EXPLORING THE AI ADOPTION CHALLENGES IN SMALL ENTERPRISES IN NON-TECHNOLOGY INDUSTRIES

by

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ABSTRACT

This study examines the challenges and strategies associated with adopting artificial intelligence (AI) in small enterprises within non-technology industries. Utilizing a mixed-methods approach, the research integrates quantitative analysis of datasets, including AI risk repositories and tools, with qualitative insights from case studies of GetTransfer, FC Beauty, and PhoenixFire. The findings reveal that while AI tools like productivity and chat applications dominate due to their accessibility and utility, small businesses face significant hurdles, including resource constraints, technical expertise deficits, and vague ethical standards. Case studies highlight contrasting approaches: internal AI development versus strategic partnerships with external experts. This study underscores the importance of resource allocation, leadership, and ethical frameworks in mitigating AI adoption barriers. The implications extend to providing actionable recommendations for small enterprises, while the study acknowledges limitations such as the narrow case study scope and reliance on secondary data. Future research opportunities include broader longitudinal studies and exploration of advanced AI applications across diverse non-technology sectors.

Contents

1. Introduction:

Artificial intelligence (AI) adoption presents tremendous opportunities as well as unique challenges for small enterprises, especially those in non-technology industries. However, research shows that AI integration in small enterprises remains limited, with only 29% of small businesses having deployed AI capabilities (Press, 2020). This highlights the need to explore strategies to mitigate impediments to AI adoption. Therefore, the purpose of this study is to identify approaches small enterprises in non-technology sectors can employ to overcome barriers to integrating AI into their operations and leveraging its benefits.

The central research question guiding this study is: What can small enterprises in non-technology industries do to mitigate the AI adoption challenges? Additional sub-questions include: What are the key barriers faced by small non-tech enterprises in AI adoption? What strategies have been successfully employed by small non-tech companies to facilitate AI integration? Answering these questions will provide valuable insights to guide small enterprises in harnessing AI's potential.

This research is significant because its findings can assist small businesses in non-technology sectors to adopt AI more readily. Enhanced AI integration can strengthen the competitiveness and sustainability of small enterprises. The study aims to produce practical strategies tailored to the unique needs of small non-tech companies based on an analysis of real-world cases.

To provide focus, small enterprises are defined as companies with fewer than 100 employees, while non-technology industries include sectors not specializing in information technology like manufacturing, construction, retail, and hospitality (Gartner, n.d.). Delimitations

include the exclusion of medium and large enterprises. Key assumptions are that participants will respond honestly, and the methodology will elicit insights representative of the target population.

This thesis is organized into five chapters covering the introduction, literature review, methodology, results, and conclusions. The following chapter presents a literature review exploring existing research on this topic.

2. Literature Review:

This literature review aims to explore the strategies employed by such enterprises to mitigate the hurdles associated with AI adoption. By analyzing the existing body of research, this review seeks to offer practical insights and guidance for small-sized enterprises striving to harness the potential of AI in their operations. Specifically, I will explore the definition of small-sized enterprises, non-technology industries, and challenges faced by those companies. This literature review aims to explore the research question: What can small-sized enterprises in non-technology industries do to mitigate the AI adoption challenges?

Definition of AI:

Artificial Intelligence (AI) has been defined and interpreted differently across various disciplines, reflecting its diverse applications and rapid advancements. According to John McCarthy, one of the founding figures in AI, it is “the science and engineering of making intelligent machines” (McCarthy, 2007). This definition emphasizes the dual aspects of AI as both a theoretical and practical field, blending the study of intelligence with the development of systems capable of tasks that typically require human cognition. McCarthy’s interpretation focuses on the foundational goal of AI: replicating human-like intelligence in computational systems.

On the one hand, IBM defines AI as “technology that enables computers and machines to simulate human learning, comprehension, problem solving, decision making, creativity and autonomy” (Stryker & Kavlakoglu, 2024). This definition highlights two critical aspects: the technological capability to perform complex tasks and the distinction between true intelligence and its simulation. AI systems, while not conscious or self-aware, effectively mimic cognitive functions like reasoning, learning, and problem-solving, enabling transformative applications in fields such as healthcare, finance, and automation. For this research, I will use IBM’s definition of AI.

Small-sized enterprises:

In the context of this research paper, it is imperative to establish a clear understanding of what constitutes a small business. A prevailing perspective defines the size of a small business based on its revenue and the total number of employees across all its business locations, as opposed to assessing each location individually (Hait, 2021). This perception of “size” is notably consistent with the criteria outlined by the U.S. Small Business Administration (SBA) in its Table of Size Standards.

The SBA’s classification system provides specific definitions based on the North American Industry Classification System (NAICS) codes, offering a comprehensive framework that accommodates a wide array of industries. Within this framework, small businesses are categorized according to their annual firm revenue, which may vary significantly, ranging from $1 million to well over $40 million (Hait, 2021). Additionally, small business categorization is also contingent on the total employment figures, which can span from 100 to over 1,500 employees, depending on the specific industry (Hait, 2021).

Furthermore, Gartner's categorization of small-sized businesses is also primarily based on two key criteria: the number of employees and the annual revenue of these organizations (Gartner, n.d.). Employee count is the most employed metric, with small businesses typically characterized as entities having fewer than 100 employees (Gartner, n.d.). In term of annual revenue, small businesses are typically identified as organizations generating less than $50 million in annual revenue (Gartner, n.d.).

For this research, I will use the definition of small business based on the number of employees using Gartner's definition – companies with fewer than 100 employees. This serves as a fundamental underpinning for the subsequent analysis in this research, enabling a more precise examination of small enterprises in non-technology industries.

Non-technology industries:

Defining a non-tech industry can be somewhat subjective, as technology has become integral to most sectors. However, non-tech industries are typically those where the primary focus and core activities do not center around the development or provision of technology products or services. These industries may use technology to some extent for various purposes but are not primarily engaged in technology-related activities.

The U.S. Bureau of Labor Statistics (BLS) classifies industries based on the North American Industry Classification System (NAICS). Non-tech industries are identified by looking at specific NAICS codes that are not inherently tech related (U.S. Bureau of Labor Statistics, n.d.). For example, agriculture, mining, construction, manufacturing, retail, healthcare, education, and hospitality are often considered non-tech industries.

On the one hand, Investopedia defines technology sector as “companies specialized in electronics, software, computers, artificial intelligence, or other things related to information technology” (Scott, 2022). Thus, non-tech industries can be categorized as those that are not belong to the technology sector.

It is important to note that the line between tech and non-tech industries is increasingly blurred as technology becomes more integrated into all aspects of business. Thus, to better categorize and tailor solutions for the targeted company groups, non-technology industries are defined as businesses that do not specialize in electronics, software, computing, artificial intelligence, or other facets associated with the field of information technology.

Barriers and challenges of AI adoption in non-technology industries:

While AI has rapidly gained traction in technology-driven sectors, its adoption in non-technology industries presents a distinctive set of barriers and challenges. This section delves into a comprehensive exploration of the hurdles that non-technology industries encounter when seeking to embrace AI technologies, shedding light on the intricacies of this transformative process.

A significant barrier stems from the limited technical expertise available within SMEs, hindering the adoption of AI (Lu et al., 2022; Polas et al., 2022). This shortage of technical skills and underdeveloped infrastructure compounds the perceived risk associated with AI integration, dissuading many SMEs from embracing this transformative technology. Additionally, cost concerns loom large, as organizations fear substantial financial outlays, despite the availability of cost-effective AI technologies such as data analytics and machine learning, which primarily demand expertise rather than expensive hardware (Hansen & Bøgh, 2021).

By contrast, according to “SMEs and artificial intelligence (AI): Antecedents and consequences of AI-based B2B practices” (Baabdullah et al., 2021), to the AI enablers, mindset and technology road mapping have a major impact on the adoption of AI practices, but not professional expertise. Out of all the criteria related to AI readiness, infrastructure and awareness—rather than technicality—had the greatest impact on the adoption of AI techniques. It was discovered that the adoption of AI methods has a major impact on SME’s business performance and relational governance facilitated by AI.

More specifically, perception of AI shapes its adoption opportunities among small businesses. The prevailing perception among stakeholders, including investors and management, often underestimates the potential benefits of AI, further impeding SMEs’ willingness to adopt this innovation (Drydakis, 2022). A common perception exists that AI is often overhyped and does not yield substantial benefits for organizations, which constitutes a significant hurdle for SMEs in their AI integration endeavors (Govori & Sejdija, 2023). On the other hand, Weber (2023) discussed the unrealistic optimism regarding AI opportunities in human resource management. This highlights the need for SMEs to have a realistic understanding of the potential benefits and challenges associated with AI adoption.

Another factor is the tendency to relying on intuition in decision-making processes rather than data-driven thoughts that further hinders the adoption of AI in small businesses. Intuition is a crucial tool, according to qualitative interviews and an empirical study done with more than 300 managers and business owners at small and medium-sized companies in West Africa (Bocco & Merunka, 2013).

To address the research question regarding strategies for mitigating AI adoption challenges, this research will employ a mixed-method approach. First, I will analyze secondary

quantitative data for an empirical examination of the extent to which AI adoption has influenced small-sized enterprises in non-technology industries. Additionally, I will employ case studies, delving into specific instances of successful AI integration within these enterprises. These case studies will provide in-depth insights into the practical strategies employed, shedding light on the real-world application of AI solutions. The combination of secondary quantitative data analysis and detailed case studies will facilitate a holistic exploration of the research question, offering valuable guidance for small-sized enterprises aiming to navigate the challenges and opportunities of AI adoption. This mixed-method strategy will facilitate a holistic exploration of the research question and yield practical insights that can guide small-sized enterprises in non-technology industries toward more effective AI adoption.

How companies are adopting AI:

The "3 Ways Companies Are Building a Business Around AI" (Hardy, 2017) provides valuable insights into three core strategies employed by businesses to harness the potential of AI:

- Scarce Data Capture: Companies, like CAMP3, secure and organize unique data to train AI, making it a strategic asset. This emphasizes the importance of acquiring and managing exclusive data.
- Data Adjacency Exploration: Businesses, such as TalkIQ, analyze conversations with AI, requiring meticulous mapping and tagging of information. This approach highlights the potential of AI-driven businesses by exploring adjacent data sources.
- Customer-Centric Focus: Companies like Blinker combine AI with industry expertise to streamline customer experiences. A deep understanding of the market is pivotal for AI success.

On the one hand, the current issues that SMEs are facing due to a lack of technology and accounting expertise are thought to be resolved by ALIAS (Tarmidi, 2018). Additionally, ALIAS is one of the first systems to use smart capture technology. By using machine learning and OCR, it will help SMEs keep better financial records.

This literature review session of current scholarly research, industry reports and real-world cases provided context and background for the present study exploring how small non-tech enterprises can mitigate AI adoption challenges. The insights informed the development of the research questions and methodology.

3. Methodology:

The purpose of this chapter is to outline the research methodology utilized to explore strategies for small enterprises in non-technology industries to mitigate AI adoption challenges. This provides a framework to systematically address the research questions guiding the study.

Purpose of the Study

This study explores strategies for small enterprises in non-technology industries to mitigate AI adoption challenges by analyzing both datasets and real-world case studies. The findings aim to guide small businesses in overcoming barriers to AI integration and leveraging its benefits effectively.

Methods

The study adopts a mixed-methods approach, integrating quantitative data analysis and qualitative case study analysis to examine AI adoption's effects on small enterprises in non-tech sectors.

1. Quantitative Analysis:
    - Data Sources:
        1. The "Cutting-Edge AI Tools: An Up-to-Date Dataset" provides details on a wide range of artificial intelligence tools currently accessible in the market (Raza, 2022).
        2. The AI Risk Database identifies over 700 risks from 43 frameworks, categorizing them by causality, timing, and seven domains with 23 subdomains, including areas like misinformation (Massachusetts Institute of Technology (MIT), n.d.).
    - Data Analysis: Statistical techniques such as pivot tables and charts were used to identify top risks and top available tools.
2. Qualitative Case Study Analysis:
    - Case Selection: Case studies of GetTransfer, FC Beauty, and PhoenixFire were chosen for their relevance in illustrating small enterprise strategies and challenges in AI adoption.

Research Questions

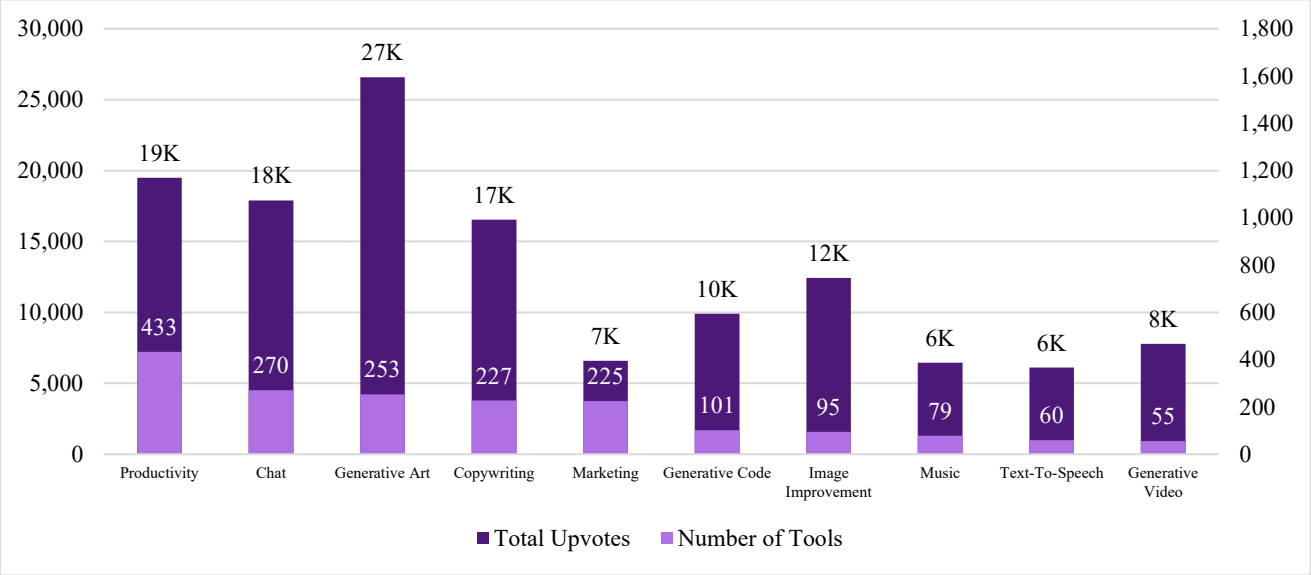
1. What challenges do small enterprises face in adopting AI?
2. Where and how should they start their AI adoption journey?
3. What types of AI tools should they prioritize?
4. What are the trade-offs between financial and operational resources during AI adoption?

The integration of quantitative metrics and qualitative insights will facilitate a robust analysis of real-world strategies and results to address the research aims. Key findings will be presented in Chapter 4.

4. Findings:

a. AI Tools to Start:

Figure 1. Top 10 Popular AI Categories



The “Cutting-Edge AI Tools: An Up-to-Date Dataset” analysis reveals significant insights into the distribution and user preferences across 28 categories of AI tools (Raza, 2022). Notably, the top 10 AI tool categories dominate the landscape, collectively accounting for 69.66% of the total 2,581 tools, equating to 1,798 tools (Figure 1). This indicates that a few categories of tools are disproportionately popular or prevalent, reflecting market demand and user reliance on specific functionalities.

Among these, productivity tools emerge as the most common category, comprising 433 tools. This prominence highlights the widespread adoption of AI in streamlining workflows, automating routine tasks, and enhancing overall efficiency in professional and personal settings.

It also reflects a strong market need for tools that can save time and optimize output, making productivity a focal area for AI innovation.

The case of PhoenixFire Design illustrates the transformative role AI productivity tools play in streamlining workflows and enhancing efficiency, supporting their prominence as the most common AI category. Using tools like ChatGPT and Google Bard, PhoenixFire accelerates its creative process by automating foundational tasks, allowing projects to reach 80% completion before manual refinement (Lewis, 2024). This demonstrates how AI saves time by handling repetitive elements, enabling teams to focus on higher-value work. The company's emphasis on "prompt engineering" highlights the importance of effective integration to maximize AI benefits, while its cost-effective adoption of accessible tools showcases how small enterprises can leverage AI without significant investment. By reducing workloads and optimizing processes, AI productivity tools fulfill a strong market demand for scalable and affordable efficiency solutions, underscoring their critical role in driving innovation across industries.

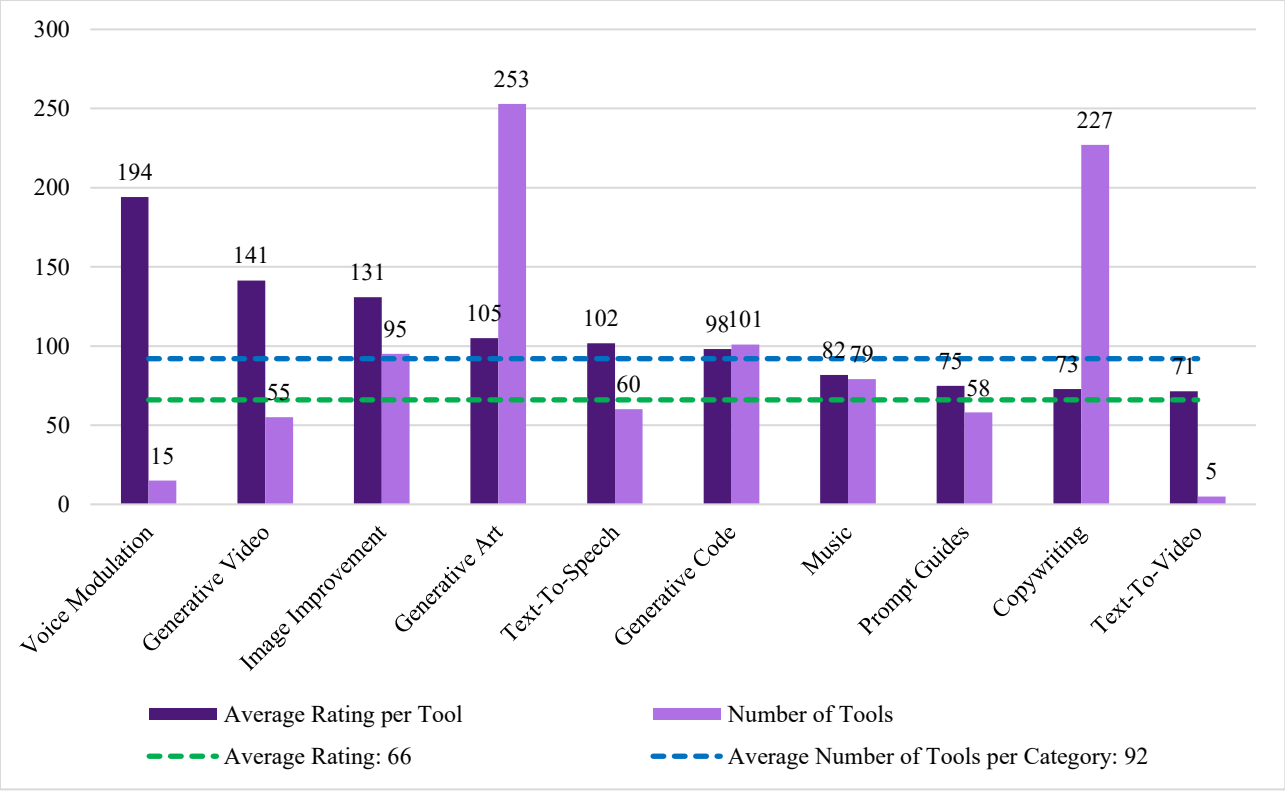
On the one hand, generative art tools, while not the most numerous, stand out for receiving the highest positive feedback from users. This suggests that these tools are not only meeting but exceeding user expectations, likely due to their creative capabilities and ability to produce visually appealing outputs that resonate with users. The high ratings also indicate that users value the unique and transformative potential of generative art tools, which often blend creativity with technical sophistication.

In addition to productivity and generative art tools, chat tools and copywriting tools also feature prominently, with 270 and 227 tools respectively. Both categories have garnered decently high user ratings, underscoring their relevance and effectiveness in meeting user needs. Chat tools, for example, are integral in customer service, personal assistance, and conversational AI

applications, while copywriting tools are valued for their ability to generate high-quality written content quickly and efficiently.

The insights highlight a few key trends in the AI tool landscape. Firstly, categories with direct and tangible utility, such as productivity and copywriting, dominate in terms of numbers. Secondly, user preferences and feedback suggest that tools offering creative and engaging experiences, such as generative art tools, are particularly well-received. Finally, the analysis underscores the diversity of AI applications, as even within the top 10 categories, there is significant variation in tool functionality and user appeal. These trends can guide further development and investment in AI tools, focusing on both widespread utility and user satisfaction.

Figure 2. Top 10 AI Categories by Rating



On the one hand, while productivity tools are the most prevalent, user preferences are shifting towards more specialized and complex categories. Referring to Figure 2, Voice Modulation tools, for instance, boast an average user rating of 194, substantially higher than the overall average rating of 66. Similarly, Generative Video and Image Improvement tools have average ratings of 141 and 131, respectively. These categories, which involve intricate audio, video, and image processing, are garnering increased user appreciation, indicating a demand for advanced functionalities beyond traditional productivity and chat applications.

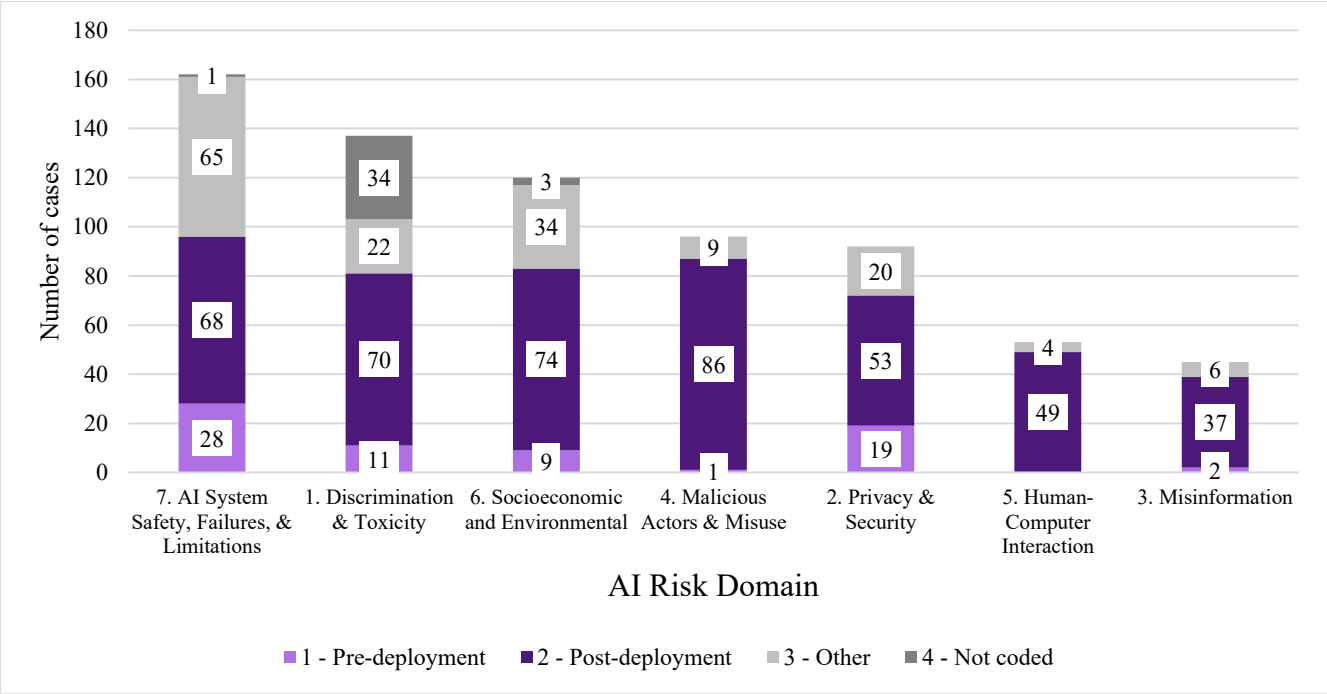
AI tools for generating image, video, and audio content exhibit significantly higher complexity compared to productivity and chat applications due to the multidimensional nature of the data they process. For example, video generation requires the AI to manage spatial relationships and ensure temporal coherence across frames, which demands sophisticated models capable of handling both spatial and temporal dependencies (Zhou et al., 2023). Similarly, audio generation involves modeling intricate temporal patterns and harmonics to produce natural and coherent outputs, which necessitates advanced signal processing techniques (Wang et al., 2023). In contrast, productivity and chat tools handle primarily linear, text-based data, which is less complex in structure and dimensionality. The added complexity in multimedia content generation stems from the need for detailed pattern recognition and high-fidelity reproduction, requiring advanced architectures and larger datasets to achieve effective results (Zhou et al., 2023; Wang et al., 2023).

b. Risks of AI adoption for small businesses

Table 1. List of AI Risk Domains and Sub Domains

AI Risk Domain and Sub Domain
1. Discrimination & Toxicity
1.0 > Discrimination & Toxicity
1.1 > Unfair discrimination and misrepresentation
1.2 > Exposure to toxic content
1.3 > Unequal performance across groups
2. Privacy & Security
2.0 > Privacy & Security
2.1 > Compromise of privacy by leaking or correctly inferring sensitive information
2.2 > AI system security vulnerabilities and attacks
3. Misinformation
3.0 > Misinformation
3.1 > False or misleading information
3.2 > Pollution of information ecosystem and loss of consensus reality
4. Malicious Actors & Misuse
4.0 > Malicious use
4.1 > Disinformation, surveillance, and influence at scale
4.2 > Cyberattacks, weapon development or use, and mass harm
4.3 > Fraud, scams, and targeted manipulation
5. Human-Computer Interaction
5.1 > Overreliance and unsafe use
5.2 > Loss of human agency and autonomy
6. Socioeconomic and Environmental
6.0 > Socioeconomic & Environmental
6.1 > Power centralization and unfair distribution of benefits
6.2 > Increased inequality and decline in employment quality
6.3 > Economic and cultural devaluation of human effort
6.4 > Competitive dynamics
6.5 > Governance failure
6.6 > Environmental harm
7. AI System Safety, Failures, & Limitations
7.0 > AI system safety, failures, & limitations
7.1 > AI pursuing its own goals in conflict with human goals or values
7.2 > AI possessing dangerous capabilities
7.3 > Lack of capability or robustness
7.4 > Lack of transparency or interpretability
7.5 > AI welfare and rights

Figure 3. Popularity of AI Risk Domains by Deployment Type



The "AI Risk Repository" dataset of 1,041 recorded cases reveals significant insights into the risk domains associated with artificial intelligence (AI) (Massachusetts Institute of Technology (MIT), n.d.). Out of these, 705 cases, constituting 67.72% of the total, were categorized into seven key risk domains. These domains include 1. Discrimination & Toxicity, 2. Privacy & Security, 3. Misinformation, 4. Malicious Actors & Misuse, 5. Human-Computer Interaction, 6. Socioeconomic and Environmental impacts, and 7. AI System Safety, Failures, & Limitations. Among these, AI System Safety, Failures, & Limitations emerged as the most frequently observed risk, accounting for 22.98% of cases (162 cases) (Figure 3). This category highlights challenges such as safety, failures, and limitations; the pursuit of conflicting goals with human values; possession of dangerous capabilities; lack of capability or robustness; lack of transparency or interpretability; and considerations for AI welfare and rights.

Following this, Discrimination & Toxicity was identified as the second most prevalent risk, representing 19.43% of cases (137 cases) (Figure 3). This domain underscores AI's potential of exposure to toxic content, unfair discrimination and misrepresentation, and unequal performance across groups. The Socioeconomic and Environmental category ranked third at 17.02% (120 cases) (Figure 3). This domain captures concerns about AI's broader impact on increased inequality and decline in employment quality, power centralization and unfair distribution of benefits, governance failure, economic and cultural devaluation of human effort, environmental harm, and competitive dynamics. These findings emphasize the multifaceted risks inherent in AI systems, each presenting unique challenges that require targeted mitigation strategies.

The temporal distribution of these risks is also noteworthy. A majority (61.99% or 437 cases) of recorded incidents occurred post-deployment, underscoring the challenges that emerge when AI systems are actively integrated into real-world applications. In contrast, only 9.92% (or 70 cases) of the risks were identified pre-deployment, indicating potential gaps in risk assessment and mitigation during the development phases. This disparity highlights the critical need for robust testing, validation, and oversight mechanisms before deployment, alongside continuous monitoring to address emerging risks effectively.

Additionally, addressing these challenges requires not only improved tools and methodologies but also a workforce of skilled talents to maintain and refine these systems over time. The complexities of mitigating AI risks demand expertise in areas such as algorithmic auditing, ethical AI design, and cybersecurity. Talented professionals equipped with multidisciplinary knowledge can identify vulnerabilities, adapt systems to changing requirements, and implement proactive measures to prevent risks from escalating. Without

skilled talent, even the most advanced risk mitigation tools may fall short, leaving systems vulnerable to failure or misuse. Therefore, fostering a pipeline of well-trained AI practitioners and ensuring ongoing education and professional development are essential to sustaining the safety and ethical deployment of AI technologies.

Table 2. Top 10 Popular AI Risk Sub-Domains

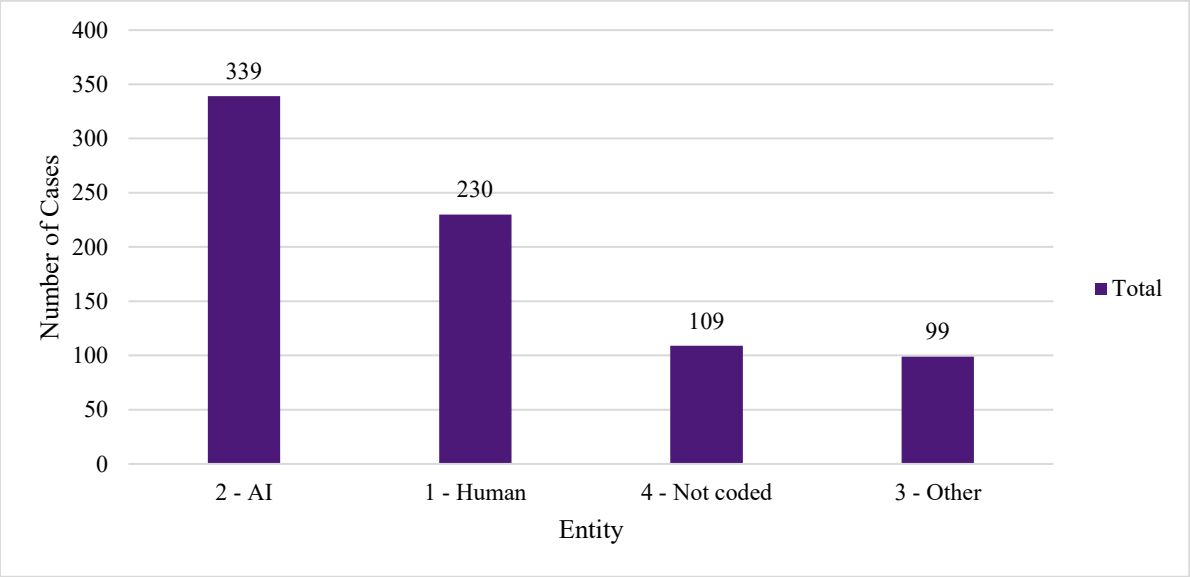
AI Risk Sub-Domain	Frequency (% of total)
1.2 > Exposure to toxic content	9.93%
7.3 > Lack of capability or robustness	8.23%
1.1 > Unfair discrimination and misrepresentation	7.09%
7.1 > AI pursuing its own goals in conflict with human goals or values	6.67%
2.2 > AI system security vulnerabilities and attacks	6.38%
2.1 > Compromise of privacy by leaking or correctly inferring sensitive information	6.10%
3.1 > False or misleading information	4.68%
4.1 > Disinformation, surveillance, and influence at scale	4.68%
5.1 > Overreliance and unsafe use	4.40%
4.2 > Cyberattacks, weapon development or use, and mass harm	4.26%
Grand Total	**62.41%**

Table 2 reveals that among the 29 AI risk sub-domains identified in Table 1, the top 10 most prevalent sub-domains account for 62.41% of all recorded cases, underscoring their disproportionate impact on the overall risk landscape. While AI System Safety, Failures, & Limitations remains the most prominent overarching risk domain, a closer look at the sub-domains indicates that exposure to toxic content, categorized under Discrimination & Toxicity, emerges as the single most common sub-domain, representing 9.93% of all cases. This finding highlights the pervasive nature of harmful content generated or facilitated by AI systems, which can have significant social and ethical implications.

Following closely, lack of capability or robustness, a sub-domain within AI System Safety, Failures, & Limitations, constitutes 8.23% of the recorded cases. This emphasizes the

challenges posed by inadequacies in AI systems' design and functionality, which can lead to operational inefficiencies, errors, or failures in critical applications. Interestingly, none of the top 10 sub-domains belong to the Socioeconomic and Environmental category, suggesting that while concerns related to broader societal and ecological impacts are significant, they are less frequently reported or identified compared to more immediate and technical risks.

Figure 4. Number of Cases by Entity



The dataset defines “Entity” as “whether the risk is presented as occurring due to a decision or action made by an AI system, Human, or something else/ambiguous.” Based on Figure 4, AI related issues are dominant with 339 cases (43.63%), followed by human involvement (230 cases or 29.6%).

Furthermore, the cases of GetTransfer and FC Beauty highlight several AI adoption challenges faced by small businesses, shedding light on critical aspects of resource allocation, ethical considerations, and expertise development (Lewis, 2024).

GetTransfer encountered challenges in developing proprietary AI solutions, requiring significant internal resources, including skilled personnel, time, and finances. Founder Alexander Pershikov emphasized the importance of clear communication to address employee concerns about AI, reflecting a common challenge of resistance to change within organizations (Lewis, 2024). Additionally, balancing resource allocation for AI initiatives against competing priorities emerged as a crucial leadership responsibility, alongside addressing ethical implications such as potential biases, job displacement, and data privacy (Lewis, 2024). These challenges underscore the complexity of integrating AI internally, particularly for small businesses with limited resources and expertise.

Conversely, FC Beauty faced challenges related to the need for expertise and risk mitigation in AI adoption (Lewis, 2024). Rather than relying solely on internal development, the company partnered with external AI specialists to integrate advanced technologies such as predictive analytics for inventory management and chatbots for customer assistance. This approach required managing collaborative dynamics, ensuring alignment with the company's strategic goals, and addressing ethical implications, such as deploying AI responsibly and transparently. Moreover, building a data-driven culture and ensuring the tangible business value of AI initiatives were critical challenges that required deliberate planning and leadership focus.

Both cases illustrate that small businesses often grapple with the dual challenge of developing in-house AI expertise and managing the complexities of external collaborations. Resource constraints, ethical considerations, and the need for effective leadership to align AI adoption with strategic objectives remain common hurdles. These challenges emphasize the need for small businesses to strategically allocate resources, leverage partnerships when necessary, and foster a culture that supports data-driven innovation.

5. Discussion:

The findings highlight that small enterprises in non-technology industries encounter various challenges in AI adoption, such as resource limitations, technical expertise deficits, and ethical considerations. The case of GetTransfer demonstrates the complexities of developing proprietary AI solutions, including the need for skilled personnel and balancing investments in AI against other priorities. Conversely, FC Beauty's reliance on external collaborations underscores the role of partnerships in overcoming expertise gaps and ensuring seamless AI integration. Both cases reveal the importance of strong leadership in aligning AI initiatives with strategic goals and fostering a data-driven organizational culture.

The quantitative analysis confirms that productivity tools dominate the AI landscape due to their direct impact on efficiency and cost savings. However, tools in complex domains like generative art and video are gaining traction due to their high user ratings and advanced functionalities. These trends indicate that small enterprises should prioritize accessible and impactful AI tools initially while gradually exploring more sophisticated applications as resources and expertise develop.

6. Implications:

The findings provide actionable insights for small enterprises in non-technology industries navigating AI adoption. First, resource allocation is critical; businesses should begin with low-cost, accessible tools such as productivity and chat AI, which offer immediate and tangible benefits in streamlining workflows and improving efficiency. These tools require minimal technical expertise and can be seamlessly integrated into existing processes. Second, strategic partnerships with external AI experts can help mitigate technical challenges, provide

access to the latest technologies, and accelerate the adoption process. Collaborating with knowledgeable partners ensures the effective deployment of AI solutions while minimizing risks. Lastly, small enterprises must address ethical concerns to avoid resistance and ensure smooth AI implementation. By aligning AI initiatives with ethical guidelines, businesses can build trust among stakeholders and ensure responsible use of AI technologies.

7. Limitations:

This study is subject to several limitations that may affect the generalizability of its findings. The reliance on secondary data sources limits the ability to capture the full spectrum of challenges faced by small enterprises in diverse contexts. While the case studies of GetTransfer and FC Beauty provide valuable insights, they represent a narrow sample and may not fully reflect the experiences of other industries or geographical regions. Additionally, the dynamic nature of AI technology presents a challenge, as rapid advancements could render some findings or recommendations outdated. These limitations highlight the need for further research to validate and expand upon the study's conclusions.

8. Next Steps:

Future research should focus on expanding the scope of analysis to include a broader sample of small enterprises across various non-technology industries, providing a more comprehensive understanding of AI adoption challenges and strategies. Collecting primary data through surveys or interviews with small business leaders would offer firsthand insights into their experiences, supplementing the secondary data used in this study. Longitudinal studies could further evaluate the sustained impacts of AI adoption, shedding light on long-term benefits

and evolving challenges. Additionally, future investigations should explore the integration of cutting-edge AI technologies, such as generative design and predictive analytics, in specific sectors, to identify innovative applications and potential best practices. These steps will ensure a more robust understanding of AI adoption dynamics and support the development of tailored solutions for small enterprises.

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