develop concrete metrics to measure rAI success, utilize process-based frameworks for systematic guidance, and conduct impact assessments to evaluate potential risks (Oliveira, 2023). Promoting transparency and open communication, both within the organization and with external stakeholders, further ensures that AI systems are developed responsibly (Herrmann, 2023; Rakova et al., 2021). By adopting these strategies, organizations can begin to adopt rAI principles and align AI technologies with broader ethical values and societal benefits.

Regulatory Challenges

The rapid pace of AI development has presented regulatory challenges for organizations attempting to adopt responsible AI practices. Practitioners are scrambling to align archaic policies to this market disruption (Bollier, 2019). For instance, the emergence of generative AI models like GPT-3 and DALL-E has introduced new ethical concerns regarding content generation and intellectual property rights that were not anticipated by existing regulations (Floridi & Chiriatti, 2020; Zhou & Nabus, 2023). The growing gap between technological advancement and regulatory preparedness creates a need for dynamic, adaptive approaches for organizations seeking to implement responsible AI practices (Cloete, 2024). Due to the dynamic nature of AI development, regulations must be flexible enough to accommodate future innovations, which can be challenging for both policymakers and organizations to implement effectively (Díaz-Rodríguez et al., 2023).

The AI regulations currently in place pose a challenge to organizations, as they are not appropriately scoped for organizations striving to implement responsible AI. Several scholars propose a risk-based regulatory framework similar to the European Union AI Act, concentrating on high-risk AI applications within sectors like healthcare and law enforcement (European Parliament, 2023; Smuha, 2019). Others, like Lucaj et al. (2023) and Vokinger et al. (2022), propose a more comprehensive regulatory framework that encompasses the entire AI lifecycle, including data collection, model development, and deployment. This regulatory ambiguity can lead to reluctance in AI adoption (Goh et al., 2024), difficulties justifying AI practices (Saidakhror, 2024), or inconsistent implementation of AI practices (Campion et al., 2020) across different sectors and jurisdictions. Additionally, it makes it challenging to balance innovation with risk mitigation. Some researchers argue that overly restrictive regulations could stifle innovation, making it harder for companies to remain competitive, while lenient regulations could result in irresponsible practices that expose society to acceptable risk (Alexander et al., 2023; Cloete, 2024).

This balancing act is further compounded by the lack of technical expertise among policymakers surrounding AI. A significant knowledge gap between policymakers and AI experts when drafting AI regulations results in poorly informed regulations that fail to address the nuances of AI (Chen et al., 2024). This lack of technical understanding among regulators leads to broad or inefficient regulations, making it difficult for organizations to attempt to implement responsible AI practices, as they must interpret and apply regulations that may not align with the technical realities of their systems.

Organizations must implement a comprehensive strategy to navigate regulatory hurdles associated with responsible AI adoption, encompassing proactive engagement, internal governance, and cross-functional collaboration. When industry leaders actively engage with the regulatory process, organizations are positioned to shape informed and adaptable policies while simultaneously developing comprehensive internal frameworks tailored to the AI lifecycle (Sadek et al., 2024). This collaboration ensures organizations are prepared for evolving regulations and demonstrates a commitment to responsible AI practices. By fostering cross-functional collaboration and investing in continuous education, organizations are positioned to build internal expertise that encourages a diverse perspective and advances education on AI best practices (Figueras et al., 2017; Zhu et al., 2021). By embracing these strategies, organizations can proactively address regulatory challenges and position themselves as responsible stewards of AI.

In conclusion, the adoption of responsible AI practices offers significant benefits to individuals, organizations, and society by promoting ethical, transparent, and accountable AI development and deployment. These practices mitigate adverse consequences, foster trust, and drive innovation responsibly. However, substantial challenges remain in the technical, organizational, and regulatory domains. Overcoming these challenges demands ongoing research, cultural shifts, skills development, and comprehensive strategies to translate responsible AI principles into practice effectively. The following section will shift the focus to explore the significant contributions of SMEs to economic growth, as well as the unique challenges practitioners encounter in adopting and utilizing AI.

Small- and Medium-Sized Enterprises

Globally, SMEs play an integral role in driving innovation (Kaira & Rześny-Cieplińska, 2019), employment (Decker et al., 2014; S. Kumar & Singh, 2023), and economic development (Oyewole et al., 2024). However, their competitive viability relies on their ability to implement advanced technologies like AI while maintaining institutional legitimacy—adhering not only to operational but also ethical standards. Although the integration of responsible AI practices offers substantial potential, implementing AI technologies presents distinct challenges for SMEs. Resource constraints, technological complexities, and organizational barriers often impede their ability to align with AI adoption effectively. This alignment is particularly salient as societal and regulatory pressures intensify the demand for ethical and transparent AI use, and SMEs are compelled to balance these pressures with their resource constraints (Shaik et al., 2023). By understanding the factors that influence strategic decisions, SMEs cannot only bolster their competitive position but also strengthen their legitimacy, a key asset in a highly interconnected and regulation-sensitive market environment (Lada et al., 2023).

SMEs constitute a cornerstone of the American economy, making them a pivotal part of the U.S. economy. The U.S. Chamber of Commerce reported approximately 33.2 million small businesses in 2023, representing 99.9% of all U.S. businesses (Ferguson et al., 2024). These statistics underscore the critical role SMEs play in driving economic growth, innovation, and employment generation (Oyewole et al., 2024). Firstly, small businesses serve as a significant employment generator, creating more than 500,000 jobs over ten years (Ferguson et al., 2024). Moreover, SMEs contribute to income generation by offering an average salary of $63,000 for their employees (Ferguson et al., 2024). While the exact percentage varies, estimates suggest that SMEs contribute around 50% to the GDP, amplifying their contributions to the overall economy (Aladin et al., 2021). Lastly, extending beyond statistics, SMEs are pivotal in fostering innovation, as they often serve as incubators for new ideas and technologies due to their flexibility and adaptability, which are essential for competitive advantage and economic dynamism (Kaira & Rześny-Cieplińska, 2019; Ng et al., 2016; Petkovska, 2015). This agility allows SMEs to respond swiftly to market changes and emerging opportunities, often outpacing larger corporations in terms of innovative output. Despite their substantial contributions, SMEs frequently face significant hurdles when adopting and leveraging new technology like AI.

SMEs contribute significantly to economic growth, innovation, and employment generation. However, the adoption and integration of transformative technologies like AI present a unique set of challenges for these organizations. While the benefits of AI are well-documented, SMEs often face significant hurdles in leveraging these advanced technologies due to their resource constraints, technological complexities, and organizational barriers. To better understand the strategic responses of AI practitioners within U.S.-based SMEs, the proposed study will delve into the multifaceted factors that influence the adoption and implementation of responsible AI practices in these enterprises.

SMEs and AI Adoption

Many SMEs are starting to investigate the potential of AI (Badghish & Soomro, 2024; Daga et al., 2023). Compared to larger organizations, SMEs are distinguished by their limited access to resources. Recent literature leverages multiple frameworks to discuss AI adoption; however, the Technology-Organization-Environment (TOE) Framework examines the interplay between technical, organizational, and environmental factors that influence adoption decisions (Sharma et al., 2022). The technological dimension encompasses the internal and external expertise, tools, procedures, and relevant technologies, both current and emerging, which influence a firm's innovation and technology adoption decisions (Eze et al., 2023). Organizational factors encompass the internal capabilities of SMEs, including the availability of resources, management support, and organizational culture, all of which play a pivotal role in determining the readiness and capacity for technological integration (Triandini et al., 2023). Environmental factors, such as competitive pressure, government support, and government regulations, significantly influence SMEs' decisions to adopt new technologies (Shahadat et al., 2023; Triandini et al., 2023). Lastly, individual dimensions focus on the knowledge, skills, and attitudes of key decision-makers within SMEs, whose perceptions and willingness to embrace innovation are critical for successful technology adoption (Budiono et al., 2020). These challenges contribute to the fact that only a small number of SMEs are effectively using AI. By comprehensively understanding these dimensions, business leaders can develop targeted strategies that foster a supportive environment for AI adoption, thereby enhancing the competitiveness and operational efficiency of SMEs.

Technological Factors

Complexity. AI systems rely on a vast amount of data. SMEs struggle with adoption due to the technical complexities of collecting, preparing, and managing the vast amounts of data required for AI solutions (Jabłońska & Pólkowski, 2017). The data must be ensured for data quality, security, and privacy, adding Yeta layer of complexity (Jabłońska & Pólkowski, 2017). Additionally, SMEs that leverage a larger company's AI model are susceptible to enduring the challenges that come with the lack of transparency that comes with some AI systems. It subjects SMEs to errors or biases in the AI-generated outputs (Agbese et al., 2022; Jabłońska & Pólkowski, 2017; Lada et al., 2023). Moreover, AI algorithms are complex mathematical models that demand a high level of technical understanding, making it challenging to resolve errors and interpret models without a high level of technical understanding (Agbese et al., 2022; OECD, 2021). These complexities underscore the need for responsible AI that is trustworthy, transparent, and explainable.

Organizational Factors

Financial Resources. Research consistently identifies that AI solutions require a significant investment in computing infrastructure, data infrastructure, and talent and many SMEs struggle to demonstrate the potential return on investment, which can be a barrier for SMEs constrained by their limited budget (Govori & Sejdija, 2023; Huseyn et al., 2024; Rawashdeh et al., 2022; Schönberger, 2023; Strategic Direction, 2023; Tominc et al., 2024). Unlike larger firms, SMEs often do not have the same level of assets and are perceived as a risk and less stable to offer to secure a loan, resulting in lenders hesitant to extend credit, higher interest rates, or outright loan denial (Amadasun & Mutezo, 2021; Miliūnaitė & Žigienė, 2023). Due to a lack of financial capacity for these investments, SME owners are often left to rely on personal assets, which increases cautionary decision-making to reduce the threat of insolvency (Fuller-Love, 2006; Zamani, 2022). However, many areas of AI are affordable, such as data analytics and machine learning, yet decision-makers are reluctant to invest as their perception leaves them uncertain regarding Return on Investment (ROI) (Grashof & Kopka, 2022; OECD, 2021). Additionally, cloud-based infrastructure has made AI tools and hardware more accessible to SMEs, potentially offering a more cost-effective approach to implementing AI solutions (Govori & Sejdija, 2023). Despite this increased accessibility, SMEs still face challenges in securing funding for AI initiatives compared to larger enterprises (Baabdullah et al., 2021; Grashof & Kopka, 2022). Accessing capital can hinder AI adoption and limit the resources necessary for technological advancement.

Skilled staff. Implementing new technologies like AI requires specialized skills. For instance, to build AI models, train algorithms, and interpret them accurately, SMEs need data scientists and machine learning engineers. With a skilled staff, SMEs are better positioned to navigate the complexities, enhance productivity and competitiveness, and successfully implement and manage AI systems (Baabdullah et al., 2021; Tominc et al., 2024). However, given the limited pool of skilled talent, SMEs grapple with finding and retaining employees with the necessary skills (Govori & Sejdija, 2023; Muminova et al., 2024). Due to limited budgets, SMEs often cannot match the attractive salaries and benefits offered by larger corporations, constraining their ability to hire and retain skilled employees (OECD, 2021; Rožman et al., 2023). To address the skill gap and keep pace with rapidly evolving AI technology, organizations should explore alternative approaches, such as maintaining ongoing investment in upskilling existing employees (OECD, 2021; Rožman et al., 2023). Studies have shown that the lack of in-house expertise can inhibit SMEs from effectively integrating and utilizing new technologies (Caldeira & Ward, 2003; Cragg & Zinatelli, 1995). These resource constraints underscore the need for SMEs to invest in and develop internal resources to improve the overall adoption of technologies and the competitiveness of the market.

Organizational Culture. Organizational culture, the company's shared values, beliefs, and practices, emerges as a critical factor in SMEs adopting new technologies. A culture that supports innovation, continuous learning, and adaptability is more likely to embrace new technologies (Nguyen et al., 2019; Rehouma, 2020). Specifically, organizations characterized by a growth-oriented culture that fosters adaptability and innovation demonstrate a higher propensity for successful technology implementation. Conversely, enterprises with conservative cultures often exhibit resistance to change and experience impediments in the adoption process (Lewis et al., 2020; Maroufkhani et al., 2020). Organizational readiness has been identified as a critical factor in ensuring that AI is not merely adopted but effectively integrated into the enterprise's daily operations (Lada et al., 2023; Maroufkhani et al., 2020). Potential barriers and benefits can be overcome and maximized in SMEs by ensuring employees understand the benefits of AI and have the necessary skills to adopt the technology (Lada et al., 2023). Without a clear understanding and awareness of AI's potential benefits, SME business owners and decision-makers are reluctant to deviate from the status quo because they are unfamiliar with potential use cases or they are concerned about the complexity of incorporating AI solutions into their existing workflows and systems (Tominc et al., 2024).

Environmental Factors

Competitive Pressure. The pressure to keep up with competitors has influenced many firms to implement new technology solutions to enhance their competitive edge. Often, the pressure to adopt new technologies can drive technology adoption more than the technology's advantages (Saka & Chan, 2020). As the global and digital landscape continues to increase, SMEs face heightened external pressures from competitors, suppliers, and buyers compared to their larger counterparts (Badghish & Soomro, 2024; Perera & Perera, 2021). This intensified pressure stems from the fear of falling behind rivals and losing a competitive edge, compelling SMEs to recognize the critical importance of adopting AI to ensure their survival and foster business development (Zamani, 2022).

SMEs are primarily driven by the competitive advantages the new technologies can offer, such as the ability to provide more efficient, modern, and faster services for their customers (Zamani, 2022). This drive for technological integration is further amplified by the understanding that increased use of digital technologies is directly linked to an SME's potential for sustainable competitiveness and growth (Zamani, 2022). As the global market becomes increasingly competitive, SMEs are pushed to acknowledge that embracing technology is not just a matter of keeping pace with industry trends but also a fundamental necessity for maintaining relevance and securing long-term viability in their respective markets.

Regulatory. The relationship between government support and technology adoption in SMEs is characterized by a dual-edged dynamic, where governmental assistance can either accelerate or impede the adoption of technology by SMEs. Given their limited resources, SMEs are often more reliant on external support systems than larger corporations (Andrade-Rojas et al., 2024). While government initiatives can potentially foster technology adoption, their effectiveness hinges on the alignment between the support provided and the actual needs of SMEs.

Recent literature suggested that the lack of government support could create significant barriers to innovation and technology adoption for SMEs (Fanelli, 2021; Indrawati et al., 2020; Zamani, 2022). Effective government support includes providing direct resources and implementing policies that encourage changes in business practices and strategies (Andrade-Rojas et al., 2024). Direct provisioning of resources involves increasing SMEs' access to financing, such as direct funding, subsidies, and tax incentives (Andrade-Rojas et al., 2024; Indrawati et al., 2020). Policy interventions can be designed to facilitate changes in innovation processes, routines, and strategies (Andrade-Rojas et al., 2024). Moreover, to maximize the effectiveness of government support for SMEs, policymakers should implement streamlined regulations and bureaucratic procedures that encourage the adoption of new technology and promote collaboration among SMEs, government agencies, research institutions, and proactive utilization of existing support programs (Indrawati et al., 2020).

Regulations surrounding AI are emerging, but due to the technology's rapid growth and the ambiguity around how AI is defined, there remains a lack of clear legal frameworks (Ruschemeier, 2023). This situation introduces uncertainty and risk for both large and small enterprises. SMEs, in particular, often lack the resources necessary to adjust swiftly to evolving data privacy laws and regulations (OECD, 2021). Additionally, SMEs are particularly vulnerable to data breaches and cyberattacks, either directly or as part of a supply chain of larger companies, due to limited resources and expertise in data security, resulting in fines and legal action (De Arroyabe & De Arroyabe, 2021; OECD, 2021). Another concern is the complexity of regulatory compliance. SME owners have acknowledged that larger enterprises often benefit from access to specialized expertise in navigating regulatory compliance requirements (Winecoff & Watkins, 2022). This disparity makes it harder for SMEs to compete for governmental support and comply with regulatory requirements. By addressing both financial and non-financial barriers faced by SMEs, governments tailor support to their unique, ultimately contributing to their competitiveness and driving economic growth.

Individual Factors

Top management. Top management, particularly CEOs, play a significant role in technology adoption and implementation within SMEs due to their influence in centralized organizational structures. Research shows that top management's perception and attitudes toward IT significantly affect the AI adoption process (Badghish & Soomro, 2024; Drew, 2003; Ghobakhloo et al., 2012; Premkumar, 2003; Qureshi & York, 2008; Thong et al., 1993). When top management champions AI adoption as a strategic priority and provide a roadmap, it encourages buy-in from employees at all levels (Lada et al., 2023). Specifically, SMEs with top management who are committed to its implementation, have a strong desire to use technology as a strategic tool and possess IT knowledge are more likely to adopt AI solutions in their organizations successfully (Badghish & Soomro, 2024; Ghobakhloo et al., 2012; Zamani, 2022). With consistent support, top management can drive AI adoption by fostering a culture that embraces innovation and change (Zamani, 2022). This change can be achieved through employee training and development, addressing concerns about AI, and committing to overall organizational readiness (Lada et al., 2023; Strategic Direction, 2023). Top management who are knowledgeable about IT can help mitigate risks associated with adoption while promoting a growth and forward-thinking mindset to leverage the technology for a competitive advantage.

Employees. Employees are widely recognized as valuable assets that directly affect a firm's survival and success. The success of technology adoption has been shown to be dependent on employees' knowledge (Juniarti & Omar, 2021), training (Estrin et al., 2003; Milovanovic, 2014), attitudes (Juniarti & Omar, 2021; Milovanovic, 2014), and involvement (Estrin et al., 2003; Ghobakhloo et al., 2012; Milovanovic, 2014) in the adoption process. Without these factors, the use and potential benefits of the technology can be limited. For instance, lack of training can result in underutilization (Bull, 2003), the barrier to adoption (Baabdullah et al., 2021; Govori & Sejdija, 2023; Muminova et al., 2024; Tominc et al., 2024), and negative employee attitudes can hinder successful implementation due to concerns about job security or disbelief in the benefits of new systems (Chaudhry, 2018; Premkumar & Roberts, 1999; Sanda, 2020; Winston & Dologite, 2002). Further studies highlighted that higher levels of IT knowledge and training contribute to greater ease of use and perceived usefulness of IT systems, which in turn lead to better acceptance and satisfaction among users (Falco et al., 2020; Zielonka & Rothlauf, 2021). Not only should employees receive continuous education and training to ensure successful adoption, but employees should also be involved from the onset to reduce resistance and ensure successful implementation (Eichler, 2022; Rehouma, 2020; Tominc et al., 2024; Van Assen, 2020). AI practitioners with deep knowledge play a crucial role in addressing the practical barriers that hinder AI adoption among domain experts (Simkute et al., 2024). They can bridge the gap between technical AI concepts and domain-specific knowledge, helping end users understand the relevance and applicability of AI in their workflows (Simkute et al., 2024). Additionally, practitioners are uniquely positioned to be aware of ethical principles, practices, and challenges that relate to business value and the trade-offs between different ethical considerations (Pant et al., 2024). Conversely, practitioners struggle with balancing business priorities with ethical concerns, especially given the rapid deployment and scalability of AI systems (M. Madaio et al., 2022; Winecoff & Watkins, 2022). In SMEs, practitioners may feel pressure to conform to external expectations surrounding AI, even if these contradict their ethical or scientific judgments (Winecoff & Watkins, 2022). This can create disconnection between the actual capabilities of AI systems and the expectations placed upon them. The successful adoption and implementation of IT in SMEs is dependent on developing employees through targeted training and active involvement in the IT adoption process from the onset. By doing so, organizations can ensure that IT systems are effectively integrated into business operations, leading to improved productivity, higher user satisfaction, and overall business success.

Despite the significant opportunities and challenges encountered by SMEs, integrating AI technologies can significantly enhance their competitive position and operational efficiencies. However, the institutional pressures that influence their approach manifest through technological complexities, organizational constraints, regulatory requirements, and individual-level factors that collectively shape how SMEs align their practices with societal expectations, regulatory requirements, and competitive norms, ultimately affecting their legitimacy and survival in the market (DiMaggio & Powell, 1983). For instance, SMEs that effectively navigate these pressures can enhance their reputation and gain competitive advantages, which are essential for their growth and sustainability (Saha et al., 2022). By understanding and adapting to these pressures, SMEs can better position themselves to introduce innovative products or practices (Yang, 2019). This responsiveness not only ensures compliance but can also cultivate new market opportunities, thereby stimulating economic growth and advancing broader societal goals (Colovic et al., 2019). Through careful examination of these pressures, this study explores how AI practitioners within SMEs navigate and respond to these institutional pressures to provide policymakers and stakeholders with better design support mechanisms that can help SMEs thrive despite the challenges posed by their institutional environments.

Conceptual Framework

As AI continues to ingrain more into daily life, understanding the choices and trade-offs that shape AI development becomes vital to the ethical deployment of AI technologies. In addition, it directly influences their legitimacy, adaptability, and overall performance in complex and dynamic environments (DiMaggio & Powell, 1983). However, organizations face various pressures when implementing new technologies, which can influence the organization's approach (Alexander et al., 2023; Sadek et al., 2024). Research has begun to emerge that suggests that internal factors, such as tight development timelines, lack of formal organizational processes, and challenging internal stakeholder dynamics, alter the structures and practices the firm adopts (Holstein et al., 2019; Hopkins & Booth, 2021; M. Madaio et al., 2022; M. A. Madaio et al., 2020; Rakova et al., 2021). Externally, the pressures can come from stakeholders who lack technical acumen (Winecoff & Watkins, 2022), government regulations (Moreira, 2023), societal influence (Ejjami, 2024), and competitive pressures to differentiate from their competitors (Alserr & Salepçioglu, 2021). However, such studies are primarily constrained to the interventions of mature organizations, leaving a gap to explore ethical AI implementation across diverse organizational contexts and developmental stages.

The growing influence of AI companies within the technology sector underscores the critical role their ethical practices play in shaping the future of society (Spiezia et al., 2021). However, there is limited research on how smaller firms handle the unique challenges that emerge from institutional pressures. For instance, SMEs often must navigate the need to secure funding and establish credibility, constraints mature organizations typically encounter less frequently (Alexander et al., 2023; DiMaggio & Powell, 1983). These decisions are exacerbated by significant resource constraints that threaten their existence, limiting the ethical AI practice that can be adopted. Ahlawat et al. (2024) suggested that SMEs capitalize on shared and flexible approaches to overcome these unique challenges. For example, piggybacking allows AI practitioners to incorporate AI ethics into pre-existing workflows, processes, and structures (Ahlawat et al., 2024). Integrating ethics into existing practices can proactively encourage product teams to consider ethical implications in their development processes. Another approach is to build reusable tools and methodologies that apply to a range of products (Ahlawat et al., 2024). Focusing on reusability enables practitioners to scale ethics efforts without duplication. While Ahlawat et al.'s strategies can be applied to organizations of any size, SMEs may face limitations due to their resource constraints, expertise, and unique competing priorities.

Existing research focused predominately on intra-organizational dynamics and meso-level interactions. Nevertheless, to comprehend the institutional complexities surrounding AI adoption and implementation, it is essential to understand the broader context of inter-organizational dynamics (Greenwood et al., 2011). Macro-level analysis examines organizations in a broader context, field-level norms, or systems, while micro-level focuses on individual dynamics (Barbour, 2017). The research on intra-organizational dynamics related to AI adoption revealed a complex interplay of cultural, managerial, and ethical factors that influence the successful integration of AI technologies. For example, studies have highlighted that the integration of AI technologies necessitates significant changes in workflows, roles, and responsibilities, which can affect productivity and organizational effectiveness if not appropriately managed (Nurlia et al., 2023). H. Chen et al. (2023) and Dabbous et al. (2021) emphasized that AI adoption hinges on top management engagement and employee acceptance. By espousing a multi-level perspective, it enables a more nuanced understanding of how factors across different levels can influence organizational behavior and outcomes. This research bridges the knowledge gap by examining inter-organizational dynamics, providing valuable insight into how organizations interact and collaborate within their broader ecosystems.

SMEs encounter challenges that affect how the trade-off between ethical responsibility and operational feasibility is navigated (M. Madaio et al., 2022). Ethical concerns are seen as roadblocks that can delay the shipping of the product, leading to ceremonial conformity or AI washing (Ahlawat et al., 2024). When organizations conform to industry expectations, they can improve their legitimacy and social and cultural fitness; however, this can clash with institutional expectations (DiMaggio & Powell, 1983). As a result, SME leaders often encounter situations that threaten their survivability, driving the structures and practices they adopt. How field-level dynamics, such as social, cultural, and economic challenges, factor into rAI practices is an underexplored area of research.

Understanding the inter-organizational institutional dynamics is necessary to understand the forces that shape how AI practitioners strategically respond (Rudko et al., 2024). Recent findings have posited that inter-organizational and institutional conditions (i.e., external pressures) are change sources that lack formal mechanisms for addressing ethical concerns (Vakkuri et al., 2020). The interdependencies between organizations and institutional environments compel SMEs to negotiate competing demands. The interplay between institutional pressures and resource constraints offers different organizational efforts to explain how organizations change.

Two theoretical frameworks—Resource Dependence Theory and Institutional Theory—address how to mitigate external pressures within its ecosystem. Each of these theories offers a unique yet complementary perspective on how organizations respond to external pressures. While each of these theories provides valuable insights, there are notable limitations that need to be addressed for a more comprehensive understanding.

Resource Dependence Theory

Resource dependence theory, credited to Pfeffer and Salancik (1978), posited that organizations are dependent on external resources; they are not entirely self-sufficient. These dependencies foster inter-organizational relationships that shape power dynamics, influencing leaders' strategic decisions and capabilities essential for survival and growth (Hillman et al., 2009; Pfeffer & Salancik, 1978). In instances where resources are scarce, organizational leaders face the challenge of balancing the organization's autonomy with external resource dependencies to mitigate power imbalances.

To mitigate dependencies, Pfeffer and Salancik (1978) outlined five strategic responses designed to reduce the risk of power imbalance: mergers and acquisitions, joint ventures, political action, board interlocks, and executive succession. Mergers and acquisitions allow organizations to reduce external dependencies by consolidating resources and expanding capabilities. Through joint ventures, firms can form partnerships that enable them to pool resources, share risks, and gain market advantages. Political action allows organizations to influence government regulation with the larger social systems to create a favorable environment. Board interlocks enable companies to utilize boards of directors to provide information, access resources, and gain legitimacy to minimize dependence or acquire critical resources. Finally, executive succession equips an organization with a CEO who can address environmental uncertainty and dependencies.

These responses enable leaders to navigate resource dependencies by proactively influencing inter-organizational relationships and the broader operating environment (Hillman et al., 2009; Pfeffer & Salancik, 1978). However, a key limitation of RDT is that it emphasizes the active role organizations play when shaping organizational behavior, neglecting internal factors, such as the social and institutional constraints that influence resource availability and organizational behavior.

In developing countries, SMEs face significant resource constraints due to their reliance on external resources. RDT has emerged as a critical framework for understanding how SMEs in developing nations can navigate their external dependencies to secure resources. For example, many SMEs in developing economies heavily rely on government initiatives to aid in digital transformation and foster digital maturity to meet market demands and maintain competitiveness (Omol et al., 2023). As SMEs in developing countries proactively manage their external dependencies and secure the resources essential for their survival and growth, the RDT framework provides a strategic approach to address these challenges and ensure their long-term viability.

Similarly, SMEs have recognized the necessity of strengthening their competitiveness through internationalization. This specific application of RDT highlights the importance of resource-centric approaches in navigating the complexities of global markets. SMEs that focus on resource development and management allow them to facilitate entry into foreign markets. In New Zealand, SMEs have leveraged international outsourcing (Raman & Ahmad, 2013), while those in the oil and gas sector adopted a resource-centric approach that is complemented by an adjustment to attitudes to have a more active involvement in the international market (Saidon et al., 2023).

In the AI sector, RDT has been applied to understand how organization navigates their dependencies in the context of technological advancements and competitive pressures. Studies have highlighted the need for frameworks that address various stakeholder dependencies. Papagiannidis et al.'s (2022) research indicates that effective AI governance requires organizations to manage their resource dependencies while ensuring compliance with ethical standards and regulations. This perspective emphasizes the interplay between AI governance and resource management in the AI sector.

Institutional Theory

Institutional theory, also known as institutionalism, explains how organizations operate within and respond to cultural, social, and regulatory pressures. The theory posits that organizations are not solely driven by efficiency and economic factors; instead, they are influenced by societal norms, values, and beliefs, shaping practices and structures to maintain legitimacy (Meyer & Rowan, 1977; Scott, 2013). According to institutional theory, organizations seek legitimacy by prioritizing social norms over efficiency to gain acceptance and reduce the risk of scrutiny from external sources. This legitimacy, in turn, positively affects access to resources (Dowling & Pfeffer, 1975). Legitimacy is a desirable outcome for organizations as it reflects social acceptance and support, which is needed for external organizations to interact with it (DiMaggio & Powell, 1983; Scott, 2013)—this societal mandate to operate forces organizations to conform to their institutional counterparts. As organizations conform to societal expectations, they become increasingly institutionalized and engage in behaviors similar to those of other organizations in their industry (Meyer & Rowan, 1977; Scott, 2013). The more legitimate organizations are perceived, the more likely they are to obtain access to resources and survive.

A core concept in institutional theory is institutional isomorphism, a process whereby organizations within the same field increasingly adopt similar practices. DiMaggio and Powell's (1983) seminal work presented the theoretical framework that examines institutional isomorphism: coercive isomorphism, mimetic isomorphism, and normative isomorphism. Coercive pressures occur when other organizations, typically those on which the organization is dependent, mandate specific organizational changes. Mimetic isomorphism manifests during periods of strategic ambiguity, leading to the imitation of established industry practices. Normative pressures are the collective cultural and social norms and values that lead to homogeneity. Recent research has employed this framework to explore how organizations adapt in response to new technologies and practices, including the increasing prevalence of AI governance and accountability (Selbst, 2021).

Moursellas et al. (2023) emphasized that coercive pressures from government and regulatory bodies significantly affect SMEs' sustainability practices, suggesting that compliance with external regulations is a primary driver of change. This is particularly evident in developing countries, where SMEs often face stringent regulatory environments that dictate operational standards, as seen in studies conducted in Uganda (Alinda et al., 2023) and South Africa (Masocha & Fatoki, 2018). These studies illustrated that government-mandated compliance in developing countries ensures adherence to operational norms but also highlights the reliance of SMEs on external entities to structure their sustainability efforts.

Saka et al. (2022) examined the adoption of Building Information Modelling (BIM) in Nigerian construction SMEs, revealing that firms often look to industry leaders as benchmarks for best practices. Similar behavior is found in the finance sector, as SMEs tend to mimic the reporting standard of more established firms to align with perceived industry norms (Sellami & Gafsi, 2018). This mimetic behavior extends to broader strategic initiatives, such as sustainability practices, where SMEs may emulate larger firms to enhance their legitimacy and competitiveness in the market (Ojo, 2022). Through various sectors, mimetic pressures have been embraced to align with industry norms, enhance legitimacy, or remain competitive.

Normative pressures can shape SMEs' corporate social responsibility (CSR) initiatives. These pressures stem from the expectations set by societal norms, industry practices, and influential institutions that guide SMEs toward socially and environmentally responsible behavior. For instance, Bihari and Shajahan (2023) discussed how institutionalized norms have led to changes in CSR practices among SMEs in India. Their study highlighted that such norms are often driven by a combination of regulatory requirements and social legitimacy-seeking behavior (Bihari & Shajahan, 2023; C. Kumar & Ganguly, 2024). This demonstrated that normative pressures could catalyze embedding CSR into the strategic frameworks of SMEs, particularly in regions where formal regulatory environments may be less robust.

In the AI sector, Tunjungsari et al. (2021) found that SMEs are more likely to adopt AI technologies when they observe successful implementations by industry leaders, indicating a strong mimetic influence. Conversely, in the manufacturing sector, coercive pressures from regulatory bodies may dominate the decision-making process as firms strive to comply with safety and quality standards (Badghish, 2024). This suggested that the context in which SMEs operate significantly shapes their responses to institutional pressures. The evidence suggested that while external pressures are a significant influence, SMEs' responses are nuanced by local contexts, industry characteristics, and resource availability.

Oliver's Framework

While both theoretical frameworks offer valuable approaches, they are not without limitations. As mentioned, RDT overlooks the sociocultural constraints, while institutionalism underestimates the role organizations actively play in managing resource constraints. Oliver (1991) contends that neither RDT nor institutionalism adequately encapsulates the intricate dynamics of organizational behavior within an institutional setting. She further claims that organizations are motivated by social or economic rewards, and each organization pursues strategies that are most advantageous in yielding resources. Oliver's (1991) framework offers a path to conceptualizing how AI SMEs attempt to manage pressures through a variety of compliance and resistance strategies.

Christine Oliver (1991) developed the guiding framework used for this research. Oliver's work integrates insights from institutional theory and RDT to predict how an organization might react to external pressures and constraints or strategically respond. The scholar posits that institutional theory can accommodate resource-dependent behavior by recognizing that organizations do not merely conform passively to institutional pressures; instead, they adopt strategic responses that range from passive to conforming, depending on their context and resource dependencies. The lower the perceived reward, the greater is the likelihood of resistance. Oliver developed a typology of five potential strategies that an organization can employ to react to institutional pressures. These core strategies, classified along a spectrum from passive compliance to active resistance, are reproduced in Table 1, which presents Oliver's typology of five strategic response and their tactics.

Table 1

Strategic Responses to Institutional Pressures (Oliver, 1991, p. 152)

Strategies	Tactics	Examples
Acquiescence	Habit	Following invisible, taken-for-granted norms
	Imitate	Mimicking institutional models
	Comply	Obeying rules and accepting norms
Compromise	Balance	Balancing the expectations of multiple constituents
	Pacify	Placating and accommodating institutional elements
	Bargain	Negotiating with institutional stakeholders
Avoid	Conceal	Disguising nonconformity
	Buffer	Loosening institutional attachments
	Escape	Changing goals, activities, or domains
Defy	Dismiss	Ignoring explicit norms and values
	Challenge	Contesting rules and requirements
	Attack	Assaulting the sources of institutional pressure
Manipulate	Co-opt	Importing influential constituents
	Influence	Shaping values and criteria
	Control	Dominating institutional constituents and processes

Strategic Responses

The first strategy organizations may use to respond to institutional pressures is *acquiescence*, the most passive response on the spectrum from passive to active. Acquiescence involves conforming to institutional pressures either consciously or unconsciously, with the driving force behind it being social legitimacy and economic gains. This response may manifest out of habitual behaviors, adhering to taken-for-granted rules and values that have become ingrained in the organization. It can also arise from mimicking successful organizations or other industry leaders. Finally, organizations can simply choose to comply, making a conscious decision to cooperate. The acquiescence response is often likely when the perceived benefits of conforming are high and align with the organization's interests.

Second, *compromise* as a strategic response involves partial conformity and attempts to find a consensus between conformity and resistance. When organizations have conflicting demands, they may adopt a compromise strategy to address institutional demands without fully aligning with them. There are three tactics under compromise: balance, pacify, and bargain. Balancing involves accommodating multiple, potentially conflicting demands, while pacifying focuses on accommodating specific institutional components. Lastly, bargaining represents a more active form of compromise, where the organization negotiates with stakeholders to secure allowances. Compromise most likely occurs when faced with multiple competing pressures and there is a high dependence on those external institutions.

The third strategy, *avoidance*, focuses on circumventing the need to conform to institutional pressures. This approach is neither passive nor active; it aims to minimize the impact of external entities on their operations. Organizations can choose to conceal nonconformity, creating the appearance of compliance; buffer operations, partially decoupling activities from external scrutiny; escape, exiting the domain altogether—this is the most extreme avoidance tactic. Avoidance most likely occurs when organizations are less reliant on external validation and the anticipated cost of full compliance is inconsistent with organizational goals.

The fifth strategy skews towards a more direct and active approach. *Defiance* is reflected when organizations openly reject or challenge external pressures. Defiant organizations can take the form of dismissal, challenge, and attack. Often, due to the lack of understanding or belief in their legitimacy, dismissal occurs when organizations ignore institutional rules and values. Organizations that choose to challenge institutional pressures actively contest the validity of the demand. Finally, the most aggressive form of defiance is attack, which is vehemently criticizing and denouncing institutional values. Defiance appears when organizations perceive the benefits of autonomy outweigh conformity and there is a low dependency on the external entity.

The final strategy organizations may pursue is the most active form of resistance: *manipulation*. Manipulation seeks to gain agency over the external force through co-optation, influence, or control. Co-optation seeks to attract influential individuals, such as board members, into the organization. By targeting the broader environment, influence tactics are used to shape acceptable practices. Finally, the most assertive tactic, control, aims to establish dominance over resources. Organizations that perceive external entities as threats and have low dependence on them appeal to manipulation.

Predictors of Strategic Responses

Oliver extended the research by exploring the factors that determine the likelihood that an organization would adopt a response. These predictors help to contextualize and operationalize the strategic responses. Oliver's predictors allowed for a better account of strategic choice and active agency, which institutional theory failed to do. Each predictor provides an analytical depth beyond reactivity, showing a strategic assessment of the benefits and constraints. Table 2 provides the questions that help better understand the driving factors that influence an organization's response.

Table 2

Antecedents of Strategic Responses (Oliver, 1991, p. 160)

Research Question	**Institutional Factor**
Why is the organization being pressured to conform to institutional rules or expectations?	Cause
Who is exerting institutional pressures on the organization?	Constituents
To what norms or requirements is the organization being pressured to conform?	Content
How or by what means are the institutional pressures being exerted?	Control
What is the environmental context within which institutional pressures are being exerted?	Context

Oliver identified ten predictive dimensions grouped into five institutional antecedents to predict an organization's strategic response. The first antecedent, *cause*, examines the underlying motivations behind institutional pressure that focus on legitimacy or efficiency. Organizations are more likely to conform when these pressures are both high and, conversely, resist when they are low. Second, *constituents* focus on the source of the pressure. Two key predictive dimensions affect constituents: multiplicity and dependence. Organizations are more likely to resist conforming when the multiplicity of constituents increases, as balancing conflicting demands becomes challenging, reducing the feasibility of compliance with conflicting expectations, and when the organization's dependence on the external entity is low. The third antecedent is *content*, which assesses the essence of the request. Consistency, reflecting alignment with organizational goals and constraints, and measuring limitations on decision-making autonomy are the two key predictive dimensions. The fourth antecedent, *control*, surveys how external entities exert pressure. Two distinct methods are acknowledged: coercion and diffusion, essentially the degree to which pressure is mandatory or voluntary. Finally, the fifth and final antecedent, *context*, accounts for the broader environmental determinants that influence an organization. Uncertainty, referring to environmental unpredictability, and interconnectedness, describing organizational relationships, are two crucial dimensions within this predictor.

Gap in the Literature

An analysis of the current research reveals a significant exploration across multiple sectors, including finance, healthcare, education, and manufacturing sectors. In the finance sector, scholars have conducted extensive research focusing on access to finance for SMEs, revealing the significance of regulatory compliance (Amadasun & Mutezo, 2021; Miliūnaitė & Žigienė, 2023; Oyewole et al., 2024; Poderys, 2015; Singh, 2023). Healthcare research has concentrated on AI's potential to improve service quality and patient outcomes, carefully examining data privacy and the ethical implications of AI-driven medical decision-making (C. Chen et al., 2024; Elendu et al., 2023; Goh et al., 2024; Möllmann et al., 2021) and the ethical implications of AI in medical decision-making (Almpani et al., 2023; Dave & Patel, 2023; Elendu et al., 2023; Rathore & Rathore, 2023; Secinaro et al., 2021). In the education sector, especially in higher education, scholars have been investigating AI's transformative potential of AI in the classroom (Dave & Patel, 2023; Rashmi, 2023) alongside its inherent challenges ((Tahiru, 2020; Saidakhror, 2024; Zhai et al., 2021) and ethical considerations (Alahmed et al., 2023; Memarian & Doleck, 2023). Lastly, in the world of manufacturing and supply chain, emerging research has focused on AI-driven optimization for production processes and supply chain management (Eyo-Udo, 2024; Joel et al., 2024) and transparency (Mir, 2024; Nimmagadda, 2023). These sector-specific investigations converge on a broader theme: the critical importance of responsible AI implementation.

The intersection of responsible AI, SMEs, and organizational response showcases three prominent concepts: the necessity for ethical frameworks (Ashok et al., 2021; Barletta et al., 2023; Prem, 2023), the importance of transparency and accountability (Cheong, 2024; Memarian & Doleck, 2023; Mensah, 2023), and the role of organizational culture has in facilitating ethical AI practices (Bley et al., 2022; Chourasia et al., 2024; Murire, 2024). A significant increase in AI usage has led to an increased focus on ethical principles to govern its development and deployment. A significant challenge emerging from these studies is the absence of a universal framework for rAI (Barletta et al., 2023). Scholars have suggested the need for a comprehensive framework that addresses different stages of the AI development lifecycle (Barletta et al., 2023; Soudi & Bauters, 2024). Essentially, these efforts aim to establish mechanisms for identifying and addressing ethical lapses, ensure transparency in AI-driven decision-making, and provide avenues for recourse when AI systems cause harm (accountability) (Lottu et al., 2024). Recent studies attested to defining clear structures and processes that support ethical AI practices (Abhulimen & Ejike, 2024; Ahlawat et al., 2024; Burrell & Mcandrew, 2023; Ufert & Goldberg, 2023).

Research trends reveal notable differences in how organizations of various sizes approach AI ethics. Larger organizations are often more scrutinized due to their visibility, resources, and influence, and have the resources to develop comprehensive AI ethics policies (De Laat, 2021; Mikalef et al., 2022; Mökander & Floridi, 2022; Stahl et al., 2021). In contrast, SMEs are less equipped to comply with rigid institutional pressures due to resource constraints. For example, Soudi and Bauters (2024) highlighted the need for SMEs to adopt responsible AI practices by proposing measures such as developing sector-specific guidelines rather than universal standards, establishing a trusted accreditation framework for organizations, providing ongoing training for employees and managers on AI ethics, raising awareness about the benefits of explainable AI systems, and encouraging risk-based assessments over principle-based approaches. Ultimately, these divergent approaches underscore the critical need for a nuanced investigation that recognizes the unique organizational and institutional contexts among enterprises of different scales.

The global perspective on ethical AI is equally complex, with four distinct regions offering unique insights: North America, Europe, Asia-Pacific, and Africa. The interplay of local cultural values, socio-economic conditions, and global ethical standards shapes each region's approach. In the U.S., research indicates a proliferation of ethical guidelines and principles from various organizations, yet there remains a lack of consensus on what constitutes "ethical AI" (Jobin et al., 2019). The emphasis is often on transparency, accountability, and fairness; however, scholarly critiques warn that overemphasis on formalized ethical frameworks might result in performative ethics that lack meaningful moral substance (Molina & Borgatti, 2021). Conversely, the EU has been at the forefront of developing comprehensive regulatory frameworks that prioritize ethical considerations, namely the GDPR and EU AI Act. The emphasis on ethical AI in Europe also reflects a broader societal expectation for technology to align with human rights and ethical standards, creating a robust institutional framework that supports ethical AI practices (Baeza-Yates & Fayyad, 2024). In Asia-Pacific, ethical AI is influenced by rapid technological advancements, according to J. Chen et al. (2021), ethical guidelines often lag behind technological development. The region also grapples with accommodating diverse cultural perspectives, requiring cross-cultural cooperation in AI ethics (Óhéigeartaigh et al., 2020). Lastly, in Africa, the discourse is marked by the lack of access to education and resources, hampering organizations' ability to engage with AI technologies and further complicating efforts to focus on the importance of the context and culture that shape its responsible use (De-Lima-Santos et al., 2024; Haidar, 2023). The issues faced in Africa—limited resources, lack of infrastructure, and insufficient research funding—contribute to the underrepresentation of developing countries, characterizing a significant gap in AI-related studies (Kiemde & Kora, 2020).

Ultimately, the research converges on a critical conclusion: rAI is not a one-size-fits-all proposition. It requires a nuanced, context-aware approach that recognizes the unique organizational and institutional challenges across different sectors and regions. Much of the current research focuses on the practical applications, frameworks, and challenges. This exposes a critical gap in understanding the complex organizational and institutional dynamics that shape responsible AI adoption strategies among SMEs. Winecoff & Watkins' (2022) notable descriptive qualitative research explored the foundational principles that guided the creation and implementation of AI technologies within AI startups. In their research, it was revealed that entrepreneurs often face a central tension between adhering to institutional pressures and maintaining scientific integrity, suggesting that resistance can manifest as a strategic choice to uphold methodological rigor in the face of external demands (Winecoff & Watkins, 2022).

The comprehensive review of existing literature reveals a significant gap in understanding how U.S.-based SMEs in the AI industry strategically navigate institutional pressures surrounding rAI. While extensive research has explored AI ethics across various sectors and global regions, there remains a notable absence of in-depth investigation into the specific mechanisms SMEs employ to maintain legitimacy and sustainability when adopting responsible AI practices. This gap presents a critical opportunity for future research to examine how SMEs in the AI industry balance institutional expectations, resource constraints, and ethical imperatives. By exploring the strategic responses of U.S.-based SMEs to these complex pressures, researchers can develop a more nuanced understanding of how smaller organizations develop and implement ethical AI frameworks, potentially uncovering innovative approaches that could inform broader industry standards and support the sustainable development of rAI technologies.

Summary

This literature review examines how U.S.-based SMEs strategically respond to institutional pressures when implementing rAI technologies. It explores the historical development of AI, highlighting periods of rapid advancement and setbacks, and defines responsible AI principles, such as transparency and accountability. The review analyzes existing theoretical frameworks, including resource dependence theory and institutional theory, and utilizes Oliver's framework to understand SMEs' strategic responses to institutional pressures. Finally, it identifies key challenges and opportunities for SMEs in adopting responsible AI, focusing on technological limitations, organizational constraints, regulatory complexities, and individual-level factors. The proposed research builds on scholarship by taking a contextual and organizational approach to responsible AI, focusing on the ethical practices that shape AI implementation. Chapter III builds on the foundation established in this literature review and provides a discussion of the research questions and hypotheses, the methodology and the rationale for choosing a qualitative design, and the proposed population, sample, instrumentation, data collection, and data analysis strategies.

CHAPTER III: METHOD

The purpose of this chapter is to introduce the research methodology that will be applied in this qualitative study, which investigates the organizational and institutional context in which rAI is developed within U.S.-based SMEs. The methodology chapter is a critical component of the dissertation, providing the foundation for understanding how the research will be conducted and ensuring transparency, rigor, and credibility in the study's design and execution. This chapter builds on the foundation laid in the introduction and literature review chapters. While the introduction outlines the purpose and significance of the research, and the literature review synthesizes existing knowledge and identifies research gaps, this chapter explains how the study will be conducted to address the identified gaps. It provides the framework for collecting, analyzing, and interpreting data in alignment with the study's purpose and research questions. The methodological clarity offered in this chapter ensures that the findings and interpretations in subsequent chapters are grounded in systematic and ethical research practices.

This study uses a basic qualitative research design that is ideal for research that does not fit into other definitions of qualitative research design but seeks to discover and explore the first-hand experience of real-world context (J. Ellis & Hart, 2023). The flexibility of a basic qualitative approach allows for an in-depth examination of the organizational and institutional factors influencing SMEs' actions while remaining adaptable to the complexity of institutional pressures and the dynamic nature of the AI industry. It aligns logically as it allows the researcher to focus on how SMEs respond to pressures without the constraints of rigidly defined qualitative frameworks like case studies or phenomenology. Additionally, the nature of institutional pressures can be explored to help contextualize the challenges SMEs face in achieving rAI adoption. Finally, the methodology supports investigating the predictors that influence strategic responses, addressing motivations behind rAI decisions.

Chapter III begins with a recap of the research purpose and questions, followed by a detailed explanation of the selected basic qualitative methodology and its suitability for this study. The chapter then outlines the population and sampling approach, including specific criteria for participant selection and recruitment strategies. Finally, it describes the data collection procedures, analysis methods using thematic analysis, measures to ensure trustworthiness, and ethical considerations for protecting participants throughout the research process.

Methodology Selected

Thorough qualitative research is underpinned by the researcher's underlying beliefs, the research question, and the chosen research method (Teherani et al., 2015). For this study, a basic qualitative methodology is particularly well-suited given its fundamental focus on understanding how SMEs interpret and make sense of their experiences with institutional pressures in rAI implementation. Merriam and Tisdell (2015) emphasized how basic qualitative research excels at uncovering how participants interpret their experiences, construct their organizational realities, and attribute meaning to their strategic responses. It focuses on the events that transpire and on the outcomes of those events from the perspectives of those involved (Teherani et al., 2015). This aligns seamlessly with the research objectives, as it aims to explore not only the responses chosen by SMEs but also the deeper meanings and interpretations underlying their strategic decisions.

. The methodology's emphasis on collecting data through interviews, observations, and document analysis will enable a systemic inquiry into a rich understanding of the complex interplay between institutional pressures and strategic responses in its natural setting (Merriam & Tisdell, 2015; Teherani et al., 2015).

Qualitative research is particularly valuable for studying highly complex phenomena that cannot be adequately examined through quantitative means alone (S. Ahmad et al., 2019). However, it can be leveraged to generate ideas or hypotheses for later quantitative research (S. Ahmad et al., 2019). The nuanced nature of institutional pressures and the variety of possible strategic responses across Oliver's typology demand an approach that can capture subtle variations in organizational interpretation and response (S. Ahmad et al., 2019). Furthermore, the post-positivist understanding that environmental and individual differences influence reality is crucial for this study, as it acknowledges the varied contexts in which SMEs operate and make decisions (Teherani et al., 2015).

While other methodological approaches like case studies or phenomenology could potentially be employed, they would be less effective for addressing our research questions. While case studies are valuable for "how" and "why" questions, they would limit our ability to identify broader patterns across multiple SMEs (Baxter & Jack, 2015). Similarly, while phenomenology might provide deep insights into the lived experiences of decision-makers, it would not adequately capture the organizational-level strategic responses that are central to our research questions (Caelli et al., 2003). The basic qualitative methodology offers the optimal balance of depth and breadth needed to understand both the individual interpretations and the broader patterns of strategic responses across different SMEs while maintaining the necessary focus on meaning-making and interpretation that is crucial for understanding institutional responses (S. Ahmad et al., 2019; Caelli et al., 2003).

Research Question(s)

This study will explore and seek to understand the answer to the following research question and sub-questions:

RQ*:* How do AI practitioners at SMEs strategically respond to institutional pressures when implementing rAI technologies?

SQ1*:* What are the institutional pressures SMEs face when implementing rAI technologies?

SQ2: What are the predictors of the strategic responses when implementing rAI technologies?

Study Participants

This section provides an overview of the population and sampling strategy. It will outline the characteristics of the target population, describe the sampling strategy that will be used, and detail the specific sampling method chosen, including the rationale for its selection and the procedures implemented to ensure a representative sample. SMEs theoretically drive this research, as these organizations typically prioritize survivability and demonstrate significant dependence on other organizations, making them particularly suitable for studying responses to institutional pressures. Therefore, the central population will be comprised of U.S.-based SMEs, specifically those that have implemented or are planning to implement AI technologies. For this research, an SME is an organization with fewer than 500 employees or less than $7.5 million in average annual receipts.

Sampling Method

A combined purposive sampling strategy, namely criterion and snowballing, will be taken to recruit a diverse group of participants. Purposive sampling is a common non-probabilistic approach for researchers who want to discover insight into a particular phenomenon (Merriam & Tisdell, 2015). It is advantageous when a targeted sample needs to be reached quickly and where sampling for proportionality is not a primary concern. One study combined the snowball and criterion strategy to recruit program managers (Green & Aarons, 2011, as cited by Palinkas et al., 2013). Given this approach's proven effectiveness in similar research contexts, this study will adopt the same combined sampling strategy to identify and recruit qualified participants. In order to begin purposive sampling, criteria must be determined to distinguish what characteristics are essential to the study (Merriam & Tisdell, 2015). Criterion sampling seeks participants who meet or exceed specific criteria with the expectation that those participants possess an intimate knowledge of the phenomenon of interest (Palinkas et al., 2013). The following are essential criteria for AI practitioners from the executive level downward to ensure participants will provide an information-rich interview:

- Employed at a U.S.-based SME.
- Involved in AI-related work for at least 3 months.
- Proficient in English.

Screening for participants who are employed at an SME directly aligns with the study's scope and research questions, which focus on U.S.-based SMEs. Participants who are embedded in this particular environment can speak to the unique pressures and challenges SMEs face. The second criterion ensures that the participants have direct experience with those pressures and challenges that affect the development of rAI and can provide firsthand insights into how their organization responds to those institutional pressures. Although an individual's current role may involve working with AI, it is beneficial for that individual to have had time to observe and participate in their organization's strategic responses to institutional pressures. Therefore, a minimum of three months in the role associated with AI work is necessary. Finally, to ensure accurate data collection and minimize the risk of misinterpretations due to language barriers, the researcher will seek only participants who are proficient in the English language. Educational level is not an essential criterion for this study; however, to understand the diversity of the group, it will be captured.

It is essential to acknowledge that by selecting individuals who meet specific criteria, the study may exclude the experiences of those who do not meet the requirements, reducing the diversity of perspectives considered (Creswell & Poth, 2016). As a result, there is a limitation on the breadth and depth of understanding of the phenomenon under investigation. This limitation is particularly pertinent in qualitative research, where the richness and variability of participant experiences are crucial for achieving a comprehensive understanding of the topic (Creswell & Poth, 2016). The exclusion of certain groups may lead to a narrower view of the subject matter and limit the ability to generalize the findings to a broader population (Palinkas et al., 2013). Therefore, it is essential to recognize the potential impact of this limitation when interpreting the study's results and conclusions.

The criterion sampling technique will be used as the initial method of sampling. Snowball sampling will complement this approach by asking initial participants to refer other qualified individuals, particularly those in different roles within their organizations (Merriam & Tisdell, 2015). The advantage of snowball sampling is that it provides a way to access the targeted population when it is difficult to identify participants. However, as with most purposive sampling, it is difficult to defend the representativeness of the population (G. Sharma, 2017).

Sample Size

In qualitative research, the scope, nature, and quality of the study determine the sample size. Generally, qualitative research recommends that data be gathered until the point of saturation (Merriam & Tisdell, 2015). The point of saturation is determined when no new information emerges from the sample, and thus, redundancy is reached (Merriam & Tisdell, 2015). A purposive sampling technique has a high chance of reaching data saturation when using information-rich participants (Shaheen et al., 2018). This sampling strategy effectively balances the need for diverse participant experiences and perspectives with the practical constraints of conducting in-depth analysis. The anticipated target sample is 15-25 participants recruited from a pool of 30 volunteers to account for attrition, aligning with previous research (Rakova et al., 2021; Winecoff & Watkins, 2022) and Hennink and Kaiser's (2021) recommendation for reaching saturation in qualitative research. The final sample size will be determined dynamically as the study progresses.

Recruitment Strategy

Participant recruitment, guided by a combined purposive sampling, will target SME AI practitioners. Strategies will include targeted outreach on LinkedIn, direct outreach through professional networks, and posts on AI and technology-related message boards and social media platforms. For any message board, LinkedIn or otherwise, written permission (see Appendix A) will be obtained from the moderator(s) to invite participants via the recruitment flyer (see Appendix B). Additionally, each participant will be asked to recommend other potential interviewees, particularly team members in different roles, to ensure comprehensive coverage of perspectives within each organization.

Researcher's Relationship

Maintaining professional distance and objectivity in this study is important to its results (Pandey, 2014). There will be no prior personal or professional connections between the researcher and potential study participants, allowing the selection process to proceed without bias or preconceptions. This professional boundary helps create an environment where participants can share their experiences openly and honestly. The researcher's commitment to neutrality throughout data collection strengthens the study's credibility. It ensures that findings emerge naturally from participant responses rather than being influenced by existing relationships or predetermined expectations.

Data Collection

This section delves into the data collection methods and instrumentations that will be used in this study. This qualitative study will harness semi-structured interviews as the primary data collection method to explore how SMEs strategically respond to institutional pressures when implementing rAI technologies. Semi-structured interviews are particularly well-suited to uncovering participants' unique interpretations of their social realities and the motivations underlying their behaviors within that context (Winecoff, 2022). The inherent flexibility and depth of this approach allow for a comprehensive exploration of complex issues related to strategic responses in the SME sector.

Interview Protocol

The data collection will center on conducting detailed semi-structured interviews with SME AI practitioners to contextualize the insights of the broader institution on an organizational level and explore three key areas: current and future company vision, perceptions of institutional pressures, and organizational values. Parties interested in participating in the study will be screened to ensure they are eligible for the study. Prior to beginning the interviews, participants will give verbal consent to participate in the study and to be recorded. Consent will be recorded in a consent log with key details for each participant, such as time, date, and a brief statement verbally indicating that they agreed. Requesting to record interviews allows the researcher to be more present and ensures the accuracy of the analysis. Participants will be invited to a password-protected videoconferencing interview via Microsoft Teams, a videoconferencing platform.

The primary data collection instrument is an interview guide (see Appendix C) designed to elicit rich descriptions to unveil the layered complexities involved in SMEs' strategic responses to institutional pressures. The instrument was developed by examining previous literature (Rakova et al., 2021; Winecoff & Watkins, 2022), assessing missing and similar themes, and ensuring they are coherent between the research questions and conceptual framework (Hennink & Kaiser, 2021). Questions were grouped into different sections, exploring the company's objectives and their use of AI within the company, then delving into questions tailored to the organizational barriers, concluding with questions regarding the social and ethical implications of the company. The open questions interview style allows probing questions to encourage the participant to reveal more detailed information about specific topics (Hennink & Kaiser, 2021).

Prior to interviewing, the researcher will seek the approval of the University of Arizona Global Campus (UAGC) Institutional Review Board (IRB) of the interview guide. Guided by the ethical principles in the Declaration of Helsinki, the National Commission for the Protection of Human Participants of Biomedical and Behavioral Research's Ethical Principles, and Guidelines for the Protection of Human Participants of Research: The Belmont Report, the UAGC IRB serves a committee charged with ensuring the ethical standards of a study prior to commencement (UAGC, 2024). The committee reviews any study involving humans or vertebrate participants to confirm that any concerns for ethical or civil rights have been addressed and that the rights of the participant are prioritized over the study.

Since this study will leverage a semi-structured interview technique, the researcher will be able to adapt to the experiences and perspectives offered by the participants, asking probing questions to gain insight into the specifics of each question. After each interview, the data will be transcribed using Microsoft Live Transcription with speaker attributions, with manual review and correction for accuracy. Participants will be given the opportunity to review their transcripts for accuracy through member checking. A secondary data analysis using Mergent Online and Dun & Bradstreet will verify company characteristics such as size, years in existence, and industry sector, adding to the credibility of the research through triangulation.

Procedure

Upon IRB approval, this study will adopt a systematic and methodological approach to the data collection described. The procedure begins a pilot testing phase to ensure a smooth interview experience and the validity of the interview guide. Subsequently, the participants will be recruited using a combined purposive sampling approach and invited to participate in in-depth semi-structured interviews conducted remotely using Microsoft

Teams. The subsequent sections will delve into each of these procedural steps in detail, providing a comprehensive account of the study's methodological framework.

Pilot testing

The data collection process will start with pilot testing of the interview protocol with 2-3 participants recruited via convenience sampling, representing approximately 10% of the projected sample size (Connelly, 2008). Pilot studies are conducted to prevent a fatal flaw in the more extensive study and to validate the adequacy of the methods and procedures (Lowe, 2019). This testing will serve multiple purposes: process evaluation, resource evaluation, management, and scientific purpose (Thabane et al., 2010). Process evaluation considers the fundamental feasibility of research procedures and protocols. This helps to ensure that the proposed procedures produce results (Yin, 2014). For example, if the recruitment method yields ineligible candidates, then it provides an opportunity to pivot to a different approach.

Resource evaluation examines time and budget constraints, ensuring the appropriate allocation of study resources. Oftentimes, studies are designed without considering a realistic timing schedule. Particularly with a semi-structured interview, where the interview is more of a conversation, the researcher can probe too long on a single topic, subsequently rushing future questions or failing to get to them at all. Pilot testing can help improve one's interviewing technique (Rallis & Rossman, 2009). Management focuses on optimizing human capital and data handling procedures to maximize research efficiency. Pilot testing can also ensure that the data collection instruments are structured in a manner that effectively captures all relevant information succinctly. The scientific purpose investigates whether the theoretical framework and hypothesized responses align with preliminary observations, laying the groundwork for the main study's theoretical underpinnings. Validating the interview protocol is critical to ensure the questions are unambiguous, the timing is appropriate, and the objectives are covered. It is often difficult to predict how participants will interpret a question (Rallis & Rossman, 2009). Lessons learned from the pilot will be iteratively documented and incorporated into the main study procedures.

Participant recruitment

The study will target AI practitioners from various U.S.-based industries with AI implementation experience, ensuring they provide rich and relevant data. Recruitment strategies include targeted outreach on LinkedIn, direct outreach through professional networks, and posts on AI and technology-related message boards and social media platforms. A recruitment flyer with relevant information regarding the study, such as the requirement to participate, the study's purpose, time commitment, and a link to participate, will be posted.

The recruitment flyer links the interested participant to a screening survey (see Appendix D). The screening survey verifies if they have the criteria to be eligible for the study (Maxim et al., 2014). The survey is attached to a workflow (see Appendix E) that checks if the participant is eligible. If they are not eligible, then they are automatically sent an email thanking them for their interest and notifying them of their ineligibility (see Appendix F). Qualified participants will be redirected to the Informed Consent form (see Appendix G), which they will sign electronically. A copy of the signed Informed Consent form will be emailed to the participant upon submission (see Appendix H). Once completed, they will be redirected to the Pre-Interview Questionnaire (see Appendix I), a 12-question survey that collects demographic information about the participant and their company. Finally, the participant will be redirected to the Microsoft Booking platform, which will allow them to select a convenient 60-minute time slot for their interview (see Appendix J). The participant will also be sent an email (see Appendix K) once they are confirmed eligible with links to each form and a unique identification code (UID) for them to complete the information later. All forms were created using JotForm, a low-code form builder, instead of Microsoft Forms due to its security, ease of use, and flexibility.

Following scheduling, participants will receive a confirmation email (see Appendix L), including a copy of the interview guide. Providing participants with the interview guide in advance aims to enhance interview efficiency by allowing them to familiarize themselves with the topics to be discussed. This transparency also ensures that participants are well-informed about the interview's scope and can prepare accordingly.

Prior to the scheduled interview, the researcher will confirm that the Informed Consent form has been received. The researcher will reach out to the participant if it has not been received. Participants who provide their consent will have their interview conducted via password-protected Microsoft Teams meetings, ensuring secure and accessible data collection. Microsoft Teams was selected as the preferred platform for interviews due to its availability within the university and its robust security features. Microsoft Teams offers enhanced security through password-protected meeting invitations, ensuring a secure and confidential environment for the interview. Microsoft Teams will be utilized for its valuable features, including the ability to record interviews and generate live transcriptions with speaker attribution. Before the interview recording begins, the researcher will verbally confirm consent, remind participants of their confidentiality rights, and request permission to record. Each semi-structured interview is anticipated to last approximately 60 minutes.

The researcher will capture a detailed record of decisions, procedures, and interpretations throughout the study, enhancing the quality of the research, enhancing transparency, and protecting accountability. Detailed record-keeping is also essential for maintaining data consistency, and comprehensive recordings facilitate a coherent and thorough analysis of the collected data (T. Li et al., 2019). This instrument is significant for facilitating practical data analysis. It is paramount to accurately interpret the complex dynamics of strategic responses to institutional pressures and ensure the study's objectives are met during the interview.

Since all interviews will be recorded through Microsoft Teams and transcribed using its built-in transcription service, the researcher will review and correct transcriptions for accuracy. After each interview has been conducted and transcribed, the researcher will send an email to each participant (see Appendix M) so they will have the opportunity to review their transcripts for accuracy through member checking. Throughout the process, all data will be stored securely in a password-protected account confidentiality.

Data Analysis

This study will leverage a thematic analysis approach to explore. Thematic analysis is particularly well-suited for this research as it enables the systematic identification, analysis, and interpretation of patterns within the dataset, thereby aligning with the study's objective of answering a focused research question (Braun & Clarke, 2012). This method allows researchers to derive codes, categories, and themes that emerge across the data, offering a comprehensive view of the underlying dynamics (American Psychological Association, 2020). Guided by a deductive approach, this analysis grounds its coding and theming in Oliver's typology. Deductive reasoning involves deriving themes and patterns directly from established ideas, making it particularly relevant for theory-driven investigations (Naeem et al., 2023). This combination of thematic analysis and deductive reasoning provides a robust foundation for uncovering actionable insights into SME strategies for rAI implementation.

Analytic engagement will commence with data collection and then will follow Braun and Clarke's (2006) six-phase approach to analyze the interview data. The analysis will begin with data familiarization through a careful review of interview transcripts. While Microsoft Teams will provide the initial transcription, the researcher will verify each transcript against the original audio recordings and incorporate participant feedback through member checking to ensure accuracy and capture essential nuances (Rubin & Rubin, 2011). This thorough review process will provide the researcher with a deep engagement with the data before coding begins, allowing familiarity with the data (Braun & Clarke, 2006).

The second phase will involve generating initial codes using ATLAS.ti. ATLAS.ti is a qualitative data analysis software that assists researchers in organizing, analyzing, and interpreting qualitative data such as interviews, focus groups, and observational notes. The coding process will be theory-driven, approaching each interview with specific questions derived from the research framework while remaining attentive to unexpected insights (Braun & Clarke, 2006). Similar to the transcription process, the researcher will review the codes and amend them as needed. Each interview will receive equal analytical attention, with data extracts potentially receiving multiple codes to capture their full complexity. It is vital to provide an equal amount of time and attention to each interview to avoid bias in the analysis and ensure that all participant's voices are equally valued and represented in the data (Braun & Clarke, 2006). ATLAS.ti's integrated AI capabilities will assist in identifying preliminary patterns, though all automated coding suggestions will be manually verified for accuracy and relevance.

In the third and fourth phases, the researcher will search for and review themes. Using ATLAS.ti's visualization features, charts, maps, and relationship networks will be created to help identify connections between codes and potential themes. Theme review will occur at two levels: first, examining how themes work in relation to coded extracts, then evaluating how well the thematic map reflects the entire dataset (Braun & Clarke, 2006). During this process, particular attention will be given to discrepant cases that do not fit emerging patterns, using them to challenge and refine the developing analysis rather than forcing them into existing themes.

The fifth phase will involve defining and naming themes to reveal their fundamental nature and relationship to the research questions. Each theme will undergo a detailed analysis to understand how it illuminates SMEs' strategic responses to institutional pressures in rAI. Theme names will be developed to be both precise and engaging, clearly communicating their core concepts while maintaining analytical rigor.

The last phase will culminate in producing a compelling analytical narrative that goes beyond mere description to present a coherent argument about how and why SMEs respond to institutional pressures in particular ways (Braun & Clarke, 2006). The analysis will incorporate vivid examples from the data to illustrate key points while maintaining focus on addressing the research questions. This analytical approach will ensure that the findings provide meaningful insights into SMEs' strategic responses, contributing to both theoretical understanding and practical application.

Trustworthiness

While understanding rather than prediction is the primary goal of qualitative research, establishing trustworthiness remains essential for ensuring the value of the findings (Merriam & Tisdell, 2015). Trustworthiness is a cornerstone of qualitative research, particularly in studies like this that aim to uncover nuanced insights into how and why U.S.-based SMEs strategically respond. Establishing trustworthiness ensures that the findings are credible, transferable, dependable, and confirmable, reinforcing the rigor and validity of the study (Lincoln & Guba, 1985). Given the complex and context-dependent nature of this study, achieving trustworthiness is critical to representing the participants' perspectives accurately and the theoretical constructs that guide this research. This study applies systematic procedures, including triangulation, member checking, audit trails, and reflexivity, to minimize biases and enhance reliability. By adhering to these measures, the research not only strengthens its methodological integrity but also enhances its capacity to provide actionable and trustworthy insights into SMEs' adoption of rAI technologies.

Credibility

Credibility addresses the accuracy and truthfulness of the findings by ensuring they authentically reflect participants' experiences (Shenton, 2004). Credibility will be established using several key strategies. First, triangulation will be achieved by cross-checking interview data against secondary sources, such as company documentation and public records, corroborating what has already been gathered (Rallis & Rossman, 2009). Next, member checking will allow participants to review their interview transcripts and preliminary findings, ensuring an accurate representation of their perspectives. Additionally, the researcher will maintain adequate engagement in data collection until reaching data saturation, where no new themes emerge. Lastly, the researcher will actively seek and analyze discrepant cases that might offer alternative explanations, strengthening the credibility of the findings through negative case analysis (Merriam & Tisdell, 2015).

Transferability

While this study does not aim for statistical generalization, the researcher will provide detailed, thick descriptions of the context and findings to enable readers to make analytical generalizations. Going through three distinct, iterative phases--sampling, data collection, and data analysis--will allow readers to assess whether the findings apply to their specific contexts through case-by-case analysis (Drisko, 2024; Merriam & Tisdell, 2015). Using this approach, the reader can test whether the theory is applicable in another context (Drisko, 2024).

Dependability

In addition to triangulation, to ensure dependability, the researcher will maintain a detailed audit trail documenting all research decisions, procedures, and analytical processes (Merriam & Tisdell, 2015). Dependability refers to the stability and consistency of the research findings over time and under similar conditions (Lincoln & Guba, 1985). This trail will include logs of participant selection criteria, interview procedures, coding decisions, and theme development (Connelly, 2016; Merriam & Tisdell, 2015). While replicating a qualitative study will not yield the same results due to changing contexts and participants, this detailed documentation will allow other researchers to understand how conclusions were reached (Merriam & Tisdell, 2015).

Confirmability

Confirmability in qualitative research refers to the extent to which the study’s findings are shaped by the participants’ responses rather than researcher biases or preconceptions (Lincoln & Guba, 1985). In this study, confirmability will be addressed through a detailed audit trail and reflexivity, with explicit acknowledgment of the researcher's assumptions, potential biases, and worldviews that might influence the research process (Connelly, 2016). The researcher will maintain a reflective journal throughout the study to document their thinking processes and decisions. Additionally, all raw data, analysis procedures, and supporting documentation will be preserved for potential external review (Connelly, 2016; Rallis & Rossman, 2009).

Ethical Concerns

This research operates at the intersection of organizational strategy and emerging technologies, both of which pose unique ethical challenges. Ensuring ethical rigor involves safeguarding participant confidentiality, obtaining informed consent, and maintaining the integrity of data collection and analysis processes (American Psychological Association, 2019). Given the sensitive nature of organizational decision-making and potential competitive implications, ethical safeguards are crucial to minimize risks to participants and organizations. Furthermore, ethical adherence enhances the credibility of the study by fostering trust with participants and stakeholders, ensuring that findings are responsibly derived and disseminated. In qualitative research, particularly when exploring topics with societal and technological implications such as rAI, addressing ethical concerns is not only a methodological requirement but foundational for conducting meaningful and impactful scholarship (Miles et al., 2014).

Ensuring ethical integrity in research requires planning to prioritize participants' well-being and implement guardrails that protect them from harm (Rani & Sharma, 2012). While temporary discomfort is an inherent risk—for example, fatigue or anxiety during a screening survey—researchers must also account for potential long-term impacts, such as the resurfacing of painful or debilitating memories (Merriam & Tisdell, 2015; Rogers, 1987). Participants' rights to self-determination must be respected, allowing them to freely decide whether to engage in the study (Rogers, 1987). Informed consent plays a critical role in this process, ensuring that participants fully understand the study's purpose, their role, the procedures involved, and their right to withdraw at any time without facing any consequences (Rallis & Rossman, 2009; Rogers, 1987). Furthermore, researchers must recognize that studies often benefit them more than the participants, making it imperative to protect participants from disadvantage or public exposure (Rogers, 1987). The ethical use of the collected information is vital to maintaining trust and upholding the integrity of the research (Rogers, 1987). This study will implement comprehensive measures to ensure the ethical treatment and protection of participants throughout the research process in accordance with APA ethical guidelines and institutional requirements.

Before the interview

All UAGC research studies must undergo institutional review, as required by the 1974 National Research Act (Rogers, 1987). The IRB is a committee that reviews the research proposal to ensure compliance with ethical standards. The UAGC IRB committee is guided by the ethical principles in the Declaration of Helsinki, the National Commission for the Protection of Human Participants of Biomedical and Behavioral Research's Ethical Principles, and Guidelines for the Protection of Human Participants of Research: The Belmont Report to ensuring the ethical standards of a study prior to commencement (UAGC, 2024).

The informed consent process will begin when potential participants express interest in the study. The recruitment flyer will have relevant information regarding the study, such as the requirement to participate, the study's purpose, time commitment, and a link to participate. Starting the process with transparency is necessary not only for informed consent but also to establish trust with the potential participants (Kaiser, 2009). Once eligibility is confirmed, the participant will receive an informed consent form explaining the study's purpose, procedures, potential risks and benefits, and their rights as participants. The form will explicitly state that participation is voluntary and that participants may withdraw at any time without consequence. It will also clarify that while the study may have more significant benefits for research than for individual participants, their information will be protected and used solely for the stated research purposes. Participants will provide consent digitally through a secure Microsoft Forms platform, and all consent documentation will be stored in an encrypted, password-protected folder accessible only to the researcher.

According to Kaiser (2009), a common occurrence in qualitative research is confidentiality breaches via deductive disclosure, combining unique traits to identify participants. Therefore, to protect the participant's anonymity and confidentiality, they will be assigned a unique identification code (UID). The researcher will use this UID to identify the participants throughout the study. All files and any mention of the participant within research documents will be replaced with the UID. This approach is intended to safeguard the participant's privacy and minimize the risk of potential breaches of confidentiality. Any other personally identifiable information (PII) will be scrubbed as soon as it has been confirmed that it is not needed (Arifin, 2018).

During the interview

To protect participant confidentiality, interviews will be conducted individually in private settings via password-protected Microsoft Teams meetings. Participants will be asked to move to a private and quiet location to protect their privacy, maximizing the guarantee that only the researcher will be able to match their identity with the recording (Arifin, 2018). While complete anonymity cannot be guaranteed due to the face-to-face nature of interviews, confidentiality will be strictly maintained (Rallis & Rossman, 2009; Rogers, 1987).

After the interview

All research data will be stored securely on personal laptops or the university's cloud solution, Microsoft O365, following NIST Digital Guidelines (Grassi et al., 2017) and CISA (CISA, 2024) password requirements. Data will be maintained in the researcher's personal UAGC Microsoft OneDrive storage with restricted access permissions for five years, as per UAGC research governance policies and APA recommendations, after which it will be destroyed. Interview recordings and transcripts will be stored securely and disposed of once they are no longer needed for research purposes.

Before the data is stored, all identifying characteristics such as names, occupations, company details, and locations will be removed or changed (Kaiser, 2009). Particular attention will be paid to avoiding deductive disclosure (Kaiser, 2009). When data is required to be transferred, it will be shared using secure methods, including password protection, email encryption, and encryption in transit. Participants' names will be kept in a document separate from their data, and only the researcher, the dissertation chair, and IRB will have access to the key, which could link the participants' names and data.

When disseminating results, careful consideration will be given to protecting participant identities while sharing meaningful findings. Results will be presented in aggregate form where possible, and specific details that could identify participants or their organizations will be carefully screened (Kaiser, 2009). The research findings will be crafted with an awareness that participants may access the published results, ensuring that shared information maintains promised confidentiality while contributing to scholarly research (Kaiser, 2009).

Summary

In summary, Chapter III describes the methodology for a basic qualitative study examining how and why U.S.-based SMEs strategically respond to institutional pressures when implementing responsible AI technologies. The study will leverage semi-structured interviews with AI practitioners from SMEs, recruited through purposive sampling combining criterion and snowball approaches. Data collection will begin with pilot testing of the interview protocol. Results from the pilot will be incorporated into the main study, where semi-structured interviews will be conducted, recorded, and transcribed. Data analysis will follow Braun and Clarke's six-phase thematic analysis approach using ATLAS.ti software, with coding grounded in Oliver's typology. The study addresses trustworthiness and ethical concerns that enhance the study's integrity and set a strong premise for the forthcoming analysis in Chapter IV. Chapter IV will delve into the empirical findings of the SME AI practitioners' experiences as they relate to strategically responding to institutional pressures when implementing rAI technologies.

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APPENDIX A: MODERATOR REQUEST

Subject: UAGC Research Study: Request to Solicit

My name is Erica Veal, a doctoral candidate at The University of Arizona Global Campus. I am conducting a study about organizational responses to internal and external pressures in small and medium-sized enterprises (SMEs) based in the United States. This study is being conducted to understand how SMEs respond to those pressures as they implement responsible AI. Your participation is invaluable in contributing to this area of research.

I am kindly requesting your permission to solicit participation from the members of the [Group Name]. I am looking for individuals who work with AI at a U.S.-based business with fewer than 500 employees. I would like to post the attached flyer. Your support would be instrumental in advancing the understanding of strategic responses to institutional pressures in the AI industry.

Please reply to this email with your response. I thank you for your time and consideration. If you have any questions or concerns, feel free to reach out to me or my dissertation chair, Cynthia Loubier-Ricca, at [redacted].

Erica Veal
Candidate, Ph.D. in Organizational Development & Leadership
Organizational Diversity
College of Doctoral Studies
The University of Arizona, Global Campus

Attachment: Recruitment Flyer

APPENDIX B: RECRUITMENT FLYER

APPENDIX C: INTERVIEW PROTOCOL

Thank you for completing the screening survey and for creating time for this interview. As a reminder, this study is about organizational responses to internal and external pressures in small and medium-sized enterprises based in the United States. This study is being conducted to understand how SMEs respond to those pressures as they implement responsible AI.

This interview is expected to take approximately 60 minutes. The questions will be open-ended to get a better understanding of the nuances of your organization. None of the questions have a right or wrong answer, and I want you to feel open to speaking freely about your perceptions. I would like to remind you of your written consent to participate in this study. Your participation in this interview is entirely voluntary. Although it is not my intention, some of the questions that I will ask may be triggering to you. If at any time you need to stop, take a break, or return to a question, please let me know. You may also withdraw your participation at any time without consequence. The information collected will not disclose any sensitive or identifiable information about you. You will receive a copy of this interview transcript to review and will be asked to read through the transcript to ensure it reflects exactly what was spoken about today. In order for me to accurately document the information you convey, I would like your permission to record this interview. If, at any time during the interview, you wish to discontinue recording or the interview itself, please feel free to let me know. Additionally, I may also take some notes throughout the interview to help me find commonalities in my findings with other interviews I have conducted. Do I have your permission to continue with the recorded interview?

- *Verify permission.*
    - *If yes, continue.*
    - *If no, stop the interview and thank them for their consideration.*

Thank you for confirming. Before I begin recording, do you have any questions?

- *Acknowledge any questions*
- *Begin recording*

Okay, let's begin.

I want to begin with some questions about your role and company.

1. Background and Company Context

- What is your role in the company?
    - How long have you been with the company?
    - Could you describe a typical day in your role?
- Could you tell me about your company?

    - How does your company use AI?
    - What problems do your company solve?
    - Who are your primary customers/users?

2. **AI Implementation and Strategy**
    - How does your organization define AI?
        - How is responsible AI defined?
        - How is this communicated across the organization?
    - Why did your team decide AI was the right approach?
        - What alternatives were considered?
        - How was this decision made?
        - Who were the key stakeholders in this decision?

3. **Institutional Pressures and Challenges**
    - What barriers does your company face in implementing AI?

      Technical Constraints:
        - What technical limitations have you encountered?
        - How do you address infrastructure challenges?

      Resource Constraints:
        - How do you manage talent acquisition and retention?

      Process Constraints:
        - What organizational policies affect AI implementation?
        - How have processes changed now that AI is being implemented?
        - Who is involved in those changes?

      Financial Constraints:
        - What financial constraints affect implementation?
        - Describe the funding landscape for your AI initiatives.
            - Prompt: Do you have multiple initiatives, and if so, are they supported by different funding sources?
        - How do investors/funders view AI implementation?
        - What are investors'/funders' expectations regarding ethical AI?
        - How do funding constraints affect your AI strategy?

      Competitive Constraints:
        - What competitive pressures influence your AI implementation?
        - Who are your main competitors?
        - How does their AI usage affect your strategy?
        - What market pressures affect your decisions?

      Regulatory Constraints:
        - How do federal/state/local requirements affect your implementation?
        - What voluntary standards have you adopted?
        - How does legal compliance integrate with AI development?

4. **Stakeholder Management**
   - Who are your key stakeholders in AI implementation?
   - How do you prioritize different stakeholder interests?
   - How do you manage conflicting stakeholder demands?
5. **Organizational Values and Ethics**
   - What are your company's core values regarding AI?
     - How are these values integrated into AI development?
     - How do you measure alignment with these values?
     - What challenges arise in maintaining these values?
   - How does your organization approach responsible AI?
     - What frameworks or guidelines do you follow?
     - How do you measure success in responsible AI?
     - What trade-offs have you encountered?
   - Can you describe collaboration across departments on AI initiatives?
     - How do different teams contribute to AI development?
     - What challenges arise in cross-functional collaboration?
     - How are ethical considerations integrated across teams?
6. **Future Vision and Strategy**
   - What is your vision for responsible AI in your organization?
     - What steps are needed to achieve this vision?
     - What obstacles do you anticipate?

I have three final questions.

7. **Closing**
   - Is there anything else you would like to share about your experience with AI implementation that we have not covered?
   - During my analysis, I may need clarity on some of your responses. May I contact you by email if I have any follow-up questions?
   - Can you recommend any other professionals that may want to participate in this study?

This concludes the interview. If you have any questions and/or concerns, feel free to contact me. I understand time is a precious commodity and I thank you for giving your time to advance research. If you are interested in the study results, let me know, and I will be happy to share a summary of the study's outcome.

APPENDIX D: SCREENING SURVEY

THE UNIVERSITY OF ARIZONA
GLOBAL CAMPUS

Screening Survey

Title of Study: Responsible AI in the U.S.: Strategic Responses of SMEs to Institutional Pressures

Researcher: Erica Veal

Institution: The University of Arizona Global Campus

Thank you for your interest in participating in this research study. This brief screening survey will help determine if you meet the criteria for the study.

Your participation is voluntary, and you may withdraw at any time without penalty. All information you provide will be kept confidential.

Note: If eligible, there will be three additional forms to fill out (digitally):

1. Informed Consent
2. Pre-Interview Questionnaire (12 questions)
3. Scheduling 60-minute interview

Is your company based in the U.S.? *

- ◯ Yes
- ◯ No

Is your organization considered a small and medium-sized enterprise (SME)? *

- ◯ Yes
- ◯ No

Does some aspect of your work related to AI? *

- ◯ Yes
- ◯ No

Have you been working with AI in your current role for at least 3 months? *

- ◯ Yes
- ◯ No

Are you proficient in English? *

- ◯ Yes
- ◯ No

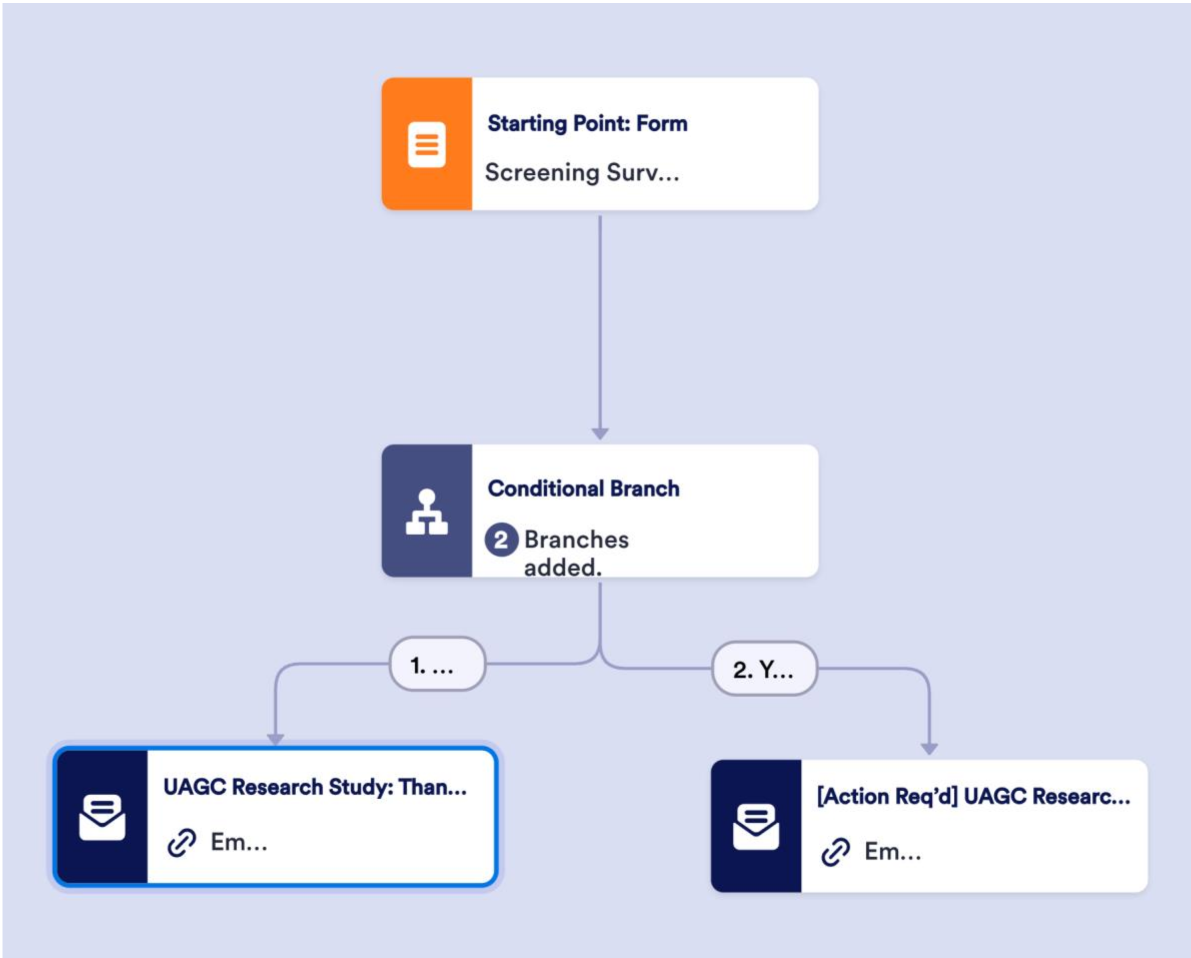
Email *

[ ]

example@example.com

Next

APPENDIX E: SCREENING SURVEY WORKFLOW



APPENDIX F: INELIGIBLE FOR THE STUDY

Subject: UAGC Research Study: Thank You for Your Response

Thank you for your interest in participating in my research study. I have reviewed your responses to the screening survey. Unfortunately, you do not meet the criteria for this study.

I appreciate you taking the time to complete the screening survey.

Erica Veal
Candidate, Ph.D. in Organizational Development & Leadership
Organizational Diversity
College of Doctoral Studies
The University of Arizona, Global Campus

APPENDIX G: INFORMED CONSENT FORM TO PARTICIPATE IN A RESEARCH STUDY

Informed Consent Form

Title of Study: Responsible AI in the U.S.: Strategic Responses of Small- and Medium-Sized Enterprises to Institutional Pressures

Researcher: Erica Veal

Thank you for considering participation in this study about organizational responses to internal and external pressures in small and medium-sized enterprises (SMEs) based in the United States. This study is being conducted to understand how SMEs respond to those pressures as they implement responsible AI. Your participation is invaluable in contributing to this area of research.

Thank you for considering participation in this study about organizational responses to internal and external pressures in small and medium-sized enterprises (SMEs) based in the United States. This study is being conducted to understand how SMEs respond to those pressures as they implement responsible AI. Your participation is invaluable in contributing to this area of research.

Purpose of the Study and the Nature of Your Participation
The purpose of this qualitative study is to understand how U.S.-based SMEs strategically respond to institutional pressures faced when implementing responsible AI. Your involvement will entail participating in a semi-structured interview, during which you will be asked about your experiences and perceptions related to implementing responsible AI. The interview will take approximately 60 minutes and will be audio-recorded and transcribed for accuracy. You will have the opportunity to review the interview recording and transcription after the interview. All recordings will be non-identifiable by your name. Demographic data will also be collected for aggregate reporting only.

Voluntary Participation and Withdrawal
Your participation in this study is entirely voluntary. There is no financial incentive for participation. You have the right to withdraw from the study at any point without any penalty, and you may choose not to answer any specific question(s).

Confidentiality
The confidentiality of your information will be maintained throughout the study. Data will be stored securely and accessible only to the research team. All participants will be assigned pseudonyms in transcripts and reports. After the study, all data will be stored securely for a specified period and then destroyed.

Risks and Benefits

There are minimal risks in participating in this study, like those encountered in everyday life. While there may not be direct benefits to you, your participation will contribute to the knowledge of responsible AI and the development of practical frameworks for responsible AI.

Results Sharing
The results of this study will be included in a dissertation manuscript, which will be made publicly available upon completion.

Right of Refusal/Withdrawal
To withdraw, please get in touch with the researcher via email with a written notice of withdrawal.

Contact Information
For questions about the study, contact Erica Veal at [redacted]. If you have concerns about your rights as a participant, contact Cynthia Loubier-Ricca at [redacted]

Consent
☐ I confirm that I am over 21.
☐ I confirm that I have read and understand the information regarding this study. I have had the opportunity to consider the information, ask questions, and have these answered satisfactorily
☐ I understand that my participation is voluntary and that I am free to withdraw at any time without giving any reason.
☐ I understand that any information I provide may be used in future reports, articles, or presentations by the research team.
☐ I understand that my name will not appear in any reports, articles, or presentations
☐ I give my informed consent to take part in this study.

Participant's Name (Printed) ______________________

Signature: ______________________

Date: ______________________

Researcher's Name (Printed): ______________________

Signature: ______________________

Date: ______________________

IRB Approval Number: __________ IRB Expiration Date __________

APPENDIX H: INFORMED CONSENT FOR RESEARCH STUDY

THE UNIVERSITY OF ARIZONA
GLOBAL CAMPUS

Informed Consent For Research Study

Title of Study: Responsible AI in the U.S.: Strategic Responses of SMEs to Institutional Pressures

Researcher: Erica Veal

Institution: The University of Arizona Global Campus

Thank you for considering participation in this study about organizational responses to internal and external pressures in small and medium-sized enterprises (SMEs) based in the United States. This study is being conducted to understand how SMEs respond to those pressures as they implement responsible AI. Your participation is invaluable in contributing to this area of research.

Purpose of the Study and the Nature of Your Participation
The purpose of this study is to understand how and why U.S.-based SMEs strategically respond to institutional pressures faced in the AI industry. Your involvement will entail participating in a semi-structured interview, during which you will be asked about your experiences and perceptions related to implementing responsible AI. The interview will take approximately 60-90 minutes and will be audio-recorded and transcribed for accuracy. You will have the opportunity to review the interview recording and transcription after the interview. All recordings will be non-identifiable by your name. Demographic data will also be collected for aggregate reporting only.

Voluntary Participation and Withdrawal
Your participation in this study is entirely voluntary. There is no financial incentive for participation. You have the right to withdraw from the study at any point without any penalty, and you may choose not to answer any specific question(s).

Confidentiality
The confidentiality of your information will be maintained throughout the study. Data will be stored securely and accessible only to the research team. All participants will be assigned pseudonyms in transcripts and reports. After the study, all data will be stored securely for a specified period and then destroyed.

Risks and Benefits
There are minimal risks in participating in this study, like those encountered in everyday life. While there may not be direct benefits to you, your participation will contribute to the knowledge of responsible AI and the development of practical

Right of Refusal/Withdrawal
To withdraw, please get in touch with the researcher via email with a written notice of withdrawal.

Contact Information
For questions about the study, contact Erica Veal at Erica.Veal@student.uagc.edu. For concerns about your rights as a participant, contact Cynthia Loubier-Ricca at Cynthia.Loubier@faculty.uagc.edu

Consent
By signing below, you confirm that you are over 21, voluntarily agree to participate, and have understood the information provided. You acknowledge that your questions have been answered satisfactorily.

IRB Approval #: 25-###-UAGC
IRB Expiration Date: MM/DD/YYYY

Consent

- [ ] I confirm that I am over 21.
- [ ] I confirm that I have read and understand the information regarding this study. I have had the opportunity to consider the information, ask questions, and have had these answered satisfactorily.
- [ ] I understand that my participation is voluntary and that I am free to withdraw at any time without giving any reason.
- [ ] I understand that any information I provide may be used in future reports, articles, or presentations by the research team.
- [ ] I understand that my name will not appear in any reports, articles, or presentations.
- [ ] I give my informed consent to take part in this study.

Decline

- [ ] I do not consent

Signature *

Sign Here

Powered by Jotform Sign Clear

Participant's Name *

Date

01-15-2025

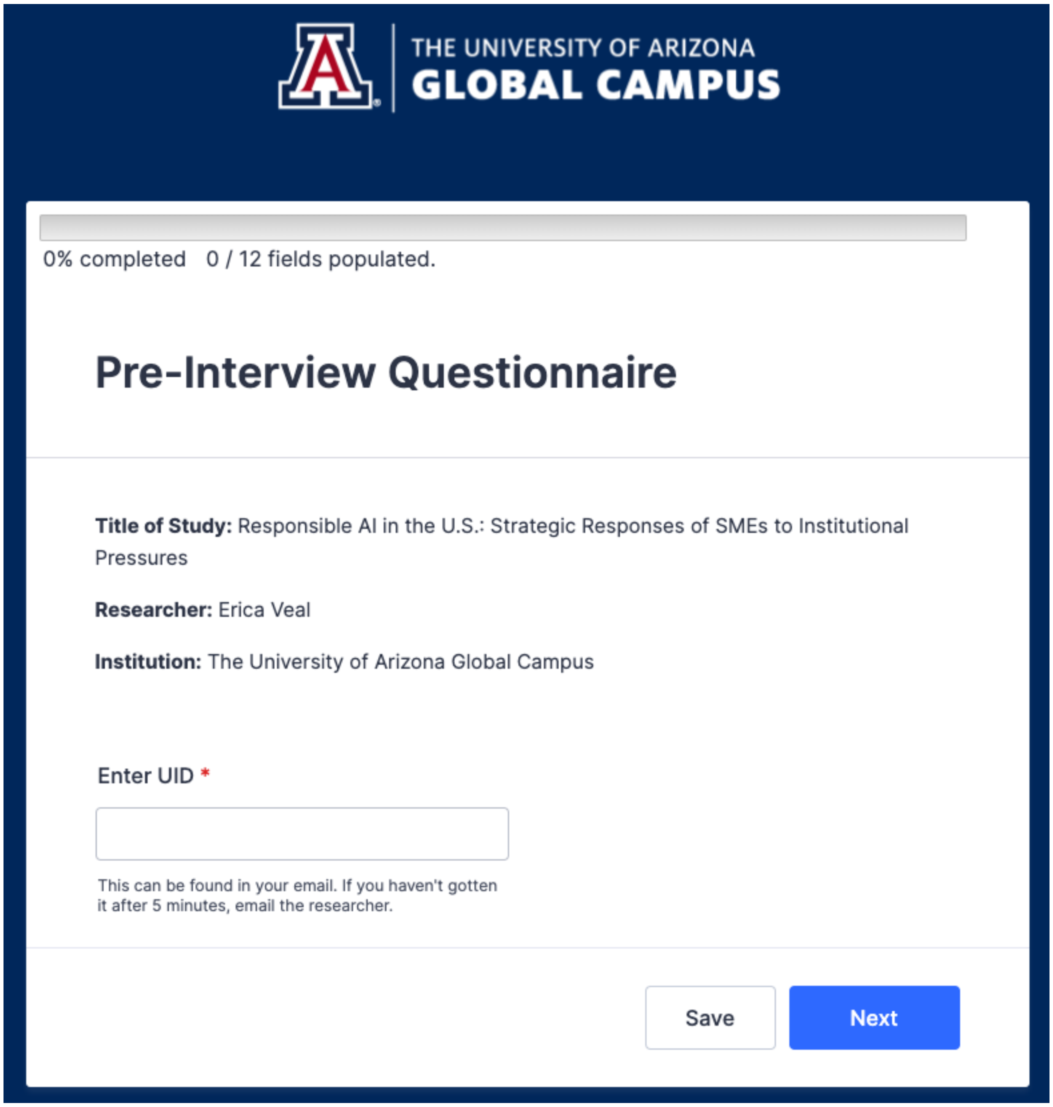
Date

Email *

example@example.com

Continue

APPENDIX I: PRE-INTERVIEW QUESTIONNAIRE



THE UNIVERSITY OF ARIZONA
GLOBAL CAMPUS

0% completed 0 / 12 fields populated.

Pre-Interview Questionnaire

Title of Study: Responsible AI in the U.S.: Strategic Responses of SMEs to Institutional Pressures

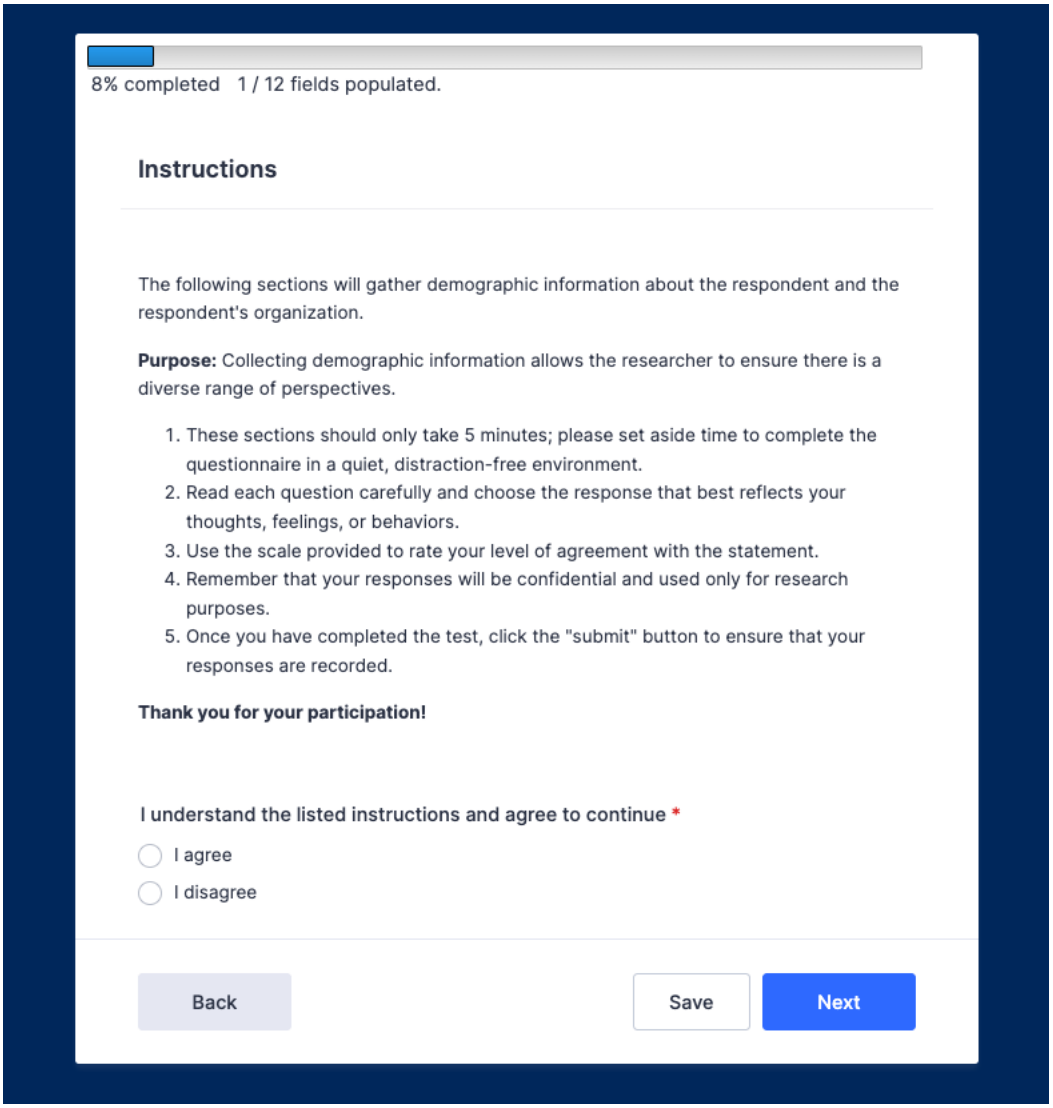
Researcher: Erica Veal

Institution: The University of Arizona Global Campus

Enter UID *

This can be found in your email. If you haven't gotten it after 5 minutes, email the researcher.

Save Next



8% completed 1 / 12 fields populated.

Instructions

The following sections will gather demographic information about the respondent and the respondent's organization.

Purpose: Collecting demographic information allows the researcher to ensure there is a diverse range of perspectives.

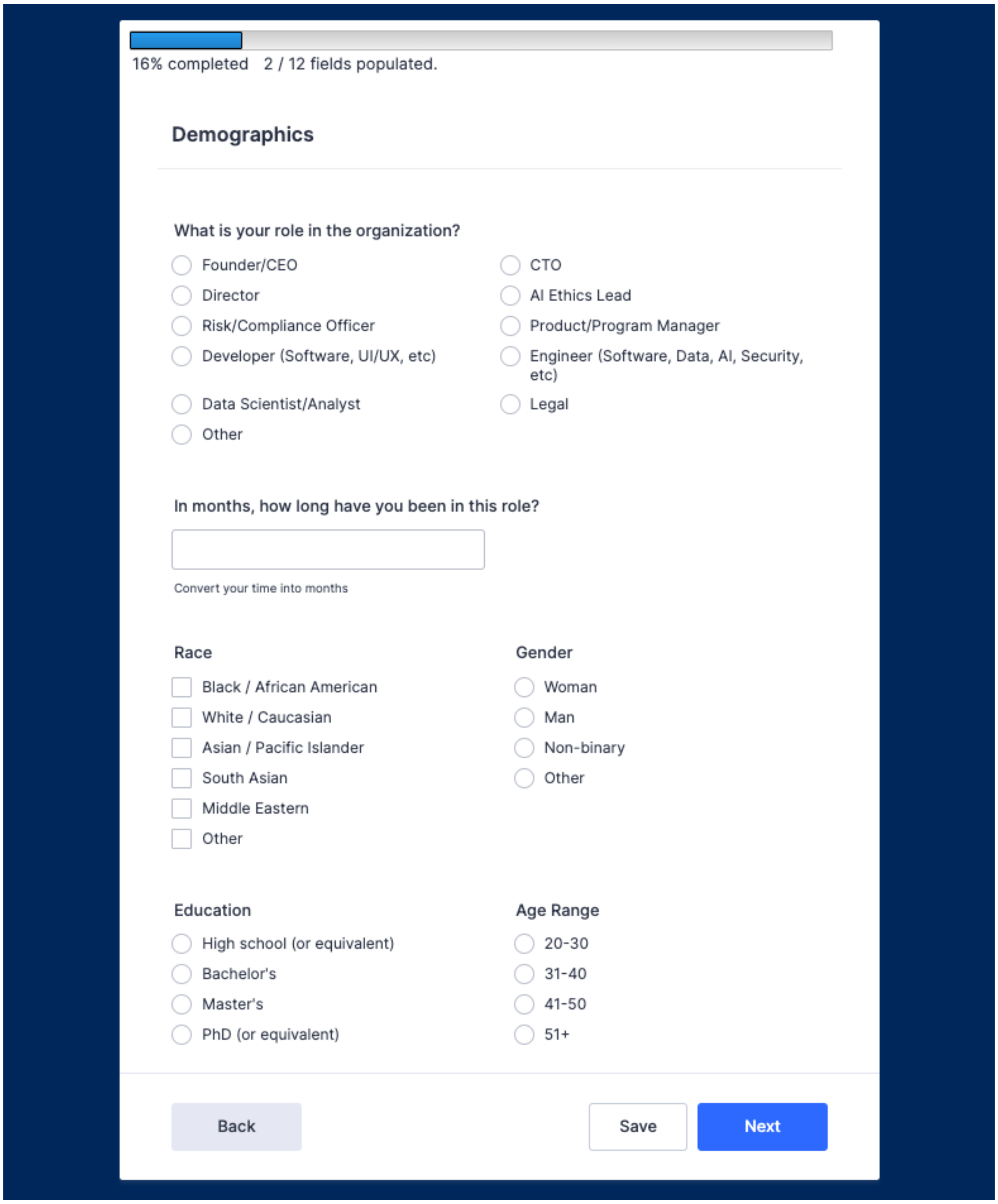
1. These sections should only take 5 minutes; please set aside time to complete the questionnaire in a quiet, distraction-free environment.
2. Read each question carefully and choose the response that best reflects your thoughts, feelings, or behaviors.
3. Use the scale provided to rate your level of agreement with the statement.
4. Remember that your responses will be confidential and used only for research purposes.
5. Once you have completed the test, click the "submit" button to ensure that your responses are recorded.

Thank you for your participation!

I understand the listed instructions and agree to continue *

- I agree
- I disagree

Back Save Next


16% completed 2 / 12 fields populated.

Demographics

What is your role in the organization?

- Founder/CEO
- CTO
- Director
- AI Ethics Lead
- Risk/Compliance Officer
- Product/Program Manager
- Developer (Software, UI/UX, etc)
- Engineer (Software, Data, AI, Security, etc)
- Data Scientist/Analyst
- Legal
- Other

In months, how long have you been in this role?

Convert your time into months

Race

- Black / African American
- White / Caucasian
- Asian / Pacific Islander
- South Asian
- Middle Eastern
- Other

Gender

- Woman
- Man
- Non-binary
- Other

Education

- High school (or equivalent)
- Bachelor's
- Master's
- PhD (or equivalent)

Age Range

- 20-30
- 31-40
- 41-50
- 51+

Back Save Next

THE UNIVERSITY OF ARIZONA
GLOBAL CAMPUS

16% completed 2 / 12 fields populated.

Company/Organization Demographics

Number of employees

- ◯ 1-10
- ◯ 11-50
- ◯ 51-100
- ◯ 101-250
- ◯ 251-500

Industry/Sector

- ◯ Technology
- ◯ Healthcare
- ◯ Finance
- ◯ Manufacturing
- ◯ Energy
- ◯ Retail
- ◯ Construction
- ◯ Government
- ◯ Other

Company's HQ location (State)

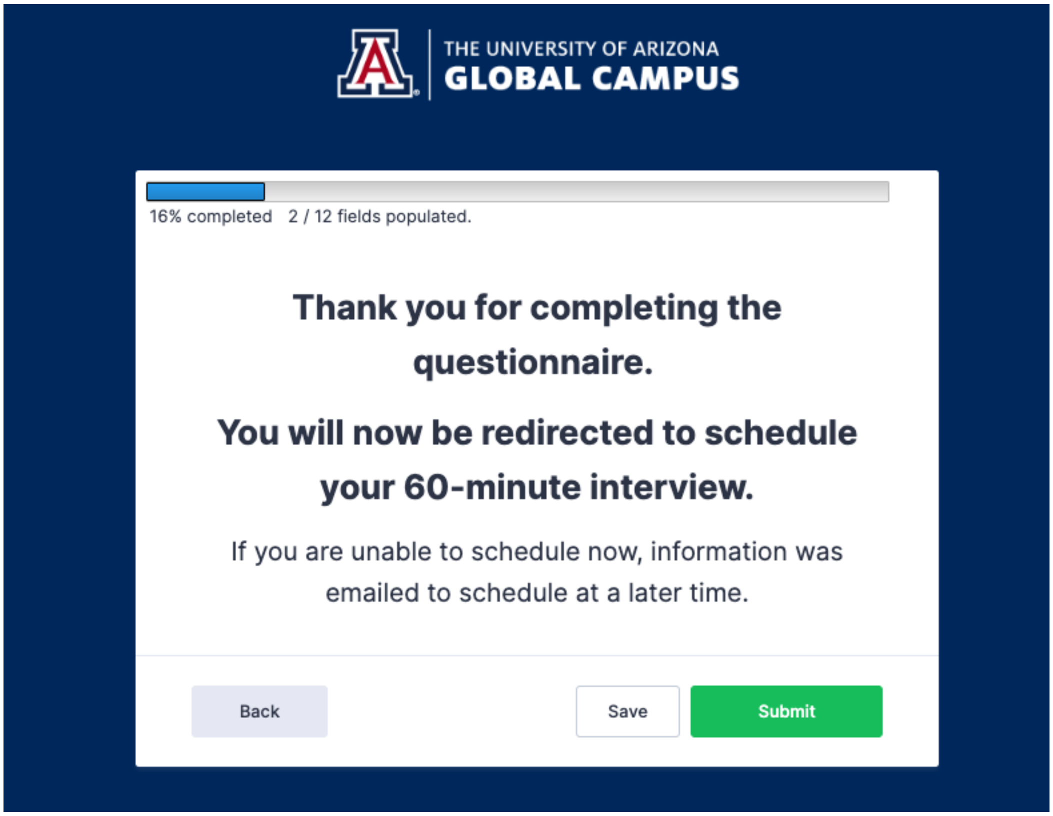
Please select

In years, how long has your company been implementing AI technologies?

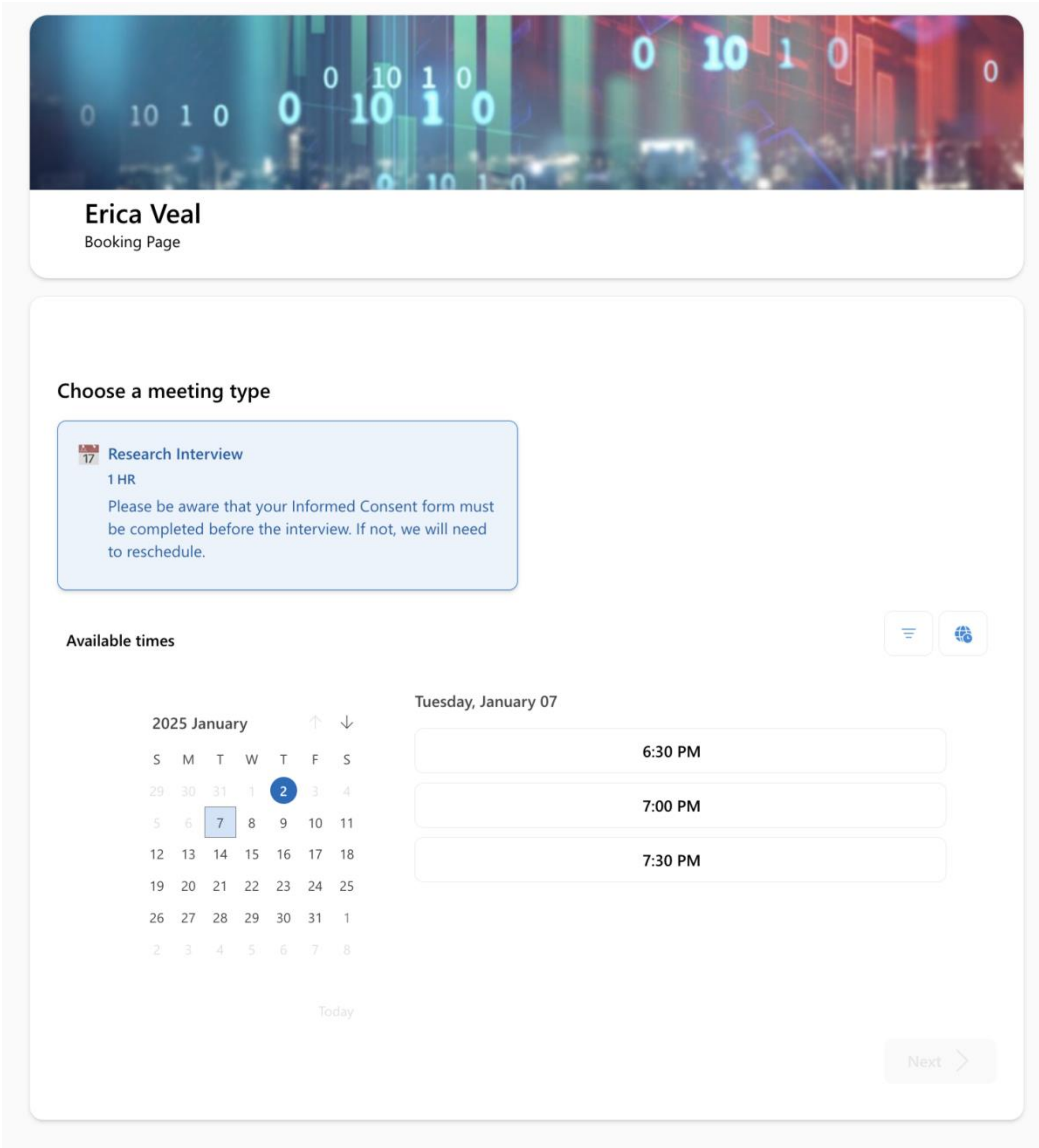
Is your organization developing AI technology, purchasing an AI solution or both?

- ◯ Developing
- ◯ Purchasing
- ◯ Both

Back Save Next


THE UNIVERSITY OF ARIZONA
GLOBAL CAMPUS
16% completed 2 / 12 fields populated.
Thank you for completing the questionnaire.
You will now be redirected to schedule your 60-minute interview.
If you are unable to schedule now, information was emailed to schedule at a later time.
Back
Save
Submit

APPENDIX J: INTERVIEW SCHEDULING



APPENDIX K: INVITATION TO PARTICIPATE

Subject: [Action Req'd] UAGC Research Study: You Are Eligible for the Study!

Thank you for completing the screening survey.

Based on your responses, you are eligible to participate in my research study, Responsible AI in the U.S.: Strategic Responses of SMEs to Institutional Pressures.

The purpose of my study is to understand organizational responses to internal and external pressures in small and medium-sized enterprises (SMEs) based in the United States. This study is being conducted to understand how and why SMEs respond to those pressures as they implement responsible AI.

Your participation in this study will help better understand how SMEs make decisions about implementing responsible AI practices. This knowledge can guide the development of frameworks and policies that promote more ethical and responsible AI technologies.

Participants in this study will be interviewed to understand their perception of what influences the decisions to comply or resist internal and external pressures. Interviews will take place virtually via Microsoft Teams and should last no more than 60 minutes.

If you are still interested, please complete the following:

1. Informed Consent Form
2. Pre-Interview Questionnaire
3. Schedule your 60-minute interview.

If you have any questions regarding your participation in the study or if you want to verify the authenticity of the study, please contact the dissertation chair, Dr. Cynthia Loubier-Ricca, via email at [redacted] or the University of Arizona Global Campus Institutional Review Board Chair at IRB@uagc.edu.

Your UID is **UAGC-P##**

Thank you again for your interest.

Erica Veal
Candidate, Ph.D. in Organizational Development & Leadership
Organizational Diversity
College of Doctoral Studies
The University of Arizona, Global Campus

APPENDIX L: INTERVIEW CONFIRMATION

Subject: UAGC Research Study: Interview Scheduled

Thank you for agreeing to participate in our research study. This email confirms your interview scheduled for [Date] at [Time].

I look forward to speaking with you. As discussed, the interview will take approximately 60 minutes and will be conducted via Microsoft Teams.

I've attached the interview guide, which outlines the topics we'll discuss. While we'll generally follow this structure, please feel free to share additional insights based on your experiences.

If you need to reschedule or have any questions before our meeting, please don't hesitate to contact me at [redacted]

Thank you again for your contribution to this research.

Erica Veal
Candidate, Ph.D. in Organizational Development & Leadership
Organizational Diversity
College of Doctoral Studies
The University of Arizona, Global Campus

Attachment: Interview Guide

APPENDIX M: TRANSCRIPT VERIFICATION EMAIL

Subject: [Action Req'd] UAGC Research Study: Interview Follow-up

Thank you for participating in our research interview on [Date].

I have attached a password-protected transcript of our conversation for your review. The password is your full UID, which you can find in your invitation email. (Please reach out if you have trouble finding it.) This review intends to ensure accuracy, allow for clarification, and provide transparency of the data to ensure your perspective was accurately captured.

If you have any changes or comments, please track them directly in the document or list them in your reply. If everything appears accurate, a simple confirmation email will suffice. Please provide your feedback within three (3) calendar days of receipt. If I don't hear from you by then, I will assume you are satisfied with the transcript as is.

Note: All communication and research materials are stored in an encrypted, secured drive and will be held no longer than 5 years from the completion of the research. Collected data for this research will never be shared beyond what is allowed by the APA.

Erica Veal
Candidate, Ph.D. in Organizational Development & Leadership
Organizational Diversity
College of Doctoral Studies
The University of Arizona, Global Campus

Attachment: Participant's Transcript