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Can organizational focus on responsible AI lead to improved AI adoption by employees?

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CAN ORGANIZATIONAL FOCUS ON RESPONSIBLE AI LEAD TO IMPROVED AI ADOPTION BY EMPLOYEES

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I hereby declare that this dissertation is my original work and it has been written by me in its entirety. I have duly acknowledged all the sources of information which have been used in this dissertation.

This dissertation has also not been submitted for any degree in any university previously."

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Abstract

The duality inherent in Artificial Intelligence technology entails that while AI has the potential to bring about transformative benefits to organizations, unintended consequences of AI applications could lead to biased and discriminatory outcomes, which could have negative consequences for the organization and society in general. Concerns about such unintended consequences are an impediment to AI adoption where unwilling employees and practitioners often fear ethical breaches, thereby, negatively impacting their engagement with AI driven applications. In response to these concerns various organizations and regulatory bodies have developed governing frameworks broadly known as **Responsible AI standards**, that set guidelines to design, develop, and deploy ethical AI.

My research is focused on studying the impact of ethical AI factors on professionals' intentions to work alongside AI and explore the mechanisms behind this relationship. I have drawn linkages with literature, on Technology Acceptance Model, that specifies the factors that impact the technology usage intentions, namely **perceived ease of use** and **usefulness of the new technology**. This study is conducted at the individual employee level as professional employees are important stakeholders that contribute towards the success or failure of any organizational initiative. Employees' perception of their organization's social responsibility inversely moderates this relationship; results suggest that when the **CSR perceptions** are low, positive effect of ethical AI factors on usage intentions is strengthened. This study can benefit management in achieving organizational goals by leveraging the full potential of AI through improved employee engagement.

Keywords: Responsible AI, AI ethics, Corporate social responsibility, employee motivation, AI adoption, Technology Acceptance Model

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Chapter1 Introduction and Preface

"Generative AI is a powerful technology that requires careful consideration and regulation to ensure that it is used for the benefit of society."

Sam Altman, CEO OpenAI

Over the past decades management research has mainly focused on complex decision making involving human managers, while repetitive tasks in operations and logistics were left out to be automated by Artificial Intelligence technology (Rahwan, 2019). Most recently, this trend has seen a shift as massive advancements in Artificial Intelligence technology, fueled by availability of faster and cheaper computational resources along with more efficient machine learning algorithms has opened multiple opportunities for organizations to benefit from AI. We have seen multiple applications of AI in almost all industries including Healthcare, Education, Financial Services and Retail. These applications span through various departments, where AI can improve the productivity of workers by taking away the bulk of tedious tasks. The most recent shift is seen in the impact of AI on professional services where we see AI tools working as assistants, where humans are collaborating with these systems in enhancing the decision making for their work-related tasks.

Since 2015 onwards, organizations have found many new use cases of AI, where deep learning algorithms proved to improve accuracy in solving problems, which were computationally complex and often required massive data processing to compute the outcome. Very recently, the year 2023 has seen the advent of Generative AI applications where AI algorithms are not just processing data but generating new content such as such as images, texts and videos which are now transforming new content generation. As we can conclude there hasn't been a dull moment in the work being done on AI adoption by the industry, but we still precariously sit at the edge of what looks like a roller coaster ride with many unanswered questions about the overall impact of AI on broader outcomes for society and professionals in general. For example, if AI is the decision maker in many critical situations related to health diagnosis, disbursement of credit, recruitment of new employees, then how should we ascribe the final responsibility of the decisions being made? Who should be accountable for failed projects? How can we ensure indiscriminatory outcomes where the resources of the society can be equitability shared across all segments of the population?

The work being done on human AI collaboration, has given rise to what some researchers call as the decision-point dilemma (Crompton, 2021), where it's not often possible to exactly pinpoint where human decision ends and AI decision begins, especially in situations where humans and AI are both a part of the complex decision-making process. This dilemma can be linked to what we often refer to as the unintended consequences of AI.

A striking example of AI's unintended bias was Amazon's experimental hiring tool, which was found to be biased against women. The tool, designed to automate the search for top talent by reviewing job applicants' resumes, inadvertently learned to favor male candidates. This bias stemmed from the tool being trained on résumés submitted over the past 10 years, predominantly by men, reflecting the male dominance in the tech industry. Consequently, the AI excluded resumes associated with female applicants, such as those from women's colleges or containing terms like "women's chess club captain." This incident highlights the critical issue of AI systems perpetuating existing societal biases if they are trained on biased data.(Bubakr & Baber, 2020).

Within the domain of location-based services, an example of unintended privacy infringement involves the cross-domain location recommendation systems. These systems aim to enhance user experience by recommending locations, such as restaurants and shops, based on user preferences and behaviors across different domains or platforms. A typical scenario involves distinct services, such as check-in services, sharing user-location interaction data to improve recommendations. However, this practice raises significant privacy concerns, as directly sharing raw interaction data between providers can lead to privacy breaches. The shared user-location data is highly sensitive, containing information about users' movements and preferences that could be exploited if mishandled or accessed by unauthorized parties. (Gao & Huang, 2019).

Past Research has shown that AI can inadvertently exacerbate workplace stress and anxiety. Especially, the rapid technological advancements and the pressures of globalization have led to increased work pace and life disruptions, causing stress and anxiety among employees (Vaidyanathan & Mahapatra, 2020). The unintended negative consequences of knowledge translation in healthcare, such as emotional labor and anxiety, highlight the emotional and psychological challenges faced by employees in adapting to new knowledge systems (Dadich & Vaughan, 2023)

Given the above uncertainty and complexity of the role of AI in business, the concept of Responsible AI emerged as a crucial approach to address the ethical and societal implications of AI. These set of guidelines establish ways in which organizations responsibly implement AI systems and enhance awareness about the nuances of working with AI. Originating from the growing recognition of the need to embed responsibility in intelligent systems, the responsible AI framework aims to move beyond mere AI ethics towards creating responsible AI ecosystems. (Stahl, 2023).

In this research I have explored the impact of Responsible AI factors such as autonomy, beneficence and transparency on the users of AI applications. Results show that when organizations adopt Responsible AI standards, employees are motivated to engage more wholistically with AI. The mechanism underlying this phenomenon is closely linked to the enhanced perceptions of AI in terms of ease of use and effort required to use AI systems. Responsible deployment of AI allays concerns about AI to make people more willing to engage with AI. I have studied the impact of the organization's reputation in terms of the Corporate Social Responsibility perceptions on this relationship between Responsible AI and improved AI usage intention. Overall results suggest that Responsible AI might be the key to unlocking the full potential of AI given that now every member of the organization needs to be willing and able to work with AI, to be able to achieve the productivity goals set out for the firms

Chapter2 Literature Review

2.1 Nuanced Definition of AI through the Management Lens

Intelligence is defined as the "ability to interact, learn, adopt, and resort to information from experiences, as well as to deal with uncertainty" (Legg, 2007). The notion of Artificial intelligence is built on the idea of intelligence which is made by humans and is hence a copy of the natural (E Walter, 2008). Even though AI has been studied in Information Systems and Management for a few decades, there is a lack of consensus on a single definition of AI.

Some of the most prominent definitions of AI emphasize the human like cognitive ability of AI to facilitate decision making. (Kaplan, 2019) defined AI as the system's ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation. The increasing capability of machines to perform specific roles and tasks currently performed by humans within the workplace and society in general.(Dwivedi, 2021). The definition of AI by (Mikalef, 2021) provides a more apt notion of AI as an agent of organizational change as "*AI is the ability of a system to identify, interpret, make inferences, and learn from data to achieve predetermined organizational and societal goals*".

2.2 Potential of Artificial Intelligence as a Firm Performance Booster

Most debates about Artificial Intelligence tend to focus on the possible damages of using AI, such as loss of human jobs, loss of autonomy and control over outcomes and even extinction of humanity. If we for once drop our own pre-formed opinions and focus on the benefits of using AI we will see that AI tools can help to create less biased results which are not influenced by past results, unlike outcomes processes by human scientists (The Economist, 2023). AI can be viewed as a tool that can be used to fuel the success of the organization by various mechanisms. Many studies from industry and academia have focused on AI as a booster of creativity by automating tedious manual tasks that would otherwise take the bulk of the time of the employees. This freed up time can be used in creative processes and hence bolster overall organizational creative performance. Others have also suggested AI can help to improve productivity by improving key performance metrics for the organization by helping to improve decisions that are based on large datasets rather than on intuition and experience (Syam, 2018). AI can be used to automate reading of legal contracts and facilitate better communication with employees as per the study published by (Davenport, 2018).

2.3 Organizational AI Adoption and it's Barriers.

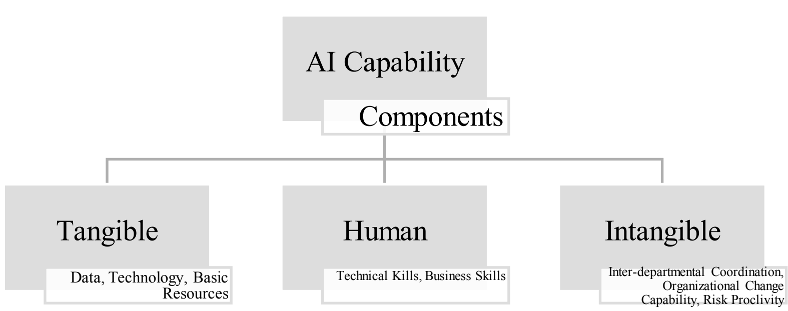
2.3.1 Factors impacting AI adoption by Organizations.

Within the contemporary landscape of organizational research, the exploration of the business value and potential of Artificial Intelligence (AI) remains quite nascent. (Ransbotham, 2017) notably shed light on the existing gap in technical competence, revealing that many organizations struggle with understanding the intricate data prerequisites and needs for AI, as well as the foundational technological framework necessary for operationalizing AI. This sentiment resonates with findings by (Davenport, 2018), who underscored the widespread struggle of harmonizing AI projects with prevailing organizational processes and systems. Particularly in the public sector, a confluence of challenges emerges, notably the dilemma of **seamlessly integrating systems** and data and assuring the **utilization of highly specialized data** for AI training, as illustrated by (Mikalef, 2021). However, the technical dimension represents only one facet of the challenge. There's a growing consensus in the literature that success of AI initiatives, transcend beyond technology. (Ransbotham, 2018) for instance, emphasizes the paramount importance of organizational dynamics like **decisive leadership** and fostering **inter-departmental synergies**. A consistent leadership vision for AI and an organizational culture of embracing AI's multifaceted potentials are key drivers. Moreover, (Davenport, 2018) findings resonate with this perspective, pointing to a knowledge gap where a significant portion of **managerial tier lacks a fundamental understanding of AI** mechanisms and workings

Furthermore, the skill requirements for AI deviates from traditional models. AI needs a novel **skill set**, necessitating a paradigm shift not just for the technical workforce but also for the managerial tiers, as suggested in various studies.

Drawing on the rich work on the Resource-Based Theory (RBT) and building on diverse studies accentuating the trials of AI adoption, (Mikalef, 2021) proposed eight cardinal resources believed to underpin AI capability. These resources, which span the tangible (like data and technology), human (such as business acumen and technical prowess), and intangible (like inter-departmental coordination), might be inherent within an organization or can be externally sourced, reinforcing the RBT's emphasis on resource control. My research focuses on the intangible resource management which concerns with the **change management capability** of the organization.

Figure 1 AI Capability and Categorization of Resources (Mikalef, 2021)



Artificial intelligence is unique from other technologies in multiple ways. One reason being that successful AI implementation needs organizations to have efficient change management. This is because, AI solutions replicate human thinking and hence any AI solution needs to be deployed in close collaboration with humans, wherein, humans need to adapt the ways they work to work alongside AI. Many past studies have focused on adoption of emerging technologies such as internet, mobile and cloud and only a handful of published research work is mainly focused on the adoption of AI tools and technologies at the organization level (Kurup & Gupta, 2022). While there have been multiple studies done on technical requirements for AI adoption by organization, few studies focus on non-technical aspects of AI adoption in the business environment (Jadhav, 2021).Successful implementation of AI requires that businesses fully comprehend the drivers along with the barriers that block the success of AI. It also needs to be noted that drivers of success of AI are very context dependent. For example, Organizations that want to use AI to get ahead need support from their leaders, a clear understanding of how AI can make them stand out, the right technical tools and people, a supportive company culture, and specific situations where AI can be used effectively (Kordon, 2020). The factors can also vary based on geographical contexts. Studies from United States and Germany found that along with leadership commitment, the **size of the company** along with the resource capacity of the organization and compatibility of existing processes with machine learning algorithms played a role in AI adoption (Eitle, 2020). In another study from Australia, organizations were keen to adopt AI only if it gave them relative advantage over competitors and had top management support (Sulaiman, 2020).

The Technology-Organization-Environment (TOE) framework helps to establish the role of context based on three overarching themes which play an important role in successful adoption and implementation of new technologies in any organization. **Technological context** is derived from organizations technological internal and external prowess. Organizations readiness and preparedness to adopt new technology which is mainly based on the compatibility of current technology with that of AI tools and systems(Richey, 2011). Organizations can use AI for solutions related to automated manufacturing processes to detecting fraudulent transactions (McKinsey Global Institute, 2018). AI can provide relative advantage only if AI solutions can improve existing processes and products (Yang, 2013) .

The **organizational context** is defined by the existence of supporting processes and structures that are fundamental for assimilating AI in the day-to-day work activities of all employees. This is mainly influenced by the leadership vision on the role of technology in the organization (Yang, 2015). The leadership support comes in the form of **budget allocations** needed for managing the changes in work and processes. **Organizations change management capacity** is the other significant factor which influences successful adoption of AI (Ambati, 2020). Since AI deployment leads to changes in work at employee level and process level, resistance to change can be a bottleneck in the success of AI projects. Past results from a large-scale survey showed that company's culture often acts as a resistance to AI implementation (Mikalef, 2021)

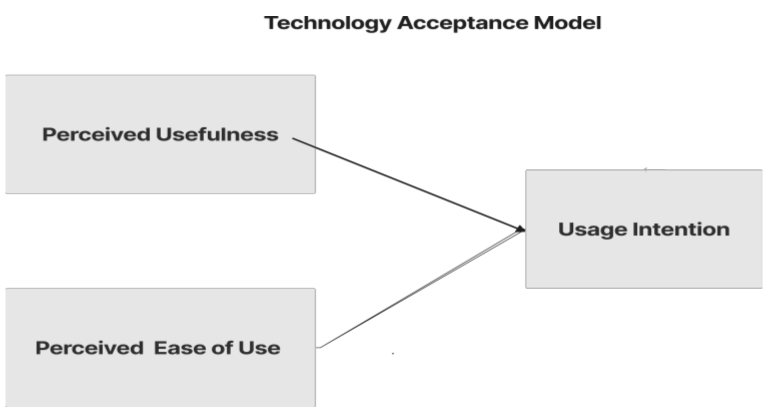
The last factor related to **environmental context** is based on the business environment in which the organization operates. Global and national competition along with the governmental policies about AI adoption, impact the pace of AI adoption by offering the right incentives to make the necessary changes to make way for AI (Gibbs, 2003). In my research, the focus is mainly on organizational ability to manage change to facilitate AI deployment.

2.3.2 Technology Acceptance Model for AI Technology

The technology acceptance model (TAM), introduced by Fred Davis, has gained wide spread popularity as a predictor of human acceptance of or rejection of technology. Technology Acceptance Model (TAM) suggests that how easy to use and useful a system appears to users, plays a crucial role in linking the system's features with its potential usage. Drawing from psychological theories, the Theory of Reasoned Action (TRA) and the Theory of Planned Behaviour (TPB), TAM has become a leading approach for understanding how people interact with technology (Davis, 1986).

The Technology Acceptance Model (TAM) is widely recognized for its effectiveness in illustrating the factors influencing individuals' adoption of information technologies. Based on the foundational principles of the Theory of Reasoned Action, the original TAM framework highlights the pivotal role of two extrinsic motivators: perceived usefulness and perceived ease of use. These factors are thought to directly impact both the intention to use and the actual usage of information technologies. Perceived ease of use is defined as the extent to which potential users anticipate that the technology in question will be effortless to use. Conversely, perceived usefulness is understood as the degree to which an individual believes that using a specific technology will enhance their job performance. Subsequent enhancements to the TAM, notably by (Bagozzi et al., 1992) incorporated the dimension of user attitude. Their revision posits that perceived ease of use and usefulness shape user attitudes towards technology, thereby influencing their behavioral intentions and actual adoption patterns. In essence, the more users appreciate the functionality and user-friendliness of a technology, the more positive their attitudes towards it, which, in turn, heightens their likelihood of adopting the technology. Due to its significant predictive capability regarding technology adoption behaviors, the TAM has been successfully applied to a diverse range of emerging technologies, including smartwatches, mobile applications, telemedicine, and virtual reality systems.

Figure 2 Technology Acceptance Model (Davis, 1986)



The Technology Adoption Model (TAM) has been widely adapted and extended to understand the factors impacting the adoption of Artificial Intelligence across various domains. Recent studies have integrated TAM with other theoretical frameworks to explore AI adoption in contexts such as smart cities, healthcare, and the financial sector. For example, a study in Pakistan extended TAM to include cultural dimensions, finding that individualism and collectivism moderated the relationship between perceived usefulness, perceived ease of use, and AI application adoption in smart cities.(Bokhari & Myeong, 2023)

In the healthcare sector, research on robot-assisted surgery in Europe employed TAM to identify factors influencing trust in the AI technology, signifying the importance of motivational factors and user experience(Sellens & Zarco, 2020). In the financial industry, TAM has been used to understand behavioral challenges of technology adoption among bank employees.(Katke, 2021) Additionally, TAM has been extended to include ethical standards, legal concerns, and trust to predict the adoption of autonomous vehicles in Thailand (S. Ramjan & Sangkaew, 2022). These adaptations of TAM underscore the model's robustness and flexibility in addressing the multifaceted nature of AI adoption

2.3.3 Employees' Role in Organizational AI Adoption

AI has the transformative potential to benefit organizations. Almost 80% of all organizations today have incorporated some form of AI in their core business functions. This marks an increase of 70% over the last 5 years (Ghosh et al., 2019). Also, most scholars agree that AI will be an integral part of the future of work (Wilson et al., 2019). Even though AI has the potential to drive improvement in efficiency, accuracy and better decision making, there is evidence to show that many companies do not experience these expected benefits despite spending, effort, time, and other resources on AI technology, finally categorizing AI initiatives as complete failures to drive any benefit to the business. (Fountaine, McCarthy, & Saleh, 2019).

Surveys done by Boston consulting Group found that 70% of the AI projects generated little or no impact and the plans to develop and use AI dropped from 20% to a meagre 4% in 2020. A report by Deloitte based on interviews of senior managers stated that almost 50% of the survey respondents find it challenging to integrate AI with existing people, processes, and systems in the organization. It can be safely concluded that, **it is imperative for employees to accept, interact with, and collaborate with AI tools.**

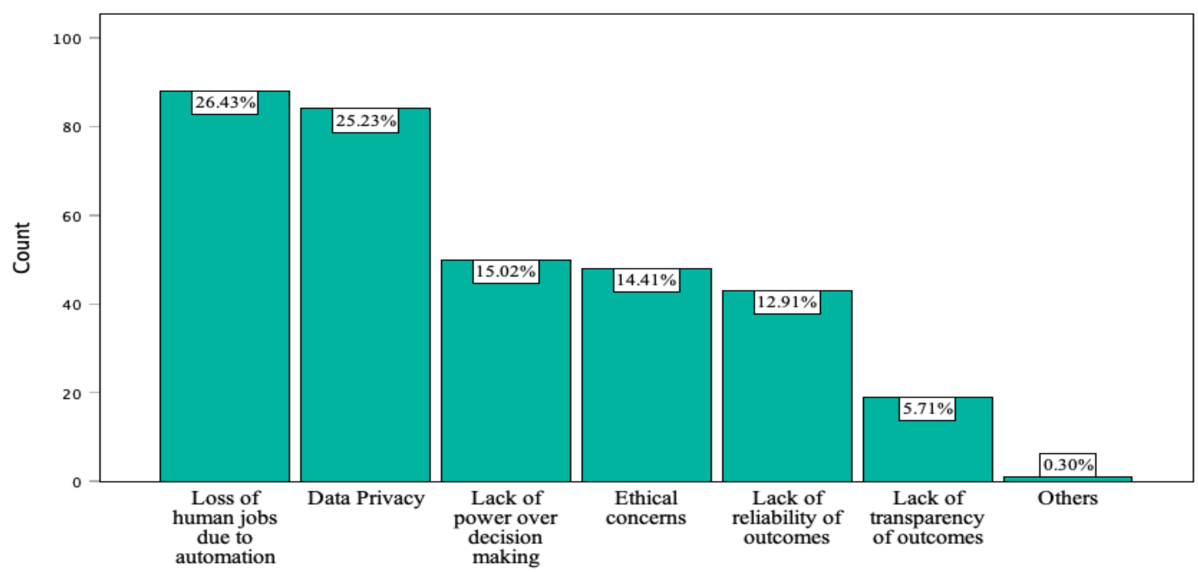
Technologies such as AI introduce new uncertainty in the working of the organization as AI usage can lead to changes in the procedures of doing work and even the work itself can massively transform(Merhi, 2022). Past works have noted **employee resistance** as one of the biggest challenges that inhibit organizational adoption of AI. All stakeholders might resist the transformation as humans generally prefer to avoid any changes to the established ways of doing work. In healthcare for example there are many obstacles in motivating practitioners to engage with AI, mainly triggered by work automation, potential displacement, and loss of workforces (Davenport & Kalakota, 2019)

Management scholars need to focus more on how employees integrate AI systems in their daily work. Currently there is lack of management research in this area. This research focuses on understanding employee's willingness to work with AI. The focus will be on understanding the role of organizational responsible AI initiatives in enhancing intention to engage with AI systems through the lens of improved perceptions of AI Acceptance.

2.3.4 AI Anxiety and Employees' Socio-behavioral Concerns about AI Technology

According to (Durth & Hancock, 2023) as Artificial Intelligence in fast making way into every aspect of business function, leaders need to think about how to integrate this technology into the day to day work of the organization. Past research has noted that AI applications when combined with human skills can massively enhance organizational outcomes (Dubey & Gunasekaran, 2019). In the study by (Yuliani & Chang, 2021), authors argue that individuals who have positive beliefs about AI tend to be more ready to collaborate with AI and learn the skills necessary for adopting AI, in comparison to those that have negative perceptions of changes made by AI in the workplace. Related to the negative emotions experienced by employees about AI in the workplace, the term AI Anxiety (Kummer & Recker, 2017) refers to concerns or fears of artificial intelligence and its potential impact on society, privacy, employment, or decision-making. It encompasses worries about the unknown consequences of AI technologies, including concerns about job displacement, loss of privacy, biases in AI algorithms. While topic of technology anxiety has been a well-studied in many contexts on technology adoption such as the concept of computer anxiety examined by (Venkatesh, 2000), very few of the studies so far have dived into AI anxiety and its impact on AI adoption. (Yuliani & Chang, 2021) empirically found that AI anxiety negatively impacts ones change readiness with respect to AI adoption. Given the duality of AI outcomes, which on one hand promise productivity gains and on the other hand could results in job losses, employee turnover and loss of privacy and reputation. Leaders need to establish mechanism to mitigate these **socio-behavioral concerns** of the employees. In the research survey conducted for this study 26% of the respondents reported the fear of job loss and lack of power over decision making as some of the biggest concerns about using AI. Other reasons were related to privacy and ethical considerations.

Figure 3 Top Concerns in using AI by Professional Workers, n = 333



2.4 Development of AI Ethics and its Significance

2.4.1 What is Responsible AI and Need for Responsible AI

In the study by (Marzouk et al., 2023) , the authors emphasized the pressing ethical and regulatory issues, particularly around themes related to transparency, bias, privacy, and control. They introduced the concepts of **Responsible AI** as a pivotal governance model which plays a key role in promoting trust and operationalizing ethics in AI implementations. More significantly, the authors translated ethical concerns into functional operations that can then be deployed by organizations and incorporated as a part of their business operations. This pivotal study presented a comprehensive overview of existing frameworks and analysed their objectives and toolkits. Authors also recognized the ambiguities in the existing landscape, and created a comprehensive framework that aims to bridge the gap between theoretical principles and real-world considerations. Such guidelines help to provide a more sophisticated approach to safe deployment of AI by converting intangible concepts related to AI ethics into usable roadmaps.

2.4.2 Organization's AI for Social Good Initiatives

Adoption of AI by all organizations has been increasing over the last few years due to accelerated development of digital technologies and massive innovation in algorithmic prowess. Even though the applications of AI for social good are work in progress, there is evidence that indicates the vast potential of AI for society and environment. Google Inc. hosted a global AI for social good challenge in 2018, calling for ideas from researchers and organizations to showcase uses of AI to tackle social challenges. The applications showed a diversity of use cases where AI could address global and local issues in developed and developing countries. The proposals identified uses of computer vision, deep learning, and natural language processing to solve many social problems. These included optimizing natural disaster relief efforts by using satellite imagery, predicting earthquakes, improving agricultural quality and yield, enabling financial inclusion by improving credit assessment for underserved population, better matching candidates to job based on skills assessment. Along with these, AI applications can also be used to facilitate better education and coaching based on development of new learning tools(Tomašev et al., 2020). AI can especially advance the development in emerging markets by lowering the cost of entry barriers for businesses that can deliver innovative solutions to the underserved population. (Strusani & Houngbonon, 2019).

Companies engage in social initiatives both for philanthropic and economic benefits. Surveys show that Investors, consumers, and employees believe in the extended role of organizations **beyond profit making**. Research has proven that social initiatives yield many benefits including enhanced financial performance. More and more companies are using AI to drive social initiatives to enhance their perceptions with stakeholders.

2.4.3 Responsible AI Standards

Even though, there are numerous examples of benefits of AI to organizations and societies, but over the recent past, implementation of AI also witnessed accidents and unintended consequences. These can be linked to the dark side of AI or technology in general, where we can question the true value being driven by technological adoption(Mikalef et al., 2022). Examples include the development of recruiting tool by Amazon that was biased against hiring women as previous data showed that men are superior performers than women since majority of the data represented employees that were men. The many instances of fake news that are often created and spread by social media without raising suspicion, or the deep fakes which represent fake profiles that are hard to distinguish from real profiles of people that can be misused very easily to perpetrate fraud and other acts based on stolen identity.

The fear of loss of autonomy, human agency, privacy, and security have all raised a level of awareness in organizations and societies in general about the unintended consequences of AI due to the **complexity of the AI algorithms and lack of transparency** of their working. This concern about **unintended consequences** of AI has led to increased interest in understanding how AI can be made safe and how can AI solutions be implemented in responsible ways. To prevent possible harm caused by AI, while still reaping its substantial benefits, there has been a parallel increase in the development of ethical guidelines and strategies for AI use. This led to the notion of "Responsible AI". Responsible AI focuses on setting standards and principles which will prevent the unintended issues created by the usage of AI solutions. These issues focus on security, biases, discrimination, transparency as the key themes. There have been a few studies on Responsible AI and the main purpose is to lay down universal standards of what continues responsible AI.

In the study by (Fjeld et al., 2020), authors aimed to draw consensus amongst the documents related to AI principles published by different entities in order to uncover common themes that could converge the fragmented discussion around this topic. Almost all organizations have some form of AI implementation guidelines to benefit internal development and use if AI. Similarly, governments and societies have published AI principles to ensure that AI driven outcomes are beneficial to the society in general. (Fjeld et al., 2020) found eight common themes and hence concluded that the varied discussions on the future and safe use of AI might be near convergence. (Mikalef et al., 2022) aggregated a summary of eight principles published by academicians and practitioners. These included "fairness, transparency, accountability, robustness and safety, data governance, laws and regulations, human oversight, societal and environmental wellbeing”. This work pointed out that most work related to Responsible AI is at societal and regulatory level and there is a lack of such studies at the organizational and business unit level. Despite the lack of sufficient empirical work in the area, the above eight key dimensions represent stakeholders from institutions, organizations, government bodies, non-profit organizations, large business corporations such as “Google Inc” to describe and identify these factors that together constitute “Responsible AI”. These are described as Fairness, Transparency, Accountability, Robustness and Safety, Data Governance, Laws and Regulations, Human Oversight, Societal and Environmental well-being.

Study conducted by (Vakkuri et al., 2020) found that the current state of AI implementation is lagging behind in most organizations and hence very much in its infancy. Even though the guidelines for implementing Responsible AI are being developed and refined, there aren’t enough tools to ensure implementation of ethical AI by those that are developing the AI tools and systems in the organizations.

Chapter3 Organizational Corporate Social Responsibility.

The concept of Corporate Social Responsibility is an idea that has been progressing for last few decades since 1950. The modern concept of CSR solidified by the marked publication of the book named “Social Responsibility of the Businessman”, by Howard R. Bowen, published in 1953. Bowen introduced the concept that the concentration of power in the large USA corporations had the power to influence the lives of millions of citizens in multiple ways. This started the ongoing debate to answer the question that “what responsibilities to society may the businessmen reasonably be expected to assume”. The real applications of CSR were introduced in 1960’s after the civil rights movement in the United States and other revolutionary movements related to the right of consumers, environment, and women (Carroll, 1999). The most widely used definition of CSR is the one coined by Archie B. Carrol in the work states that “Corporate social responsibility encompasses the economic, legal, ethical, and discretionary(philanthropic) expectations that society has of organizations at a given point in time” (Carroll, 2021)

3.1 Important role of Employees as Stakeholders in the success of CSR

One of the definitions of CSR by Aguinis states that “context-specific organizational actions and policies that take into account stakeholders’ expectations and the triple bottom line of economic, social, and environmental performance” (Aguinis 2011, p. 855). This view of CSR focuses on encouraging stakeholder engagement to achieve the organizational objectives related to the economic, social, and environmental performance. Many studies on CSR focus on external stakeholders such as customers, as public perceptions of CSR play in important role in defining the success of the firm. Employees have been identified as the most important internal stakeholders that influence the success of CSR in multiple ways (Greenwood et al., 2011). Research in CSR is fragmented at the level of analysis and the focal stakeholders. Most CSR researchers have looked at organizational or institutional level CSR and few studies have been done at the individual employee level. There has been multilevel CSR research which considers various levels of organizational strategy including firm level objectives such as firm culture, motives and leadership, and individual level factors such as employee incentives and willingness to engage in CSR(Lindgreen & Swaen, 2010)

When considering employee engagement and perceptions of CSR, it's important to highlight the **voluntariness** aspect related to engaging in CSR as the social activities that CSR concerns itself extends beyond the regulatory requirements of conducting business. Very often CSR activities are related to fundraising and volunteering tasks where employees can choose to participate based on their individual perceptions and attitudes towards organizational CSR strategy(Hejjas et al., 2019).

3.2 Organizational Identification

Organizational identification encapsulates the degree to which individuals aligns their identity with that of their organization, experiencing a sense of oneness or belonging. The origins of Organizational identification are rooted in the social identity theory which states that individuals categorize themselves into groups, that influence their self-identity and behaviour. (Ashforth & Mael, 1989) Extended this theory to the organizational context, suggesting that individuals derive part of their self-identity from their membership in organizations. This conceptualization of Organizational Identification suggests that individuals perceive their organization's successes and failures as their own, fostering a deep psychological bond between the individual and the organization. Previous studies have identified several antecedents to Organizational Identification, ranging from individual to organizational factors. At the individual level, the need for self-enhancement and the need to reduce uncertainty, are key drivers of

Organizational Identification. Individuals are motivated to identify with organizations that enhance their self-esteem and provide a sense of belonging and security (Pratt, 1998). For individuals, high levels of Organizational Identification are associated with increased job satisfaction, organizational commitment, and a willingness to engage in CSR behaviours (Van Dick & Christ, 2006). When organizations implement Responsible AI, employees should feel aligned with the AI related goals that are now linked to fostering social well-being of all stakeholders. It would be logical to hypothesize that the relationship between Responsible AI and AI adoption intention could be mediated by organizational identification as people will feel inclined more inclined to engage with the chosen AI tools for the employees.

3.3 Impact of CSR perceptions on employee's organizational performance

CSR activities leads to greater employee-organization oneness. This finding is based on constructs of **social identity theory** which states that individuals tend to categorize themselves and others into social groups such as organizational membership, gender orientations or religious affiliations (Ashforth & Mael, 1989). Since, employees associate themselves and their goals with the organizations they work with, **organizational identification** is a form of social identification. Organization identification is defined as "the process by which the goals of the organization and those of the individual become increasingly integrated and congruent" by (Hall et al., 1970). Study by (Zappalà et al., 2019) found that as per **social identity theory,** organizational identification makes employees align their own goals with that of the organization. Especially when organizations implement CSR related initiatives employees feel enhances oneness with the organization inspired by feelings of prestige and respect (Turker, 2009) Increased oneness is associated with positive employee work outcomes such as work creativity and innovative job performance(Grant & Berry, 2011)

3.4 Linkages between Perceptions of Organizational Responsible AI and CSR

Responsible AI establishes a set of guidelines about how AI should be developed , deployed and governed, in a manner that ensures well-being of all stakeholders. This view of Responsible governance of AI is closely linked with the idea of organizational Strategic CSR which establishes the extended role of organizations as social agent that have the responsibility to ensure positive impact of their actions on all stakeholders.

In this study I establish the linkage between Responsible deployment of AI and perceived CSR to achieve the desired benefits of AI investments. I am hypothesising that the Employees' view of their organizational CSR acts as a moderator to the main relationship between Responsible AI and intention to use AI.

Chapter4 Research questions and Hypothesis Development

The significance of this study lies in exploring the relationship between Responsible AI principles, AI acceptance beliefs, and employee engagement with AI, while considering the mediating factors and the impact of employees' existing perceptions of Corporate Social Responsibility (CSR). The study aims to answer four research questions that are crucial for improving employees' engagement with AI, regardless of the industry or sector in which the firm operates. Firstly, the study investigates whether Responsible AI principles lead to improved AI acceptance beliefs by employees. By adhering to ethical guidelines and ensuring transparency, fairness, and accountability in AI systems, organizations can potentially foster a positive perception of AI among their employees, thereby enhancing AI acceptance.

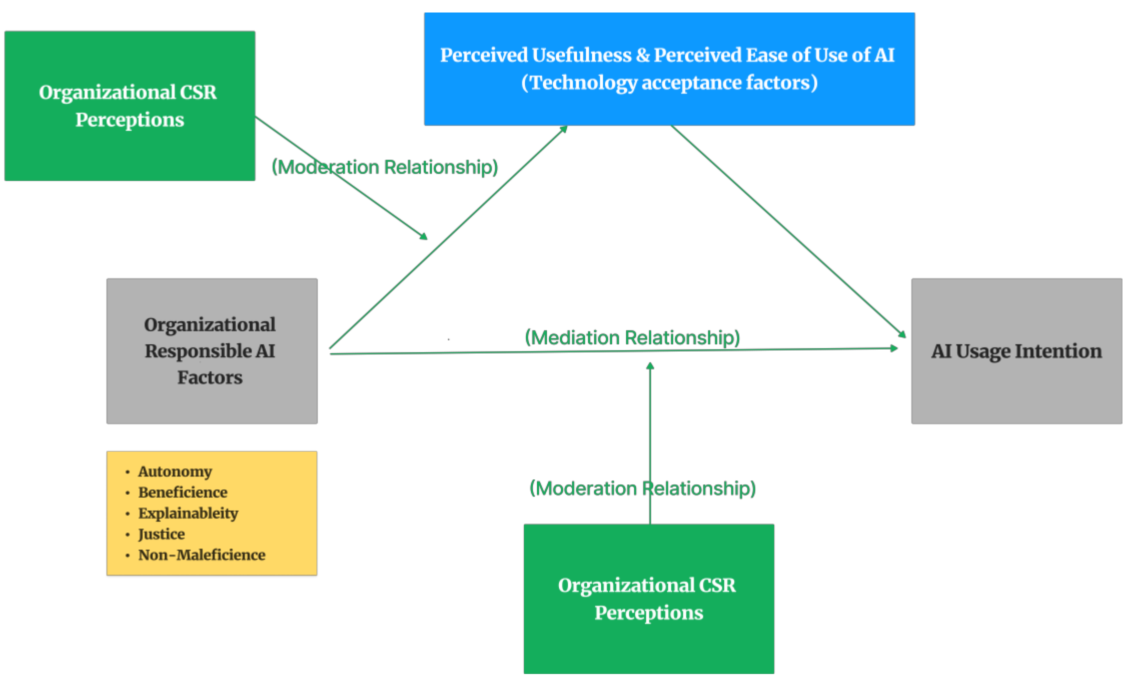
Secondly, the research examines if Responsible AI adoption by organizations can lead employees to better engage with AI. Responsible AI adoption can create a trustworthy environment that encourages employees to interact with AI systems more effectively, ultimately improving their engagement with the technology.

Thirdly, the study seeks to understand the mechanism behind this relationship and identify the mediators. By exploring the underlying factors that influence the relationship between Responsible AI adoption and employee engagement with AI, the study can provide valuable insights into the processes that facilitate or hinder this relationship. Lastly, the research investigates how the relationship between Responsible AI adoption and employee engagement with AI is impacted by employees' existing perceptions of CSR. Employees' perceptions of their organization's commitment to social responsibility may influence their acceptance and engagement with AI, as they may view Responsible AI adoption as an extension of the company's CSR initiatives.

In summary, this study aims to provide a comprehensive understanding of the role of Responsible AI principles in improving employees' engagement with AI, while considering the mediating factors and the impact of employees' existing perceptions of CSR. The findings from this research can offer valuable insights for organizations looking to enhance AI acceptance and engagement among their employees, ultimately contributing to the successful integration of AI in various industries.

4.1 Proposed Theoretical Model and Hypothesis.

Figure 4 Theoretical Research Model



4.1.1 Hypothesis1) Relationship between Responsible AI and AI Adoption Intention

Positive perceptions of organizational Responsible AI implementation lead to improved AI adoption intention by employees. In chapter2, I had illustrated that there are multiple barriers to AI adoption for organizations and these include factors related to technology, organization, and the broader industrial environment in which the organization operates. Employee resistance to change could be driven by factors such as reluctance to lose control (Connor, 1992) and cognitive rigidity related to close mindedness that prevents people from adjusting to new situations (Fox, 1999). In the case of Artificial intelligence applications, many of these reasons are related to the characteristics of the AI systems that are often too complex to be fully comprehended by employees who are supposed to work alongside these systems. Survey results showed that loss of autonomy and lack of privacy were some of the top concerns that prevented people from fully engaging with AI. Study by (Wang et al., 2021) found that responsibly deploying AI improved healthcare practitioners engagement with AI by generating positive responses towards it.

Hence, we can rationally hypothesis that Responsible AI factors, Beneficence, Non-Maleficence, transparency of the system, employee's control on the AI decisions and Justice, are instrumental in mitigating the concerns about the unknown consequences of AI.

Beneficence: The principle of beneficence says AI should be developed for the common good and benefit of humanity. AI should enhance wellbeing, socio-economic opportunities and prosperity for society as a whole.

Non-Maleficence: The principle of non-maleficence states AI should do no harm. It requires not creating injury to others and not imposing unreasonable risks.

Transparency: AI transparency refers to the ability to understand how an AI model reaches its decisions, including the logic, data and processes involved. It encompasses explainable AI techniques and clear communication to stakeholders about the AI system's capabilities and limitations.

Human Autonomy: AI systems should respect human autonomy, the capacity for self-determination and to make decisions according to one's own values. AI should avoid manipulation and enhance knowledge and agency of users.

Justice: AI should be fair and treat everyone equally, without bias towards or against certain groups. AI used for decision-making (e.g. loans, medical diagnosis) should make the same recommendation for anyone, regardless of personal characteristics like race, gender, or socioeconomic status.

Hypothesis1 states that the positive perceptions of Responsible AI factors will lead professionals to have improved intention to adopt AI and encourage them to continue using it in their work activities.

4.1.2 Hypothesis 2) Relationship between Responsible AI and Technology Acceptance

Positive perceptions of Responsible AI by employees have a positive impact on Technology acceptance beliefs, namely Perceived ease of use and Perceived usefulness of the AI System, referred jointly as Technology Acceptance Index. The Technology Acceptance Index (TAI) is a composite measure comprising of two main beliefs that are **perceived ease of use** and **perceived usefulness of AI technology**. The two beliefs stated above are taken from Technology Adoption Model that has successfully being used to study the adoption of technology in various domains and contexts. Core TAM states that perceived ease of use and perceived usefulness of technology, impact the technology usage intention. An Important extension of TAM was developed by (Venkatesh & Davis, 2000) who proposed various antecedents that impact the perceived ease of use and perceived usefulness of technology. The authors identified two main groups of antecedents into anchors and adjustments. Where anchors are pre-existing beliefs about the technology and adjustments are beliefs that are developed by continued use of technology. These antecedents include factors such as subjective norm or influence of other people on the person's decision to use technology. Desire to maintain desirable reputation and image, relevance to the job scope and the extent to which the technology helps to do the job well along with the ability to get tangible results are some of the known antecedents. Henceforth, a vast number of studies introduced various extensions of TAM that looked at new factors and variables as antecedents of the two beliefs of TAM. A factor that influences perceived ease of use and perceived usefulness is the technology anxiety or computer anxiety. In article by (Saade' & Kira, 2006), authors found that the emotional state of the users had a direct impact of their technology acceptance beliefs. Based on this rationale, in my research I hypothesis that beliefs about responsible deployment of AI, will impact the perceived ease of use and perceived usefulness of AI systems, as Responsible AI factors mitigate the anxiety about using AI technology. For example clear understanding of the AI system will enhance user's confidence in AI and hence lead to better perceptions about AI's usability and usefulness.

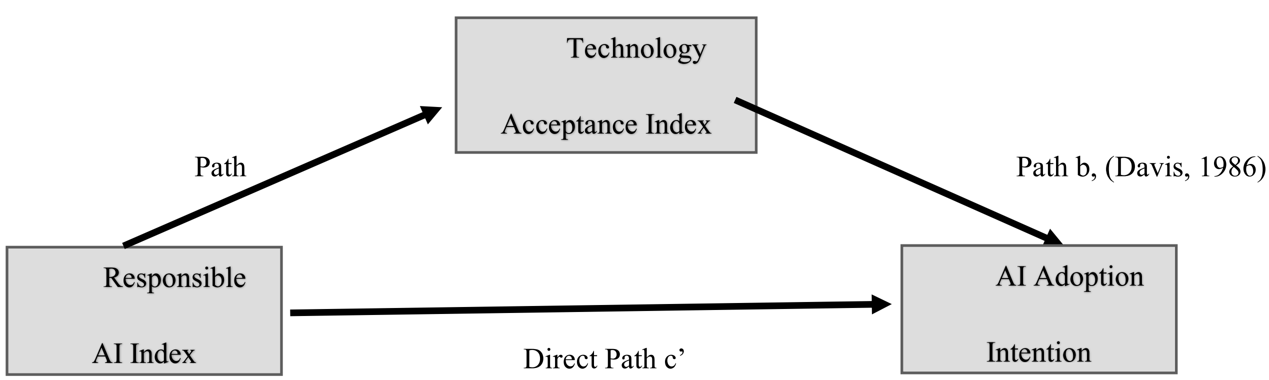
4.1.3 Hypothesis 3) Relationship between Technology Acceptance and AI Adoption

Technology acceptance beliefs for AI, namely Perceived ease of use and Perceived usefulness of the AI System, referred jointly as Technology Acceptance Index are positively linked with AI adoption intention as per the Technology Acceptance Model (TAM) by (Davis, 1986)

4.1.4 Hypothesis 4) Mediating role of Technology Acceptance Index

Positive perceptions of Responsible AI by employees lead to improved AI adoption by employees and this relationship is mediated by Technology acceptance beliefs, namely Perceived ease of use and Perceived usefulness of the AI System, referred to as Technology Acceptance Index. Based on the rationale presented in the above three hypothesis, we can reasonably suggest that Responsible AI influences AI adoption Intention, through the technology acceptance beliefs acting as a mediator. The mediation is a statistical method that can help us explain the mechanism by which a causal agent X influences the outcome, Y (Hayes, 2013). Conceptually, in this study, Responsible AI factors (RAI) affect the AI adoption intention (AIA), through the intervening variable, defined as Technology acceptance index (TAI) . These two pathways as depicted below, one of which is direct and the other indirect are possible ways in which the antecedent, X influences

Figure 5 Mediation Model for the Study



4.1.5 Hypothesis 5) Moderating role of CSR Perception

a) *The relationship between Responsible AI and Technology acceptance perceptions is **moderated** by perceived Corporate Social responsibility.*

b) *Positive perceptions of Responsible AI by employees lead to improved AI adoption intention by employees. This relationship is **moderated** by perceived Corporate Social responsibility.*

Firm's Strategy for implementing responsibilities related to the firm itself and all its stakeholders is represented by the overall CSR Strategy (Shaukat & Qiu, 2016). Some scholars have introduced the idea that CSR strategy improves firms environmental and social performance by boosting the innovation capabilities (Broadstock & Matousek, 2020). Corporate Social Responsibility (CSR) enhances the long-term sustainable performance of the company by nurturing positive connections with stakeholders and reducing negative environmental effects through efficient products and processes, while advocating responsible utilization of resources, and giving precedence to societal upliftment (Rajesh, 2023).

Past research shows that employees resist using new technology as they have socio-behavioural concerns about new innovation such as AI (Khanzode & Sarma, 2021). Given that CSR helps companies strengthen the positive reputation with the employees due to strong ties with the community (Yuan & Cao, 2022), we can expect that perceived CSR will mitigate some of the social-behavioural concerns about the AI initiatives introduced by the organization. Given that Responsible AI factors improves Technology acceptance perceptions of the employees by a similar mechanism, in this hypothesis I suggest that perceived CSR moderates the relationship between Responsible AI factors and the Perceived Ease of Use and Perceived Usefulness of the AI technology. The rationale is that both Responsible deployment of AI and Perceived CSR influence the socio-behavioral concerns of the employees about AI technology. Hence, the moderating role of perceived CSR on the relationship between Responsible AI factors and Technology Acceptance Index and the relationship between Responsible AI factors and AI Adoption Intention.

Chapter5 Details of the Research Sample

5.1 Research Sample Collection

Three pilot studies were conducted before the final sample was collected. The pilot studies included variations in variables to check for the effectiveness of the survey questions that measures the dependent variable. Once the survey questions were finalized based on the scales for each construct, the final survey was rolled out. In order to construct the research sample, randomly chosen professionals from the three countries, USA, Singapore and Australia, were contacted. The pre-screening criteria included only those that are currently employed and have worked with AI in some form. Self-employed people were not included in the sample as many survey questions were related to perceptions of Corporate social Responsibility of the employers.

The final dataset included 333 respondents who are working professionals that interact with Artificial Intelligence applications in their daily professional work. Study included respondents from United States of America, Singapore, and Australia, where 228 respondents were from United States of America, 55 from Australia and 50 were from Singapore. Since, the questions included individual perceptions of AI from personal and organizational perspective, individuals that are salaried employees of an organization were qualified participants for the study. Link to the survey questions has been provided in the Appendix section B of this report.

5.2 Sample Details and Demographics

The details of the survey respondents are given below.

Figure 6 68.5% respondents belong to USA followed by Australia and Singapore

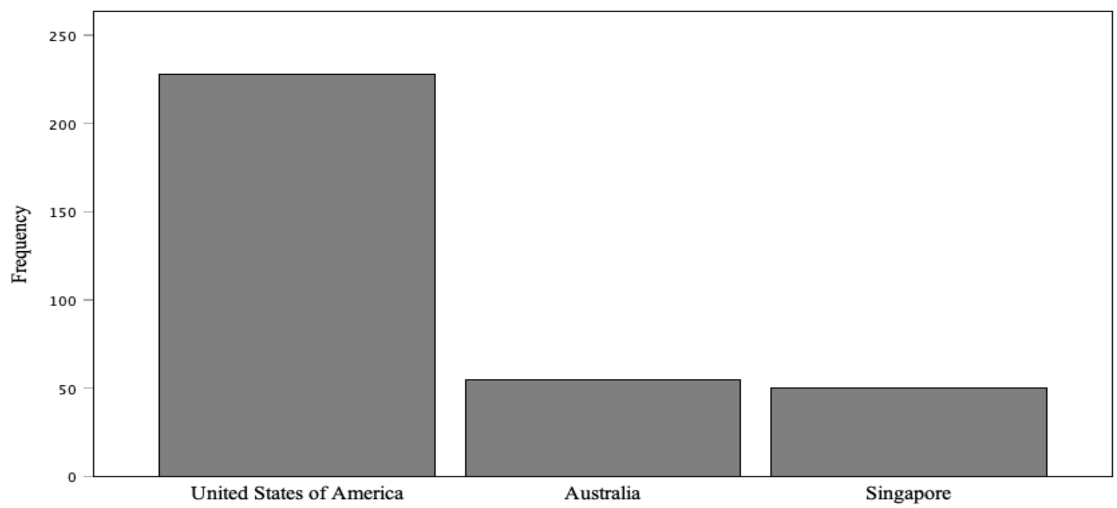


Figure 7 There are 62.2% Females in the Respondents.

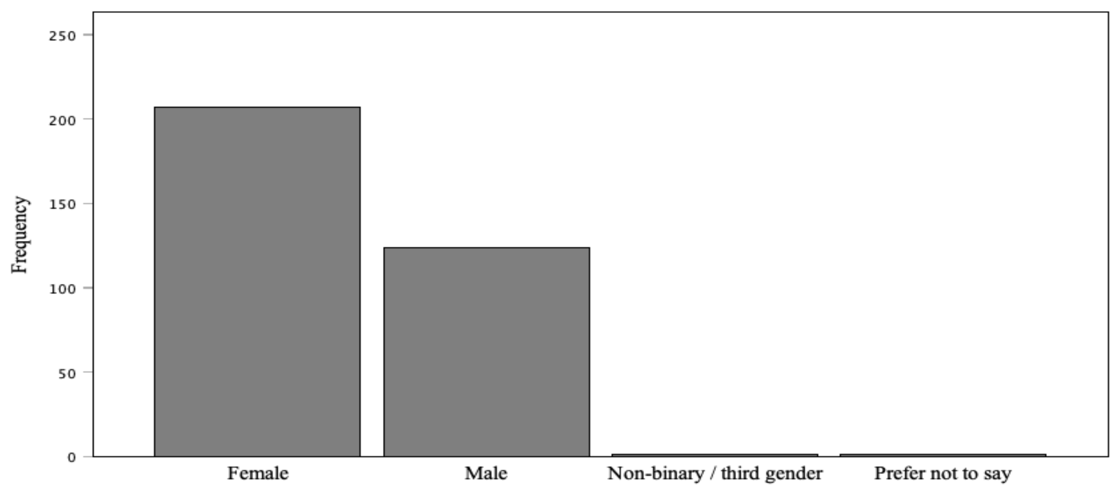


Figure 8 Over 52% Respondents are above 35 years of Age.

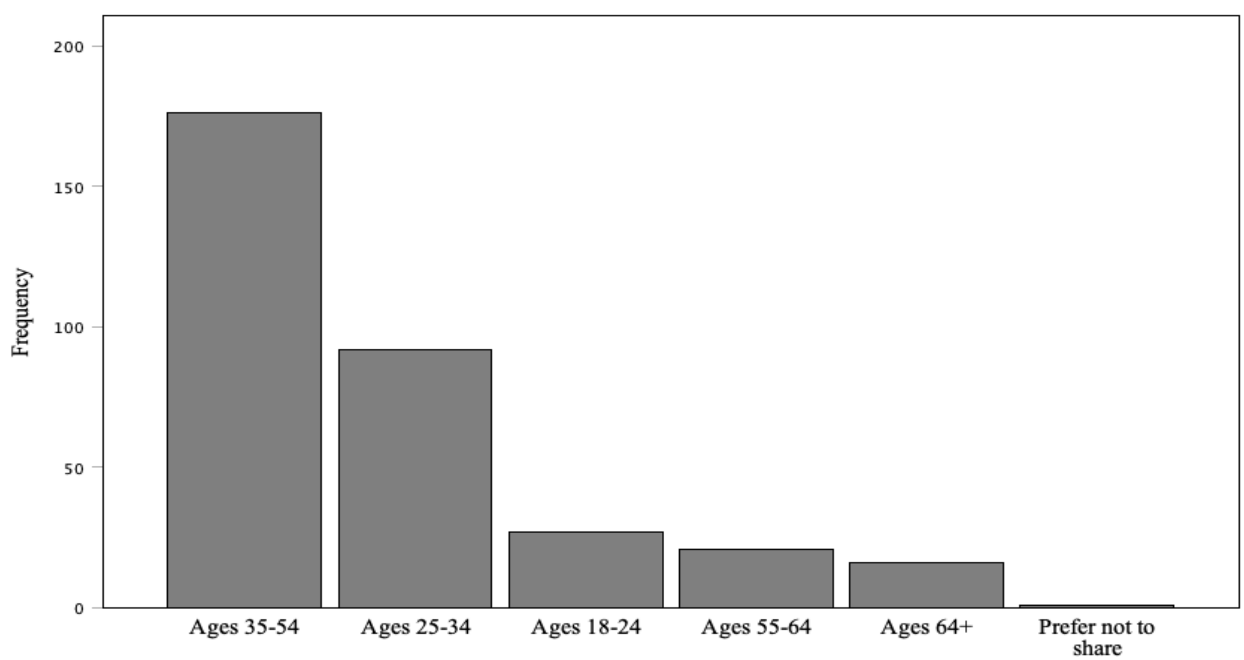
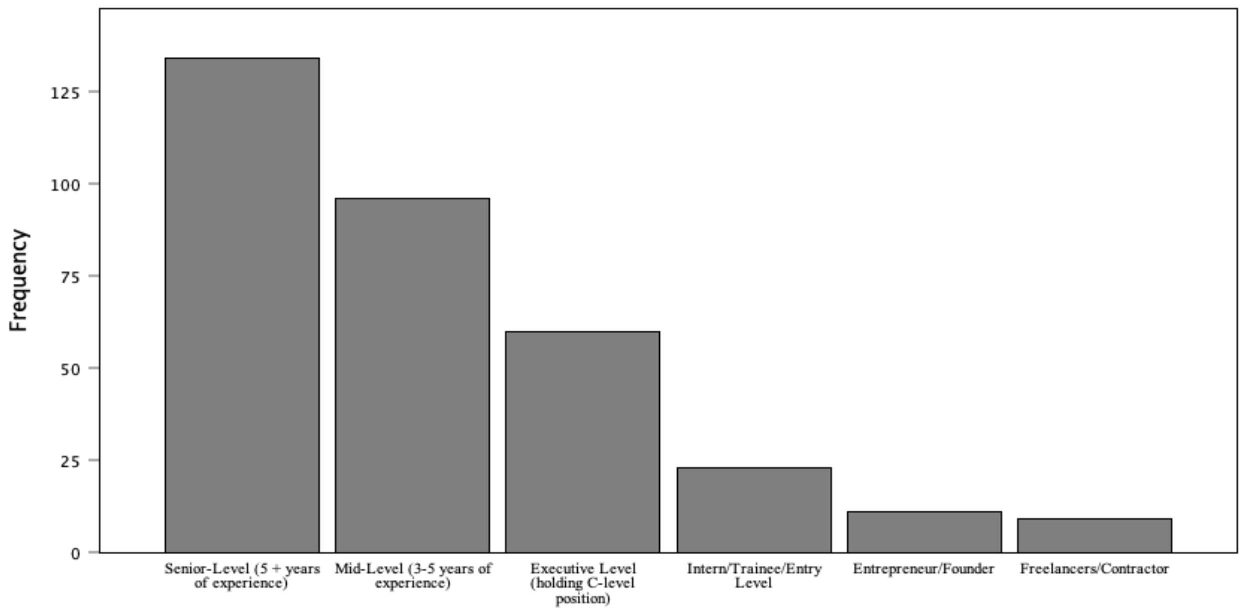


Figure 9 There are 40% respondents with over 5 years of experience and 18% are Executives.



5.3 Automation vs. Augmentation

In the recent times, evolving nature of applications in management has led to renewed interest in AI in management and most prominent researchers have segregated two distinct ways in which AI can be used in management, these are name “Automation” and “Augmentation”. Automation means that the AI systems completely takes over the task to be performed and does not need any human supervision or collaboration. Whereas Augmentation is defined as the collaboration of humans and AI working together to accomplish tasks. Three prominent AI scholars in management (Davenport & Kirby, 2016) (Daugherty & Wilson, 2018) (Brynjolfsson

& McAfee, 2014) have taken a stance that gives higher value to augmentation over automation and normatively prescribe organizations to prioritize augmenting managerial tasks rather than fully automating them. In the survey respondents we note that along with Automation and Augmentation, many professionals are now using AI as a personal assistant to enhance professional productivity. This could be linked to more than 70% of the professionals using tools such as ChatGPT as shown in figure below. Results also show that more tasks are automated rather than augmented as per Figure 9 below.

Figure 10 Role of AI at work for n= 333

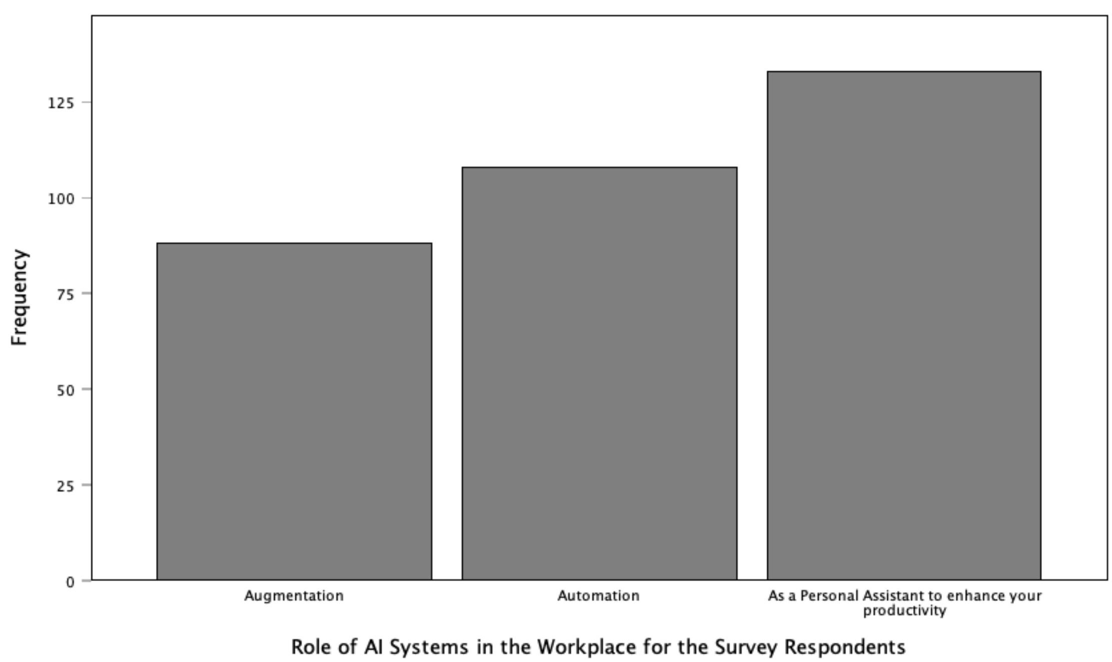


Figure 11 Most people are not sure about the ease with which their work can be augmented.

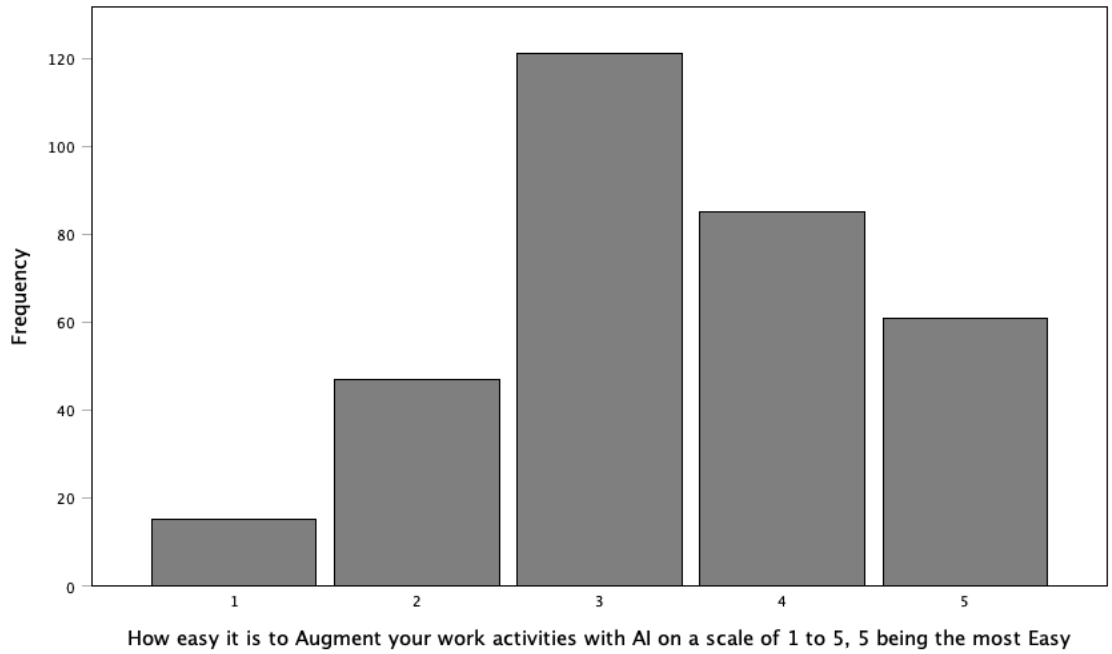
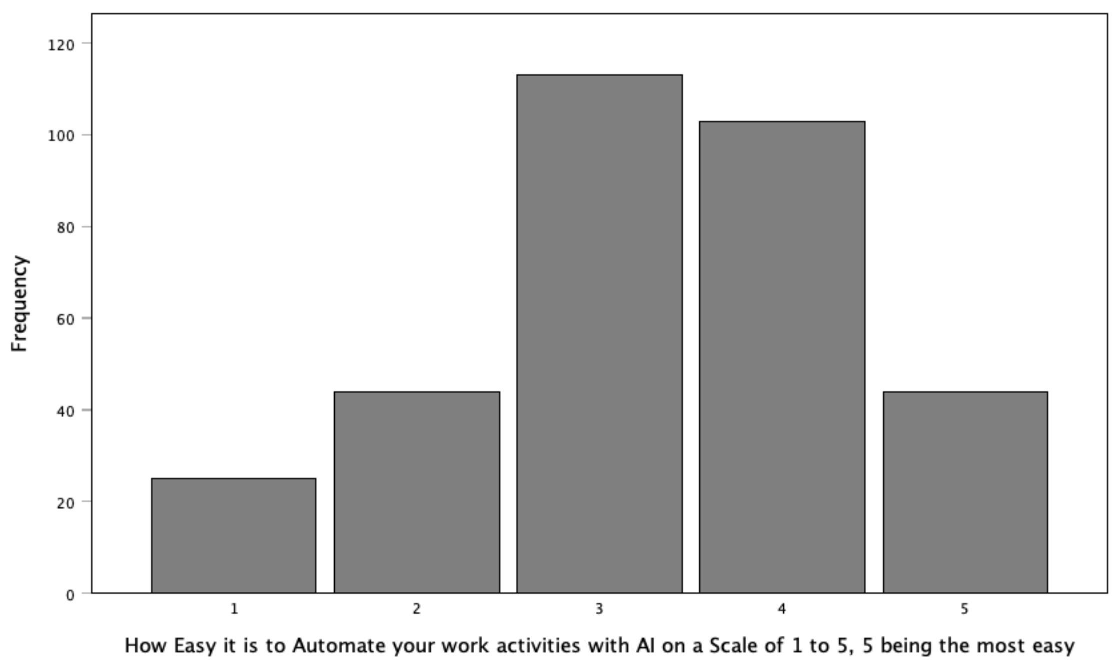


Figure 12 Most people report that their professional work can be easily automated.



5.4 Survey Responders' Interactions with AI Systems

Figure 13 Above 75% of the professionals are using ChatGPT for personal tasks.

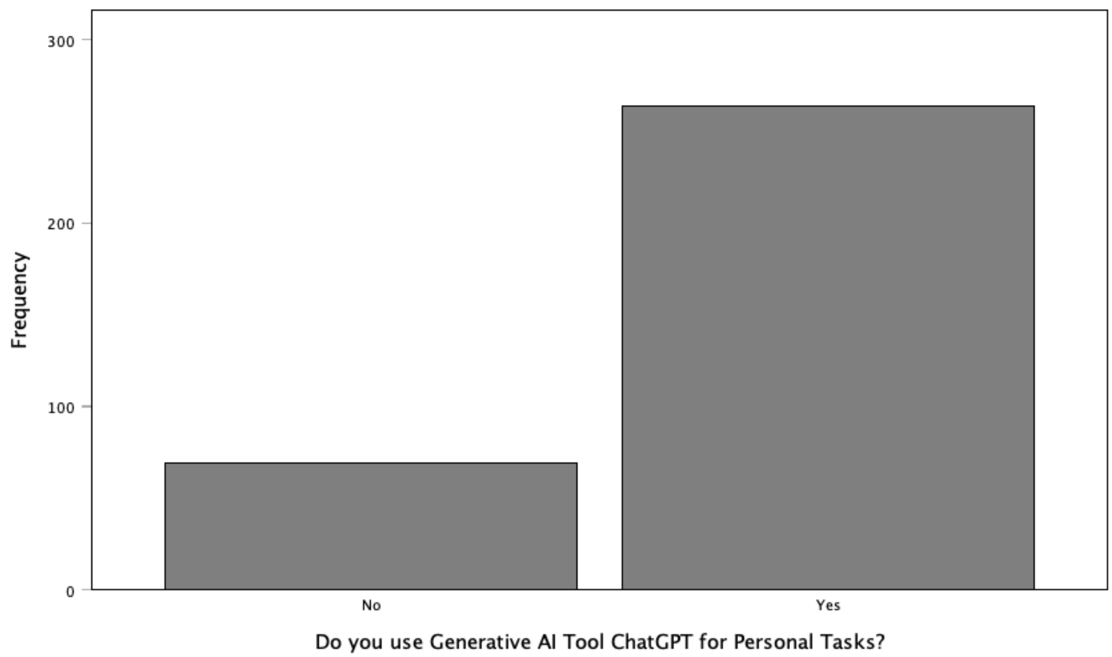


Figure 14 Intentions to Depend on AI outcomes

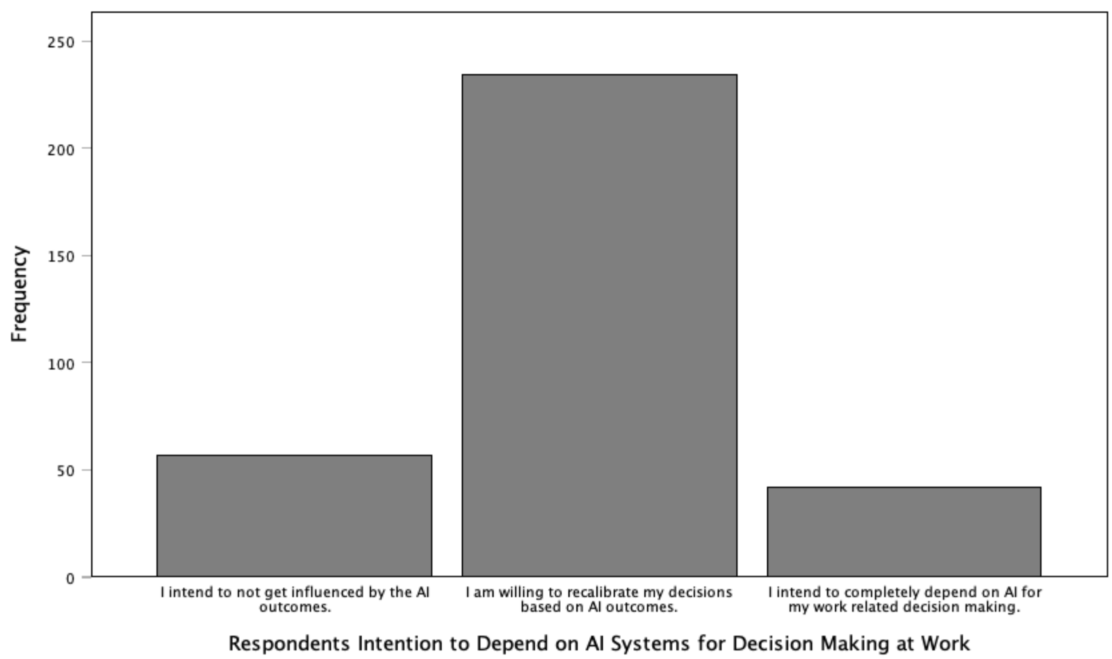


Figure 15 Beliefs in the accuracy of AI outcomes

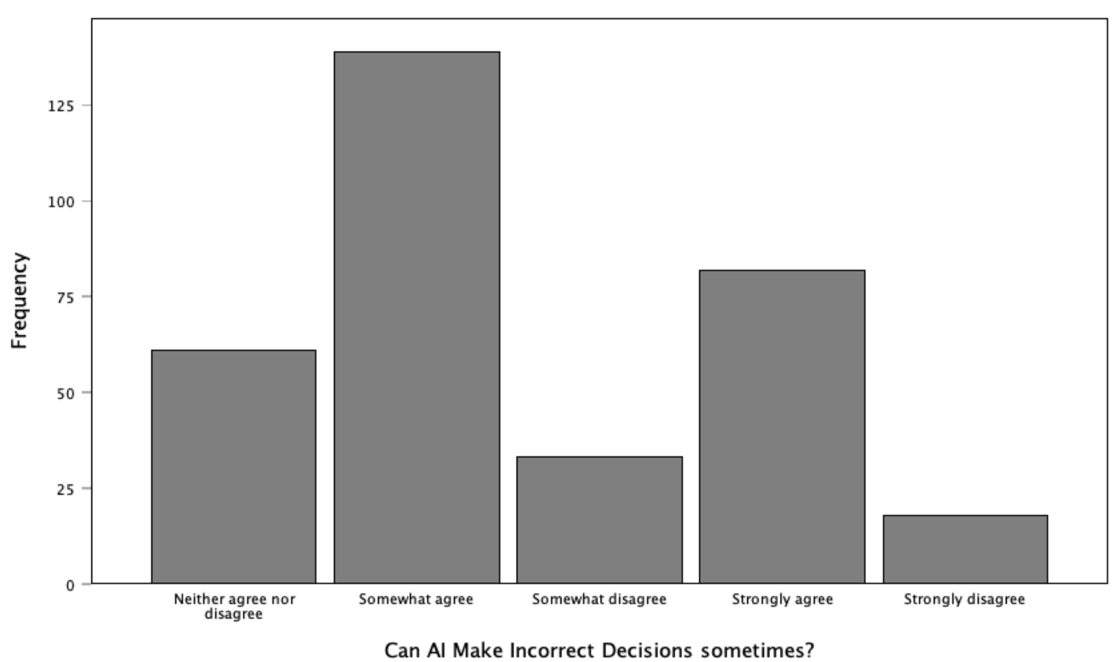
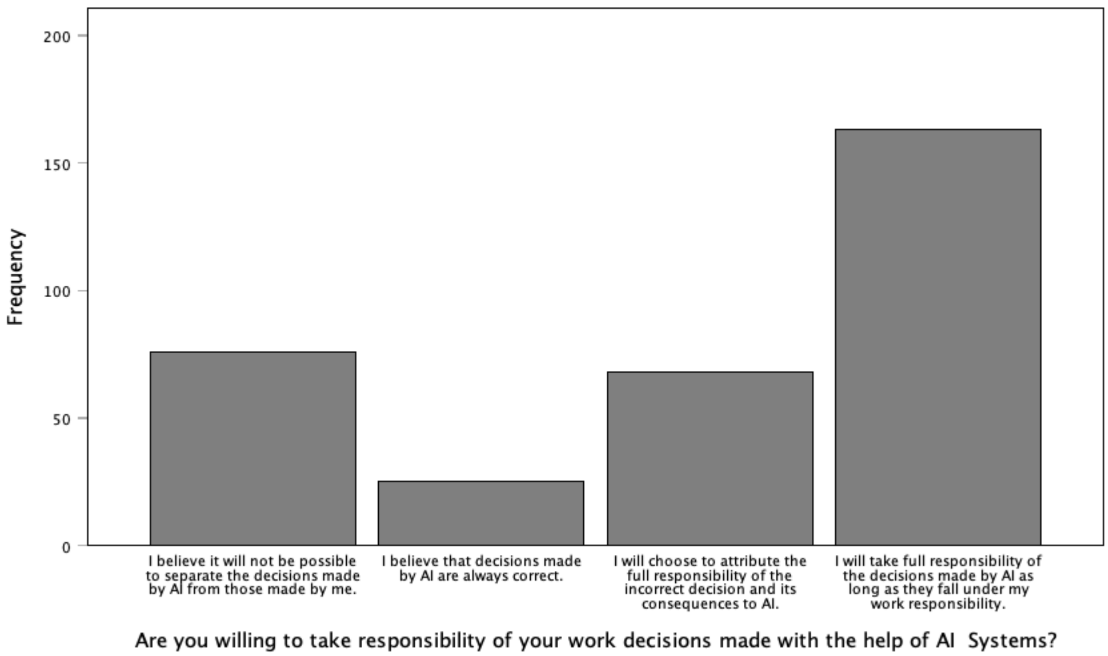


Figure 16 Most respondents are willing to take Responsibility of AI outcomes.



Chapter6 Measures and Constructs

This section, describes the variables that were used in the research. These variables were created using the published scales as detailed below. The distribution of these variables along with the scales used to measure them, have been discussed below.

6.1 Responsible AI Components

In this study I focus on the five components of Responsible AI that were proposed by a study published by (Floridi et al., 2018). These are beneficence, non-maleficence, autonomy, justice and explainability. Together these five factors make up the Responsible AI index, as discussed below.

6.1.1 Autonomy

As per the self-determination theory, Autonomy is important to humans. With respect to AI, autonomy implies the power of humans over the decisions made by them, when working alongside autonomous AI systems (Floridi, 2021). Human like intelligence of AI systems gives rise to concerns about AI taking complete control over tasks, whereby, AI systems have the potential to reduce human autonomy over the work done by them. As AI transforms work force, it’s important to ensure that employees feel in control of the decisions and choices being made by them. Hence, Responsible AI factor related to human autonomy, mandates that AI systems must always be controlled by humans and hence should operate in a controllable manner where humans have the final control on all its area of functioning. The scale used in this research was introduced by (Chen & Vanteenkiste, 2015). Table shown below provides the details of perceptions of human autonomy over decision making in situations where I and humans are collaborating. We see that more than 50% of the respondents in the survey somewhat agree to strongly agree that AI technology promotes their autonomy in work decision.

Table 1 Descriptive Statistics for Perceptions of Autonomy in AI Systems, n = 333

Autonomy Criteria	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree	Sum
AI technology makes me feel a sense of choice and freedom in the work activities I undertake.	3%	8%	22%	45%	23%	100%
AI technology makes me feel that my work-related decisions reflect what I really want.	2%	10%	26%	38%	24%	100%
AI technology makes me feel that I have been doing what really interests me in my job.	4%	6%	25%	38%	27%	100%

6.1.2 Beneficence

Implies that AI should be implemented in ways that ensure social well-being of customers and employees and society in general. An important aspect of practitioners' professional identity is linked to their work giving them the opportunity to do greater good to the society. According to (F Martela & R.M., 2016) positive social behaviours are linked to emotions of well-being. Scale for Beneficence that was used in this study has been is adopted from (F Martela & R.M., 2016). Over 40% of the respondents felt that AI positively influences the well-being in general.

Table 2 Descriptive Statistics for Perceptions of Beneficence in AI Systems, n = 333

Beneficience Criteria	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree	Sum
I feel that AI systems/technology has a positive impact on practitioners and customers.	2%	6%	23%	43%	26%	100%
The things AI systems/technology does contribute to the betterment of society.	2%	6%	22%	44%	26%	100%
AI systems/technology has been able to improve the welfare of practitioners and customers.	5%	5%	21%	46%	24%	100%
In general, the influence of AI systems/technology in the lives of practitioners and customers is positive.	3%	6%	21%	43%	27%	100%

6.1.3 Transparency and Explainability

Transparency and explainability of AI systems corresponds to the level of clarity with which users of the system can understand the reasoning behind the decisions made by the system. Scaled used was adopted from (Haesevoets & De Cremer, 2019). As per the table below, out of the diverse set of respondents in the survey, over 40% had positive perceptions of the transparency of AI systems in their organizations, while under 15% believed that the AI systems were lacking in their ability to explain the underlying processes in a clear manner.

Table 3 Descriptive Statistics for Perceptions of Explainability in AI Systems, n = 333

Explainability Criteria	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree	Sum
To what extent do you perceive the communication about AI technology in your organization as transparent.	2%	10%	30%	36%	22%	100%
To what extent do you think that how AI systems/technology works is communicated openly with practitioners.	1%	10%	30%	40%	19%	100%
To what extent do you think that relevant information about AI technology is shared among all practitioners in your organization.	3%	10%	28%	41%	19%	100%
To what extent do you think that practitioners within your organization share relevant information with each other.	3%	11%	29%	39%	18%	100%
To what extent do you think that practitioners within your organization communicate candidly with each other.	3%	9%	25%	43%	21%	100%

6.1.4 Justice

Justice relates to ensuring that the resources available in the society, equitably benefit all individuals. If the algorithmic decisions made by the AI system are perceived to be fair by the employees, they will be more willing to collaborate and work alongside these systems. Scale used in this research was adopted from (Newman & Fast, 2020). As per the table below, under 10% of the survey respondents, disagreed with the ability of AI systems to make just decisions.

Table 4 Descriptive Statistics for Perceptions of Justice in AI Systems, n = 333

Justice Criteria	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree	Sum
In my opinion the outcome of AI systems/technology assisted decisions was fair.	2%	7%	24%	42%	26%	100%
The process by which AI systems/technology facilitated decisions was fair.	3%	6%	24%	44%	23%	100%
I am satisfied with the way in which the AI systems/technology assisted decisions.	2%	4%	27%	41%	26%	100%
AI systems/technology often makes decisions in an unbiased and neutral manner.	4%	6%	24%	42%	25%	100%

6.1.5 Non-Maleficence

Non-maleficence refers to the responsibility to not induce harm intentionally to any individuals. With respect to AI systems this converts into the responsibility to focus on avoidance of any kind of harm. This could be related to the misuse of personal information on which the algorithmic decisions are made by the AI system. The descriptive statistics show the distribution of responses related to the items on the non-maleficence scale as designed by (Carlos Roca & Jose Garcia, 2009). While most survey respondents had positive perceptions of the non-maleficence of AI systems, under 15% had extreme negative views on this ability to prevent harm.

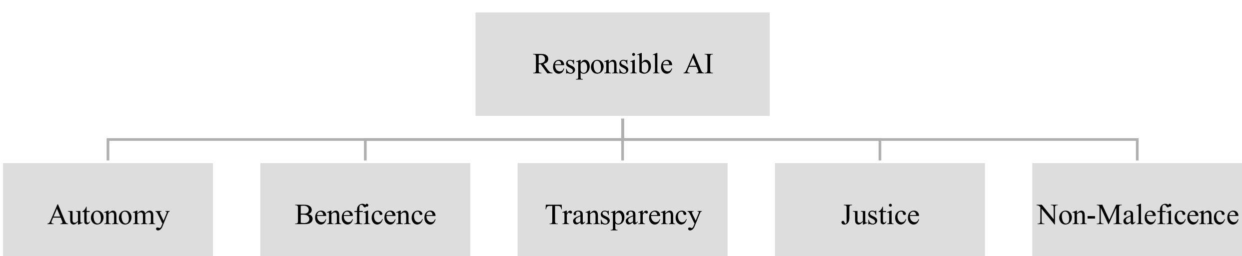
Table 5 Descriptive Statistics for Perceptions of Non-Maleficence in AI Systems, n = 333

NonMaleficience Criteria	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree	Sum
I think the AI systems/technology has sufficient technical capacity to ensure that the data about customers I send cannot be modified by a third party.	3%	10%	24%	40%	23%	100%
AI systems/technology has enough security measures to protect customers' personal information.	3%	13%	26%	34%	24%	100%
When I send customers' data via the AI systems/technology, I am sure that they will not be intercepted by unauthorized third parties.	4%	13%	28%	32%	23%	100%
I think the AI systems/technology has sufficient technical capacity to ensure that no other organization will supplant customers' identity.	3%	7%	26%	38%	25%	100%

6.2 Organizational Responsible AI index

The responsible AI index is an index that measures the degree to which organizations are developing and implementing AI in a responsible manner. The five factors described above are the components that are used to define the Responsible AI index.

Figure 17 Components of Responsible AI Index



Responsible Index = Degree of (Autonomy , Beneficence , Transparency , Justice , non-Maleficence). Our hypothesis suggests that adherence to Responsible AI adoption mitigates the fear of negative consequences of AI.

6.3 Perceived Corporate Social Responsibility (CSR) Index

Perceived CSR is defined as the perceptions of organizational stakeholders on the impact of company's strategies and operating policies on the well-being of all its main stakeholders along with the impact on the environment. (Glavas & Godwin, 2013). For this research, I used the scale developed by (Maignan & Ferell, 2001) to measure the Corporate Social Responsibility Perception across the four components of CSR namely, economic citizenship, legal citizenship, ethical citizenship and discretionary citizenship as per the figure 6, shown below.

Figure 18 Components of Corporate Social Responsibility (CSR)

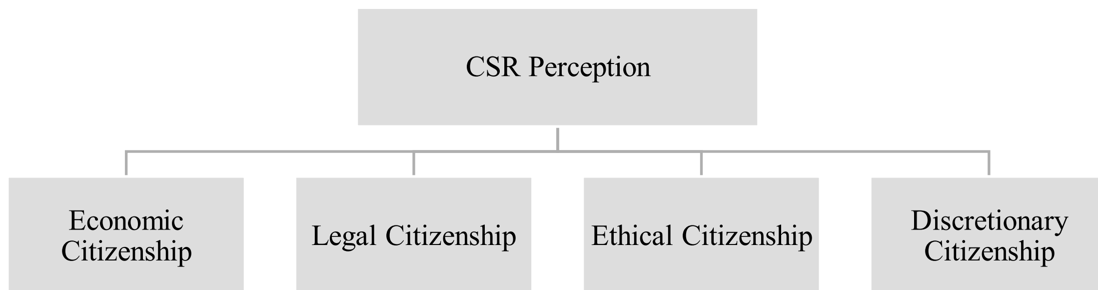


Table 5, Table 6, Table 7 and Table 8 describe the perceptions of CSR in the survey population. More than 50% of those surveyed had positive perceptions of the Corporate Social Responsibility shown by their respective organizations, on all the four components related to Economic, Legal, Ethical and Discretionary Citizenship.

Table 6 Descriptive Statistics for Perceived Economic Citizenship for Organizational CSR, n = 333

Economic Citizenship	**Strongly disagree**	**Somewhat disagree**	**Neither agree nor disagree**	**Somewhat agree**	**Strongly agree**	**Sum**
Our business has a procedure in place to respond to every customer complaint.	2%	6%	13%	42%	37%	100%
We continually improve the quality of our products.	2%	6%	11%	39%	42%	100%
We use customer satisfaction as an indicator of our business performance.	2%	5%	19%	38%	36%	100%
We have been successful at maximising our profits.	2%	5%	22%	39%	31%	100%
We strive to lower our operating costs.	4%	3%	17%	42%	33%	100%
We closely monitor employees' productivity.	2%	7%	19%	37%	36%	100%
Top management establishes long-term strategies for our business.	3%	7%	14%	41%	35%	100%

Table 7 Descriptive Statistics for Perceived Legal Citizenship for Organizational CSR, n = 333

Legal Citizenship	**Strongly disagree**	**Somewhat disagree**	**Neither agree nor disagree**	**Somewhat agree**	**Strongly agree**	**Sum**
Managers are informed about relevant environmental laws.	1%	7%	22%	35%	35%	100%
All our products meet legal standards.	1%	5%	16%	32%	46%	100%
Our contractual obligations are always honored.	1%	4%	17%	37%	42%	100%
The managers of this organization try to comply with the law.	3%	5%	16%	33%	44%	100%
Our company seeks to comply with all laws regulating hiring and employee benefits.	2%	3%	16%	33%	45%	100%
We have programs that encourage the diversity of our workforce (in terms of age, gender, or race).	2%	5%	18%	35%	41%	100%
Internal policies prevent discrimination in employees' compensation and promotion.	1%	5%	17%	39%	38%	100%

Table 8 Descriptive Statistics for Perceived Ethical Citizenship for Organizational CSR, n = 333

Ethical Citizenship	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree	**Sum**
Our business has a comprehensive code of conduct.	2%	3%	13%	40%	43%	100%
Members of our organization follow professional standards.	2%	4%	15%	35%	45%	100%
Top managers monitor the potential negative impacts of our activities on our community	3%	7%	19%	34%	38%	100%
We are recognised as a trustworthy company.	2%	3%	15%	37%	43%	100%
Fairness toward co-workers and business partners is an integral part of our employee evaluation process.	2%	5%	17%	35%	41%	100%
A confidential procedure is in place for employees to report any misconduct at work (such as stealing or sexual harassment).	2%	5%	15%	30%	48%	100%
Our salespersons and employees are required to provide full and accurate information to all customers.	1%	5%	14%	35%	44%	100%

Table 9 Descriptive Statistics for Perceived Discretionary Citizenship for Organizational CSR, n = 333

Discretionary Citizenship	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree	Sum
The salaries offered by our company are higher than industry averages.	7%	11%	23%	35%	24%	100%
Our business supports employees who acquire additional education.	3%	5%	23%	36%	33%	100%
Our business encourages employees to join civic organizations that support our community.	3%	8%	22%	38%	29%	100%
Flexible company policies enable employees to better coordinate work and personal life.	3%	7%	18%	39%	33%	100%
Our business gives adequate contributions to charities.	3%	6%	22%	37%	33%	100%
A program is in place to reduce the amount of energy and materials wasted in our business.	4%	8%	20%	36%	32%	100%
We encourage partnerships with local businesses and schools.	3%	8%	18%	37%	35%	100%
Our business supports local sports and cultural activities.	3%	6%	21%	36%	34%	100%

6.4 Technology Acceptance Index for AI Systems

The widely used Technology Acceptance Model(TAM) first introduced by (Davis, 1986) states that the attitude and usage intention of users towards a technology is strongly influenced by two main beliefs. One of which is **perceived usefulness** which is the degree to which the professional believes that using the technology will improve his/her work performance. The second is **perceived ease of use of Effort Expectancy** which is defined as the degree to which the person believes that using the system would be free of effort. In this study, I have used the pre-existing scales to measure these two beliefs. The original scales for technology acceptance beliefs are taken from (Venkatesh et al., 2003).

Figure 19 Components of Technology Acceptance Index

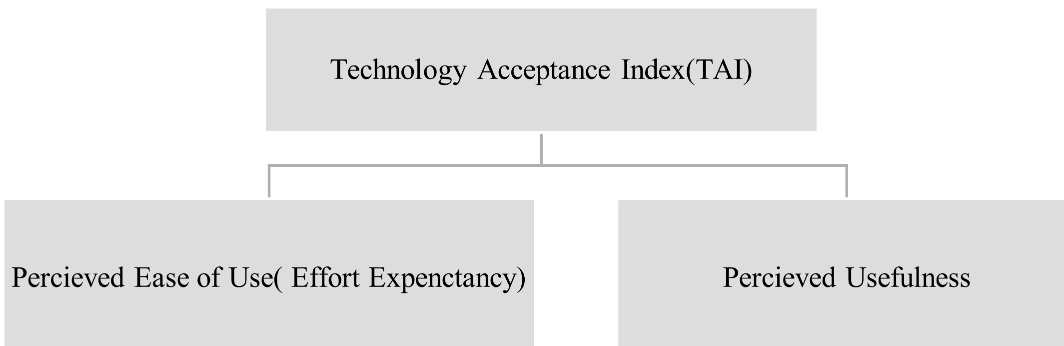


Table 10 Descriptive Statistics for Perceived Usefulness of AI Systems, n = 333

Perceived Usefulness	**Strongly disagree**	**Somewhat disagree**	**Neither agree nor disagree**	**Somewhat agree**	**Strongly agree**	**Sum**
I find AI systems/technology is useful in my work.	2%	5%	15%	44%	35%	100%
Using AI systems/technology enables me to accomplish task quickly.	2%	5%	18%	42%	33%	100%
Using AI systems/technology increases my productivity.	2%	7%	18%	39%	35%	100%
Using AI systems/technology will increase my overall performance at work.	2%	4%	19%	41%	34%	100%
AI systems/technology increases collaboration within departments.	2%	5%	20%	38%	34%	100%
AI systems/technology increases collaboration across departments.	2%	5%	22%	40%	32%	100%

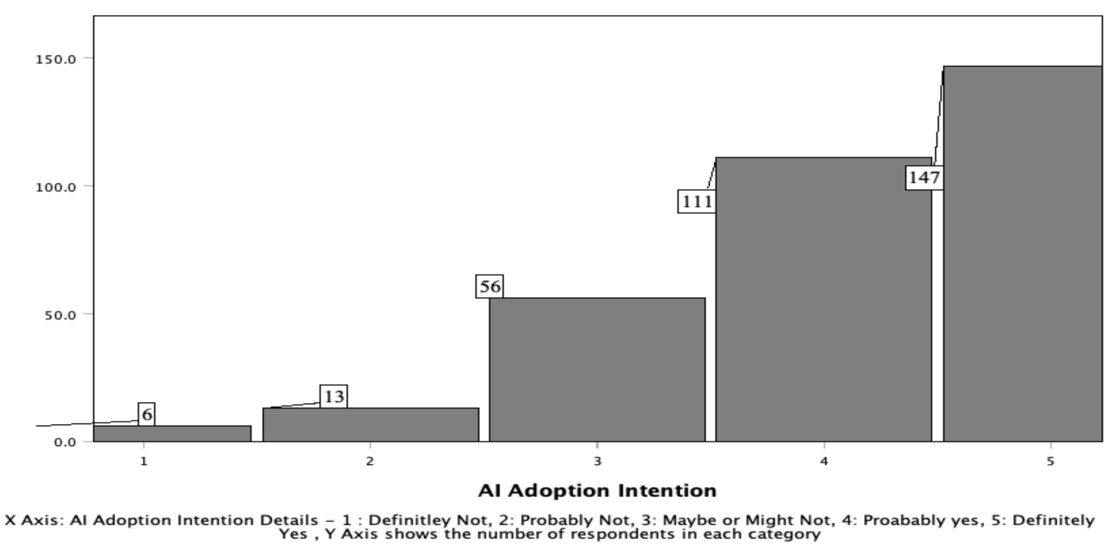
Table 11 Descriptive Statistics for Perceived Ease of Use, of AI Systems, n = 333

Perceived Ease of Use	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree	Sum
My interaction with AI systems/technology is clear and understandable.	3%	6%	16%	38%	38%	100%
It easy for me to become skillful in using AI systems/technology to do my work.	2%	6%	18%	40%	33%	100%
I find AI systems/technology easy to use.	2%	5%	19%	36%	39%	100%
Learning to use AI systems/technology is easy for me.	1%	4%	18%	41%	35%	100%

6.5 Dependent Variable - AI Adoption intention

The willingness of practitioner and employees to engage with AI tools, technologies, and decision outcomes in their daily work is defined as the AI Adoption Intention, which is the dependent variable in this research. This is influenced by employees' perceptions of AI and their attitudes towards AI. The survey question given below that was used to measure the DV, is based on the scale introduced by (Moons & Pelsmacker, 2012) which is "How likely are you going to use AI technology in your job in the future?"

Figure 20 Distribution of AI Adoption Intention for the survey respondents.



6.6 Descriptive Statistics of Variables Used in the Study

The correlation statistics in table 12, demonstrate a positive relationship between main variables of the study. We can see that Responsible AI is significantly and positively related to AI adoption Intention (correlation value 0.596) and with Technology Acceptance Index (correlation value 0.795).

Table 12 Descriptive Statistics and Correlation Analysis, n = 333

	Mean	**SD**	**AI Adoption Intention**	**Responsible AI Index**	**Technology Acceptance Index**	**Corporate Social Responsibility Index**	**Technology Job Dummy**	**Experienced Professionals Dummy**	**Age Above 35 Dummy**	**Female Gender Dummy**	**USA Country Dummy**
AI Adoption Intention	4.14	0.95	--								
Responsible AI Index	3.75	0.73	.569**	--							
Technology Acceptance Index	4.01	0.73	.572**	.776**	--						
Corporate Social Responsibility Index	4.03	0.68	.528**	.669**	.795**	--					
Technology Job Dummy	0.24	0.426	.147**	.206**	.206**	.108*	--				
Experienced Professionals Dummy	0.58	0.494	.170**	.186**	.165**	.181**	.143**	--			
Age Above 35 Dummy	0.64	0.481	0.078	0.07	0.046	.138*	0.007	.227**	--		
Female Gender Dummy	0.62	0.486	-0.086	-.257**	-.195**	-.110*	-.191**	-0.083	-0.057	--	
USA Country Dummy	0.68	0.465	0.039	0.073	0.07	0.083	0.105	-0.05	0.029	0.004	--

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

6.7 Internal Consistency of the Constructs

Internal consistency reliability in Table13 reflects the extent to which responses of the multiple items align and reflect consistency in responses. Each of the index in the study is made up of multiple constructs that consist of several items. Cronbach alpha measures the inter item reliability, which in this case is above the acceptable threshold of 0.70.

Table 13 Internal Consistency Reliability as shown by Cronbach Alpha is above 0.70, n = 333

Composite Score	Construct	Cronbach's Alpha	Number of Items
Responsible AI Index	Beneficience	0.8630	4
	Non Maleficience	0.8796	4
	Transparency	0.8629	5
	Autonomy	0.8112	3
	Justice	0.8337	4
Corporate Social Responsibility Index	Economic CSR	0.8778	7
	Legal CSR	0.8760	7
	Ethical CSR	0.8916	7
	Discretionary CSR	0.8748	8
Technology Acceptance Index	Percieved Usefulness of AI Technology	0.8874	6
	Effort Expectancy of AI Technology	0.8384	4

Chapter7 Data Analysis Results

The survey data was analyzed to test the statistical significance of the hypothesized relationships. This section describes the details of the analysis that was done and discusses the results obtained in detail. Linear Regression analysis has been used to describe the relationship between independent and dependent variables in this study. To test the stated hypothesis, Ordinary Least Square technique has been used for estimating the coefficients of the linear regression equations.

7.1 Hypothesis 1: Relationship between Responsible AI and AI Adoption Intention

Hypothesis 1 states that Positive perceptions of organizational Responsible AI lead to improved AI adoption intention by employees.

Table 14 Responsible AI has a positive significant relationship with AI Adoption Intention

Model		Unstandardized Coefficients		t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error			Lower Bound	Upper Bound
1	constant	1.3651	0.2248	6.0718	0.0001	0.9228	1.8074
	Responsible AI Index	0.7409	0.0589	12.5805	0.0001	0.6251	0.8568
a. Dependent Variable: AI Adoption Intention							
b. R Squared = .0.3235 , F-Statistic = 158.2							
c. N = 333							

Results shown in Table 14, suggest that the relationship between Responsible AI and AI adoption Intention is significant (b = 0.7409 , SE = .0589 , t = 12.58 , p < .001) , hence hypothesis is supported.

7.2 Hypothesis2: Relationship between Responsible AI and Technology Acceptance

Positive perceptions of Responsible AI by employees have a positive impact on Technology acceptance beliefs, namely Perceived ease of use and Perceived usefulness of the AI System, coded jointly as Technology Acceptance Index.

Table 15 Responsible AI has a positive significant relationship with Technology Acceptance Index

Model		Unstandardized Coefficients		t	Sig.	95.0% Confidence Interval for B	
		B	**Std. Error**			**Lower Bound**	**Upper Bound**
1	**(Constant)**	1.1248	0.1315	8.5519	0.0001	0.866	1.3835
	Responsible AI Index	0.7701	0.0345	22.3522	0.0001	0.7023	0.8379
a. Dependent Variable: Technology Acceptance Index							
b. R Squared = .6015 , F-Statistic = 499.6							
c. N = 333							

Results shown in Table 15, suggest that the relationship between Responsible AI and AI adoption Intention is significant ($b = 0.7701$, $SE = .0345$, $t = 22.35$, $p < .001$), hence hypothesis 2 is supported.

7.3 Hypothesis 3: Relationship between Technology Acceptance and AI Adoption

Positive relationship between Technology Acceptance Index and AI Adoption Intention. Technology acceptance beliefs, namely Perceived ease of use and Perceived usefulness of the AI System, coded jointly as Technology Acceptance Index are positively linked with AI adoption intention as stated by the Technology Acceptance Model (Davis, 1986)

Table 16 Positive Relationship between Technology Acceptance Index and AI Adoption Intention

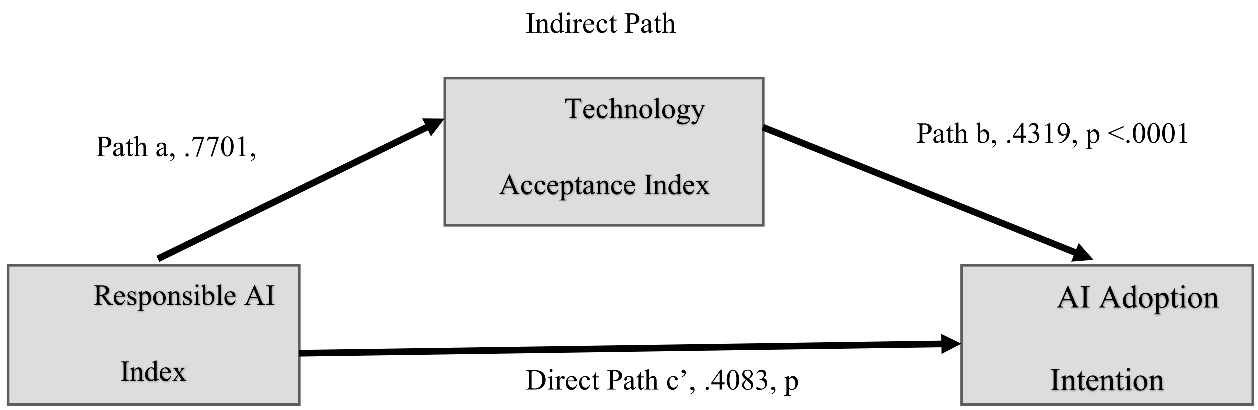
Model		Unstandardized Coefficients		t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error			Lower Bound	Upper Bound
1	constant	0.8793	0.2407	3.6526	0.0003	0.406	1.3528
	Responsible AI Index	0.4083	0.0904	4.5162	0.0001	0.23	0.5861
	Technology Acceptance Index	0.4319	0.091	4.7441	0.0001	0.253	0.611
a. Dependent Variable: AI Adoption Intention							
b. R Squared = .3667 , F-Statistic = 499.6							
c. N = 333							

Results shown in Table 16, suggest that the relationship between Technology Acceptance Index and AI adoption Intention is significant (b = 0.4319 , SE = .091 , t = 4.74, p < .001), hence hypothesis 3 is supported.

7.4 Hypothesis 4: Role of Technology Acceptance Index as a Mediator is supported.

Positive perceptions of Responsible AI by employees improves employee's AI adoption Intention and this relationship is **mediated** by Technology acceptance beliefs, namely Perceived ease of use and Perceived usefulness of the AI System, coded jointly as Technology Acceptance Index. To investigate the research question related to hypothesis 4, a simple mediation analysis was performed using PROCESS. The outcome variable was AI Adoption Intention, and the predictor variable was the Responsible AI index. The mediator variable for the analysis was AI Acceptance Index. Supporting Hypothesis 4, Technology Acceptance Index significantly mediated the effect of Responsible AI factors on the AI Adoption intention. Where the indirect effect = 0.3326, 95% CI [.1683, .4888], proportion of total effect mediated = 44%.

Figure 21 Mediation Results



7.5 Hypothesis 5: Role of CSR as a Moderator

5a) The relationship between Responsible AI and Technology acceptance perceptions is moderated by CSR perceptions.

5b) Positive perceptions of Responsible AI by employees lead to improved AI adoption intention and this relationship is moderated by CSR perceptions.

Figure 22 Process Model 8 By Andrew Hayes

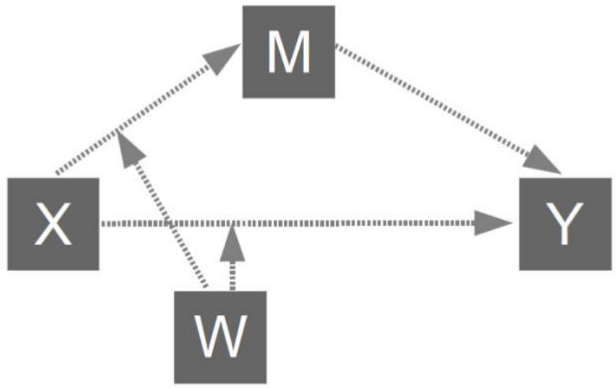


Table 17 Model Coefficients for Technology Acceptance Index as the outcome variables

Term	Coefficient	SE	t	p	LLCI	ULCI
Constant	4.0351	0.0233	173.54	0	3.9894	4.0809
Responsible AI	0.4521	0.0379	11.9372	0	0.3776	0.5266
CSR	0.5082	0.0422	12.0297	0	0.4251	0.5913
Interaction Term	-0.0753	0.0343	-2.1972	0.0287	-0.1428	-0.0079
a. Dependent Variable: Technology Acceptance Index						
b. R Squared = .0.7435 , F-Statistic = 317.8						
c. N = 333						

Table 18 Model Coefficients for AI Adoption Intention as the outcome variables

Term	Coefficient	SE	t	p	LLCI	ULCI
Constant	3.1177	0.4564	6.8309	0	2.2198	4.0155
Responsible AI	0.4151	0.0925	4.4865	0	0.2331	0.5971
Technology Acceptance Index	0.2654	0.1125	2.359	0.0189	0.0441	0.4867
CSR	0.188	0.1034	1.8181	0.07	-0.0154	0.3915
Interaction Term	-0.1228	0.0705	-1.7431	0.0822	-0.2615	0.0158
a. Dependent Variable: AI Adoption Intention						
b. R Squared = .0.3813 , F-Statistic = 50.5						
c. N = 333						

The hypothesised moderated mediation model (Figure 22) was tested in a single model using Combined Moderated Mediation Analysis, an approach **to assess the significance of the indirect effects at differing levels of the moderator** (Hayes, 2013) . Responsible AI index was the predictor variable, with Technology acceptance index as the mediator. The outcome variable was AI Usage intention and perceptions of organizational Corporate Social Responsibility is the proposed moderator. **Moderated mediation analyses** tests the conditional indirect effect of a moderating variable (i.e., perceptions of organizational Corporate Social Responsibility) on the relationship between a predictor (i.e., Responsible AI index) and an outcome variable (i.e., AI Usage intention) via potential mediators (i.e., Technology acceptance index). The "PROCESS" macro, was used to test the significance of the indirect (i.e., mediated) effects moderated by Perceived CSR, i.e., conditional indirect effects. This model explicitly tests the moderating effect on the predictor to mediator path (i.e., path a). An index of moderated mediation was used to test the significance of the moderated mediation, i.e., the difference of the indirect effects across levels of need for Perceived CSR (Hayes, 2015). Significant effects are supported by the absence of zero within the confidence intervals.

The mediation model establishes that Perceptions of Organization's Responsible AI adherence positively and significantly effects employees' intention of using AI in the future. The mediation variable Technology Acceptance index is the mechanism by which Organization's Responsible AI effects intention of using AI that means that Organization's Responsible AI effects Technology Acceptance index and in turn Technology Acceptance index effects intention of using AI. This research aims to answer the question of how and just whether.

The interaction between Responsible AI and Corporate Social Responsibility(CSR) predicting AI Adoption Intention was found to be **marginally significant** ($b = -0.1228$, $SE = 0.0705$, $t = -1.7431$, $p = 0.0822$).The p-value of the interaction term is 0.0822, which is marginally above the conventional cutoff for statistical significance ($p < .05$). **This suggests that the moderation effect of CSR on the Responsible AI - AI Adoption Intention relationship is not statistically significant at the 5% level but is close to being significant**. The negative coefficient (-0.1228) indicates that as CSR increases, the strength of the relationship between Responsible AI and AI Adoption Intention decreases. Overall, while the moderation effect of CSR on the Responsible AI - AI Adoption Intention relationship is not statistically significant at the conventional 5% level, its marginal significance and the direction of the interaction suggest it may still be of interest in understanding the dynamics between these variables.

The interaction between Responsible AI and CSR in predicting Technology Acceptance Index was found to be **significant** ($b = -0.0753$, $SE = 0.0343$, $t = -2.1972$, $p = 0.0287$). The p-value of the interaction term is 0.0287, which is below the conventional cut-off for statistical significance ($p < .05$). **This indicates that the moderation effect of CSR on the relationship between Responsible AI and Technology Acceptance Index is statistically significant.** The negative coefficient (-0.0753) implies that as CSR increases, the effect of Responsible AI on Technology Acceptance Index decreases. In summary, CSR serves as a significant moderator in the relationship between Responsible AI and Technology Acceptance Index, indicating that the effect of Responsible AI on Technology Acceptance Index varies depending on the level of CSR.

Chapter8 Additional Qualitative Study

In this research, I conducted unstructured interviews to gauge participants perceptions of AI Ethics and its impact on the employees engagement with AI Systems. The participants were recruited using convenience sampling by reaching out to the network of known professionals to understand their views about the Responsible AI practices undertaken by their organizations, their experiences working with AI and perceptions of AI Systems. The questions asked were broad and included in Appendix B of this report.

8.1 Results from the Qualitative Study

Participant1 *"I believe that if employees know that AI has been deployed ethically, this would enhance the trust people have in the organization"*

Participant2 "*Companies should invest in training employees about AI so they can fully understand the consequences of these applications"*

Participant3 "*I believe if Responsible deployment of AI will help to pacify some concerns related to the unknown outcomes of AI"*

Participant4 *" I am concerned that AI automation might replace me, ethical AI is important but the concerns still remain"*

Table 19 Summary of participant responses

	Type of AI Worked with	Perceptions of AI Ethics	Impact of AI Ethics on engagement with AI
Participant 1	Chatbots, Image generative tools	Privacy, copyright Infringements	Pacify the concerns to some extent, enahnce organizational reputaiton
Participant 2	Facial recognition tools, conternt creating tools	Biases, plagirism, Lack of understanding about how AI works	Feel safe about using AI and fully embrace it but the issue is that people don't quite know understand the system they are using
Participant 3	HR recruitment screening	Biases and Privacy related to surveillance	Better engagement due to understanding of AI outcomes
Participant 4	Generative AI tools	Issues related to false informaiton	Reduce lack of trust on outcomes and undrstanding of how content is being generated

As we can see from the results of the qualitative study, participants expressed their concerns and perceptions regarding the ethical deployment of Artificial Intelligence (AI) within their organizations. Participant 1, who has experience with chatbots and image generative tools, highlighted privacy and copyright infringements as major ethical concerns. Participant believes that ethical deployment of AI can pacify these concerns to some extent and enhance the organization's reputation, suggesting that "if employees know that AI has been deployed ethically, this would enhance the trust people have in the organization." Similarly, Participant 2, working with facial recognition and content creating tools, pointed out biases, plagiarism, and a lack of understanding about how AI works as significant issues. This emphasizes the need for companies to invest in training employees about AI to fully understand and embrace its applications safely. On the other hand, Participant 3, involved with HR recruitment screening, focused on biases and privacy issues related to surveillance, noting that better engagement could be achieved through a deeper understanding of AI outcomes. Participant 4, who works with generative AI tools, raised concerns about the dissemination of false information, suggesting that addressing these issues could reduce the lack of trust in AI outcomes and improve understanding of how content is generated. Overall, the participants highlighted the importance of responsible AI adoption in enhancing engagement, trust, and understanding of AI within organizations, pointing towards a need for ethical considerations and employee education in AI deployments. Most participants indicated that Ethical AI would improve their engagement with AI due to better understanding of the AI related outcomes.

8.2 Limitations of the qualitative study:

While convenience sample proved to a practical approach to data collection as a supplement to the main study conducted for the purpose of this research, it does have some drawbacks. The participants for this qualitative study, might not be fully representative of the broader population as they might belong to a narrow subgroup. This can raise issues of biased opinions.

Chapter9 Robustness Checks on the Research Findings

This section elaborates the multiple, robustness checks that were undertaken to establish the causality of the relationship between the main Independent Variable (Responsible AI) and the Dependent Variable (AI Adoption Intention).

9.1 Adding Control Variables to rule out Competing Explanations

I accounted for various control variables in order to rule out any confounding effects. **Contextual factors** that could impact technology usage intention cited in literature (Huang, 2003) (Padilla-Meléndez, 2013),(Straub, 1997) include factors such as gender and cultural diversity. To enhance the robustness of the findings, I have accounted for three different types of control variables based on demography, technology experience and expertise and cultural differences. The intention to use AI could be influenced by the responders demographic characteristics such as **age and gender**. Technology profile of the job scope that the professional undertakes could also affect the intention to use AI, hence I have added a control variable that checks for the **jobs that are in based in the technology department** of the organization. To remove any effect of cultural differences based on geographic location of the respondent a control variable that checks for location to be United States, as a reference, has been added. The following five control variables have been accounted for: Technology related job profile, years of Experienced/ level of seniority of Professionals, age of the professional, gender and country of residence. Results in Table 16, show that Responsible AI index continues to have a significant positive relationship with AI usage intention even when control variables are added into the model.

Table 20 Model for Dependent Variable as AI Usage Intention with Control Variables

Coefficients^a	Model1	Model2
(Constant)	3.882***	1.164***
Technology Job	0.254*	0.08
Experienced Professionals	0.274**	0.114
Age	0.082	0.059
Female Gender	-0.099	0.144
USA Country	0.069	-0.008
Responsible AI Index		0.739***
a. Dependent Variable: AI Adoption Intention		
* P ≤ 0.05		
** P ≤ 0.01		
*** P ≤ 0.001		

9.2 Testing the Effect of Responsible AI Components on AI Adoption Intention

I checked the individual relationship of each of the five Responsible AI factors on the AI usage intention and Beneficence, Non-Maleficence and Autonomy are found to have statistically significant effect on AI usage intention. However, due to high correlation between the factors there is high multi-collinearity in the results and the signs cannot be reliably interpreted.

Table 21 Effect of Responsible AI Components on AI Usage Intention

Coefficients^a	Model	Significance Level
(Constant)	1.209**	<.001
Beneficience	0.565***	<.001
Non_maleficience	-0.221**	0.007
Transparency	0.094	0.227
Autonomy	0.293***	0.001
Justice	0.034	0.733
a. Dependent Variable: AI Adoption Intention		
* P ≤ 0.05		
** P ≤ 0.01		
*** P ≤ 0.001		

Table 22 Pearson's Correlation Coefficient Between Responsible AI Components

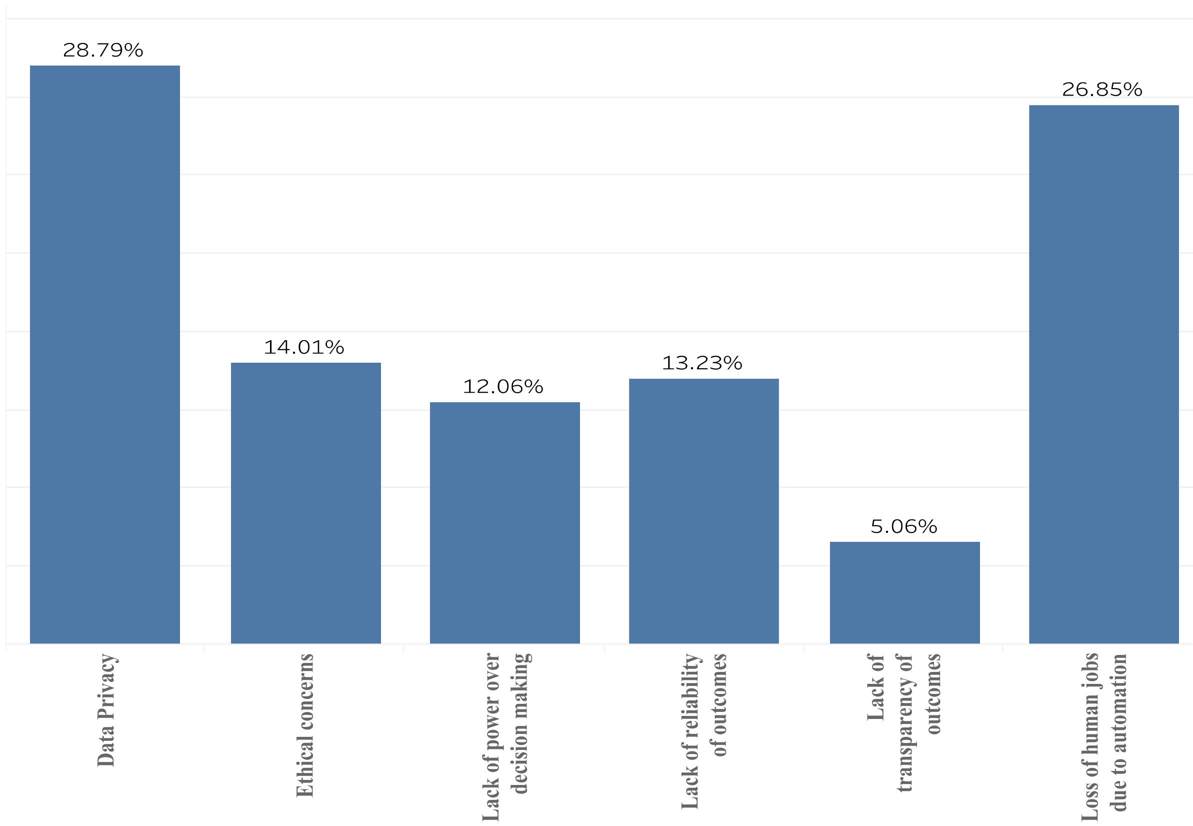
	Beneficience	**Non_maleficience**	**Transparency**	**Autonomy**	**Justice**
Beneficience	--				
Non_maleficience	.746**	--			
	<.001				
Transparency	.656**	.683**	--		
	<.001	<.001			
Autonomy	.764**	.753**	.648**	--	
	<.001	<.001	<.001		
Justice	.767**	.750**	.685**	.791**	
	<.001	<.001	<.001	<.001	

**. Correlation is significant at the 0.01 level (2-tailed).

9.3 Checks for Reverse Causality

To rule our reserve causality, I tested the ethical perceptions of AI amongst survey respondents with high AI usage. Figure 21, displayed below shows that AI usage does not itself cause positive beliefs about AI Ethics. As shown below in this selected population of the responders who are currently using AI intensively, 28.79% have privacy concerns, 12% fear loss of automation in decision making, 14% have concerns about ethics of AI in general. These results suggest the lack of reverse causality between the IV and DV in the study.

Figure 23 Concerns about AI for those using AI, n = 143 out of total n = 333



9.4 Heterogeneity Post hoc tests to check for generalizability across subgroups.

Subgroup analysis has been used in research to establish consistency and generalizability of research findings across various subgroups of the population. These groups are based on gender, age , industry and other sources of variance in the data that impact the generalizability of the results and research findings (Schühlen, 2014). For the purpose of this study, I have checked for heterogeneity post hoc across Firm size, Gender, industry of occupation and Country of residence to ascertain if the findings hold across the subgroups and subsegments.

9.4.1 Country Subgroups

I tested the results across the three countries United States of America, Australia, and Singapore to test the findings and the results show that Responsible AI has a significant relationship with AI Adoption intention as per the tables 18, table 19 and table 20.

Table 23 Regression Results, Country = United States of America, n = 228

Model		Unstandardized Coefficients		t	Sig.	95.0% Confidence Interval	
		B	Std. Error			Lower Bound	Upper Bound
	(Constant)	1.2052	0.259	4.647	<.001	0.694	1.716
	Responsible AI Index	0.7829	0.067	11.673	<.001	0.651	0.915
a. Dependent Variable: AI Adoption Intention							
b. R Squared = 0.376, F-Statistic = 136.3							
c. N = 228							

Table 24 Regression Results, Country = Australia, n = 55

Model		Unstandardized Coefficients		t	Sig.	95.0% Confidence	
		B	Std. Error			Lower Bound	Upper Bound
	(Constant)	2.5772	0.692	3.723	<.001	1.189	3.966
	Responsible AI Index	0.4181	0.189	2.212	0.031	0.039	0.797
a. Dependent Variable: AI Adoption Intention							
b. R Squared = 0.085, F-Statistic = 4.892							
c. N = 55							

Table 25 Regression Results, Country = Singapore, n = 50

Model		Unstandardized Coefficients		t	Sig.	95.0% Confidence	
		B	Std. Error			Lower Bound	Upper Bound
	(Constant)	1.4708	0.688	2.138	0.038	0.088	2.854
	Responsible AI Index	0.7013	0.183	3.829	<.001	0.333	1.07
a. Dependent Variable: AI Adoption Intention							
b. R Squared = 0.234, F-Statistic = 14.66							
c. N = 50							

9.4.2 Gender Subgroups

Tables 21 and 22 show that the relationship between Responsible AI and AI adoption Intention is significant for Males and Females

Table 26 Regression Results, Gender = Female, n = 207

Model	Unstandardized Coefficients		t	Sig.	95.0% Confidence	
	B	Std. Error			Lower Bound	Upper Bound
(Constant)	1.3078	0.273	4.792	<.001	0.77	1.846
Responsible AI Index	0.7693	0.074	10.332	<.001	0.623	0.916
a. Dependent Variable: AI Adoption Intention						
b. R Squared = 0.342, F-Statistic = 106.8						
c. N = 207						

Table 27 Regression Results, Gender = Male, n = 124

Model	Unstandardized Coefficients		t	Sig.	95.0% Confidence	
	B	Std. Error			Lower Bound	Upper Bound
(Constant)	1.2779	0.432	2.959	0.004	0.423	2.133
Responsible AI Index	0.7453	0.107	6.996	<.001	0.534	0.956
a. Dependent Variable: AI Adoption Intention						
b. R Squared = 0.286, F-Statistic = 48.94						
c. N = 124						

9.4.3 Company Size Based Subgroups

Company Size based subgroups are created by categorizing the companies based on their size, on the number of employees where **small** size corresponds to firms with under 200 employees, **middle** size with 200 to 5000 and above 5000 are categorized as **large** firms. Irrespective of the Size of the firm, results show that Responsible AI has a significant impact on AI Adoption Intention

Table 28 Regression Results, Small Companies with under 200 employees, n = 150

Model	Unstandardized Coefficients		t	Sig.	95.0% Confidence	
	B	Std. Error			Lower Bound	Upper Bound
(Constant)	0.8215	0.308	2.666	0.009	0.213	1.43
Responsible AI Index	0.8795	0.082	10.776	<.001	0.718	1.041
a. Dependent Variable: AI Adoption Intention						
b. R Squared = 0.440, F-Statistic = 116.1						
c. N = 150						

Table 29 Regression Results, Medium Sized Companies with 200 to 1000 employees, n = 109

Model	Unstandardized Coefficients		t	Sig.	95.0% Confidence	
	B	Std. Error			Lower Bound	Upper Bound
(Constant)	1.291	0.448	2.881	0.005	0.403	2.179
Responsible AI Index	0.7545	0.116	6.526	<.001	0.525	0.984
a. Dependent Variable: AI Adoption Intention						
b. R Squared = 0.285, F-Statistic = 42.59						
c. N = 109						

Table 30 Regression Results, Large Sized Companies with more than 1000 employees, n = 74

Model	Unstandardized Coefficients		t	Sig.	95.0% Confidence	
	B	Std. Error			Lower Bound	Upper Bound
(Constant)	2.4779	0.443	5.592	<.000	1.594	3.361
Responsible AI Index	0.4685	0.116	4.035	<.001	0.237	0.7
a. Dependent Variable: AI Adoption Intention						
b. R Squared = 0.184, F-Statistic = 16.28						
c. N = 74						

9.4.4 Industry Based Subgroups

Focusing on the main industry of the respondents to check for validity of the results across the various industries, I have created subgroups for Healthcare, Financial Services, Education, Information systems, Retail and Construction. We get significant results in all the groups except for Financial Services.

Table 31 Regression Results, Industry = Healthcare, n = 43

Model	Unstandardized Coefficients		t	Sig.	95.0% Confidence	
	B	Std. Error			Lower Bound	Upper Bound
(Constant)	1.0608	0.535	1.981	0.054	-0.021	2.142
Responsible AI Index	0.8285	0.142	5.836	<.001	0.542	1.115
a. Dependent Variable: AI Adoption Intention						
b. R Squared = 0.454, F-Statistic = 34.06						
c. N = 43						

Table 32 Regression Results, Industry = Education, n = 27

Model	Unstandardized Coefficients		t	Sig.	95.0% Confidence	
	B	Std. Error			Lower Bound	Upper Bound
(Constant)	1.1579	1.009	1.148	0.262	-0.919	3.235
Responsible AI Index	0.7078	0.285	2.486	0.02	0.121	1.294
a. Dependent Variable: AI Adoption Intention						
b. R Squared = 0.198, F-Statistic = 6.181						
c. N = 27						

Table 33 Regression Results, Industry = Information Systems, n = 96

Model	Unstandardized Coefficients		t	Sig.	95.0% Confidence	
	B	Std. Error			Lower Bound	Upper Bound
(Constant)	1.6957	0.434	3.909	<.001	0.834	2.557
Responsible AI Index	0.6962	0.109	6.412	<.001	0.481	0.912
a. Dependent Variable: AI Adoption Intention						
b. R Squared = 0.304, F-Statistic = 41.12						
c. N = 96						

Table 34 Regression Results, Industry = Retail, n = 53

Model	Unstandardized Coefficients		t	Sig.	95.0% Confidence	
	B	Std. Error			Lower Bound	Upper Bound
(Constant)	0.6142	0.519	1.183	0.242	-0.428	1.656
Responsible AI Index	0.8878	0.144	6.181	<.001	0.599	1.176
a. Dependent Variable: AI Adoption Intention						
b. R Squared = 0.428 , F-Statistic = 38.21						
c. N = 53						

Table 35 Regression Results, Industry = Financial Services, n = 34

Model	Unstandardized Coefficients		t	Sig.	95.0% Confidence	
	B	Std. Error			Lower Bound	Upper Bound
(Constant)	2.2814	1.136	2.008	0.053	-0.033	4.595
Responsible AI Index	0.4708	0.279	1.686	0.101	-0.098	1.039
a. Dependent Variable: AI Adoption Intention						
b. R Squared = 0.082 , F-Statistic = 2.844						
c. N = 34						

Table 36 Regression Results, Industry = Construction, n = 33

Model	Unstandardized Coefficients		t	Sig.	95.0% Confidence	
	B	Std. Error			Lower Bound	Upper Bound
(Constant)	1.1707	0.745	1.572	0.126	-0.348	2.69
Responsible AI Index	0.7898	0.191	4.145	<.001	0.401	1.178
a. Dependent Variable: AI Adoption Intention						
b. R Squared = 0.357 , F-Statistic = 17.18						
c. N = 33						

Chapter10 Discussion

This research can guide organizations in achieving the intended gains from AI technology via the adoption of Responsible AI initiatives. Firstly, Responsible AI sets the standards that ensure that AI contributes towards the organizational and societal benefits by adhering to a set of governance criteria for safe usage. Secondly, statistically significant results from this study show a direct linkage between Responsible AI factors and employee's intention of using AI, which can help organizations in improving attitudes towards AI and reap benefits of AI. The relationship between Responsible AI factors and employees intention to engage with AI is mediated by the individual employee's beliefs about AI. This suggests that Responsible AI can positively enhance the perception of AI systems by making them safer.

This research will be the first of its kind to evaluate the impact of implementing Responsible AI on improving the usage intention of those that are the key users of the technology to drive its benefits. Theoretically, the results help to establish the link between responsible AI and other Corporate Social Responsibility initiatives by organizations and add to the well-studied corpus of research that links Corporate Social Responsibility to improved organizational performance. Overall, this study can guide organizations in improving the attitudes of its employees towards AI via Responsible implementation and adoption. The research question aims to explore the intricate relationship between responsible AI factors and employee engagement with AI, particularly through the lens of mitigating AI anxiety. Previous studies have laid a foundation for understanding the multiple impacts of AI on the workforce. This concern is echoed in reports which emphasize the importance of addressing AI anxiety by educating the workforce and engaging employees in the AI journey to alleviate fears and equip them for future challenges(EY, 2023). The novelty of the proposed research lies in its focus on the role of responsible AI factors as influencers on employee's intention to use AI. While existing literature has identified the prevalence of AI anxiety and its detrimental effects (Kummer & Recker, 2017), there is a gap in understanding how responsible AI practices can specifically influence employee engagement and mitigate these anxieties. The research by (Wang et al., 2021) suggests that responsible AI signals such as autonomy, beneficence, explainability, justice, and non-maleficence are positively related to employee engagement. This study seeks to build upon these findings by examining how responsible AI factors can be leveraged to not only alleviate AI anxiety but also enhance employee intention to use AI, thereby contributing to a more nuanced understanding of the dynamics at play in the integration of AI into the workplace.

10.1 Research Limitations

At the same time, there are certain limitations of this research. Even though, the sample size, was sufficient to establish statistical significance, a bigger dataset would have enabled a more detailed analysis based on the generalizability of the phenomenon over various types of industries and job roles. Future studies can include more nuanced view of job roles and take into account, the criticality of the decision being made by professionals using AI. This could help to empirically measure, if the relationship between Responsible AI factors and AI engagement intention is moderated by risk level associated with the AI decision outcome.

10.2 Recommended Future Works

Since, this research is focused on understanding individual perceptions about AI, future work can consider other individual level traits related to personality and experience that can influence one's perceptions of AI. Culture of the country of residence and organizational culture can be other constructs that can have potential impact on the main relationship being studied in this study. Another possible limitation of the study could have been induced by the wide spread use of the OpenAI Inc.'s , conversational chatbot, ChatGPT, which became a quick success within months of release(Thorbecke, 2023). Most responders reported to using this tool at the time this survey was conducted. This phenomenon could have lowered the resistance towards AI, which might have driven some bias in the survey results.

10.3 AI Ethics and Regulatory Landscape

Given AI Ethics is still in its infancy, this is one of the first studies of its kind, in the domain, that mainly investigates nontechnical factors that can influence AI adoption. As various regulatory bodies and organizations develop more thorough guidelines on AI usage, the issue of AI Ethics will become more mainstream, one that needs to be dealt with urgency. Organizations that have ensured AI has been adopted ethically, will have an advantage over those that have not yet prioritised it. It's time when management scholars can no longer afford to avoid the impact of AI Ethics and it's nuances on the work force, as we are officially in the era of omnipresent Artificial Intelligence and it's wide spread impact on individuals and organization cannot be trivialized. Many regulatory bodies are now actively taking steps to implement Responsible AI practices by developing frameworks and regulations that can mitigate the negative consequences of unintended consequences of AI. Here are some notable examples from recent developments in this area.

10.3.1 Responsible AI Adoption by Monetary Authority of Singapore

The Monetary Authority of Singapore (MAS) has adopted the FEAT framework to govern the use of Artificial Intelligence and Data Analytics (AIDA) in the financial sector ("MAS Report," 2018). FEAT stands for Fairness, Ethics, Accountability, and Transparency - principles designed to promote the responsible deployment of Artificial Intelligence and Data Analytics technologies by financial institutions. By adhering to FEAT, firms offering financial products and services must ensure their AI and data analytics practices are fair, ethical, accountable, and transparent. This strengthens data governance and fosters public trust in these emerging technologies. The FEAT Principles represent a significant regulatory step toward striking the right balance between innovation and consumer protection in the financial industry's AI adoption. MAS is establishing checks to mitigate risks like algorithmic bias, privacy violations, and unintended consequences as AI plays an increasingly pivotal role. The overarching goal is to create an environment that enables financial firms to harness AI's potential while upholding ethical standards and safeguarding customers' interests. FEAT is an example of adoption of Responsible AI by the regulatory bodies to ensure safe deployment of AI.

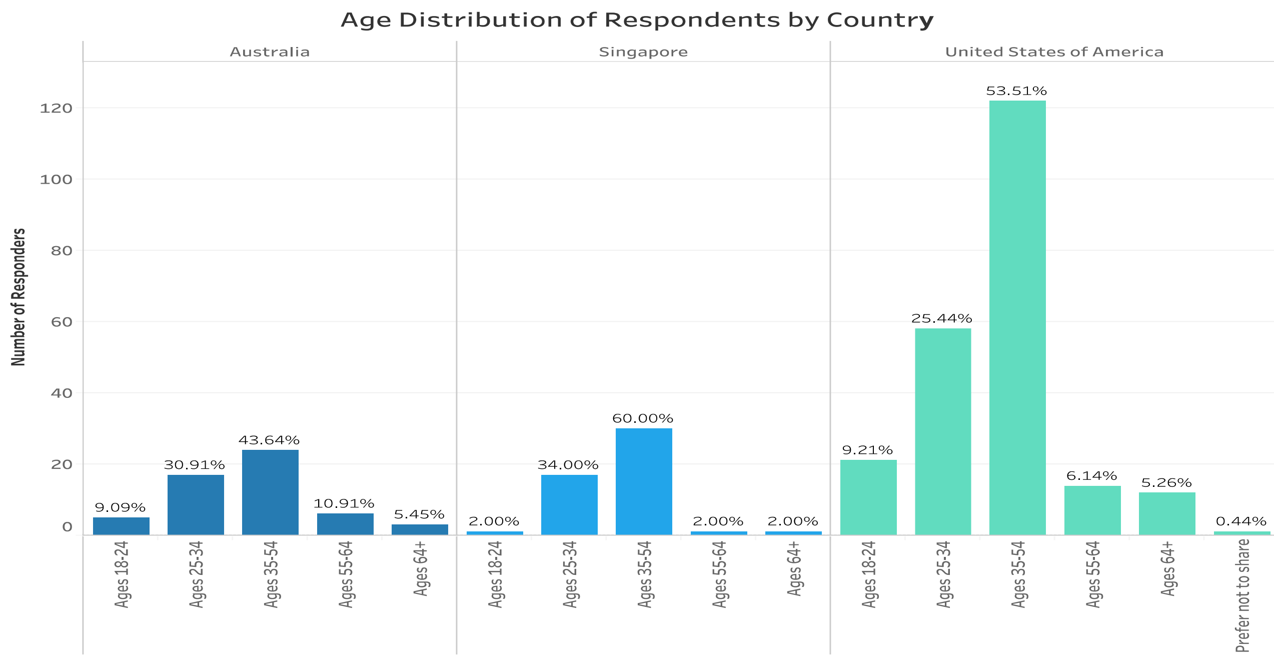
10.3.2 Recently Approved European union AI ACT

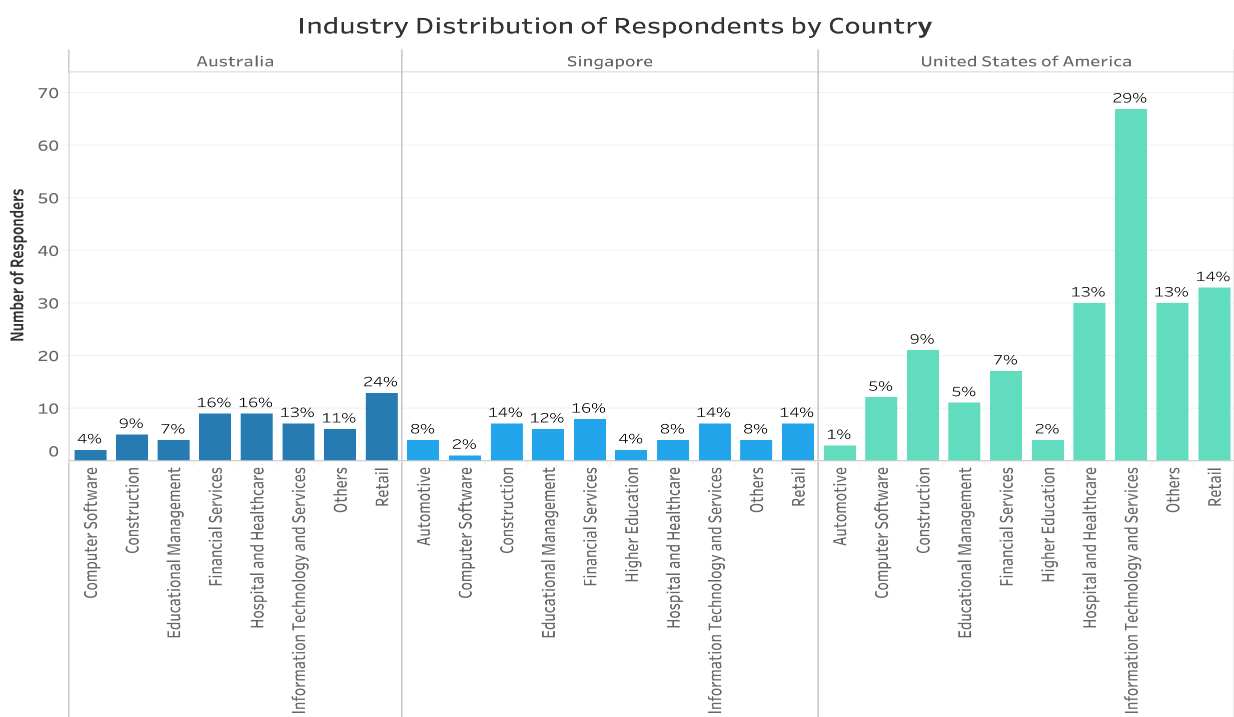
The recently adopted EU Artificial Intelligence Act (EU AI Act) presents a significant step towards fostering responsible AI development and adoption. The Act utilizes a risk-based approach, categorizing AI applications based on their potential impact and imposing stricter regulations on high-risk applications, such as facial recognition systems, to ensure fairness, transparency, and accountability(European Pariament, 2024) . Additionally, the Act bans certain unethical applications with high potential for societal harm, such as social scoring and untargeted collection of facial data . Furthermore, the EU AI Act emphasizes the need for transparency and explainability in AI models, aligning with the goals of responsible AI research to demystify the "black box" nature of AI decision-making . Finally, the Act emphasises the importance of human oversight in high-risk AI development and deployment, ensuring that humans remain ultimately responsible for AI decisions and mitigating the risk of AI becoming a tool for unchecked power or replacing human judgment altogether (ComplexDiscovery, 2024). By establishing this comprehensive legal framework, the EU AI Act aims to build trust in AI across society and foster an environment where AI serves the greater good in a responsible and ethical manner.

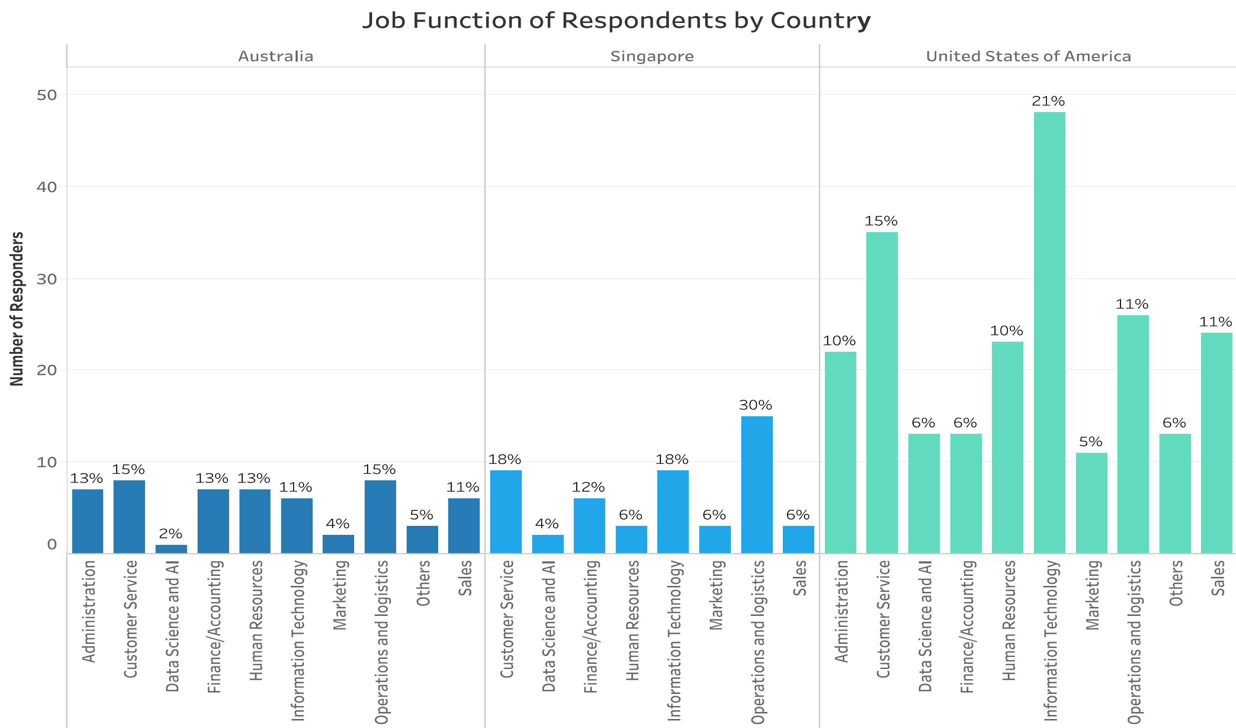
These are just examples of regulations we have seen recently, the future will witness many more regulations to ensure Responsible use of AI. Overall through this research, my aim is to progress the work being done in understanding the impact of Responsible AI from a management lens as AI is no longer just a computer science problem, but rather a new paradigm to define the work being done by employees at all levels.

Chapter11 Appendix

11.1 Appendix A: Additional Demographic Details of the Sample






Job Function of Respondents by Country
Australia
Singapore
United States of America
Number of Responders
50
40
30
20
10
0
13%
15%
2%
13%
13%
11%
4%
15%
5%
11%
18%
4%
12%
6%
18%
6%
30%
6%
10%
15%
6%
6%
10%
21%
5%
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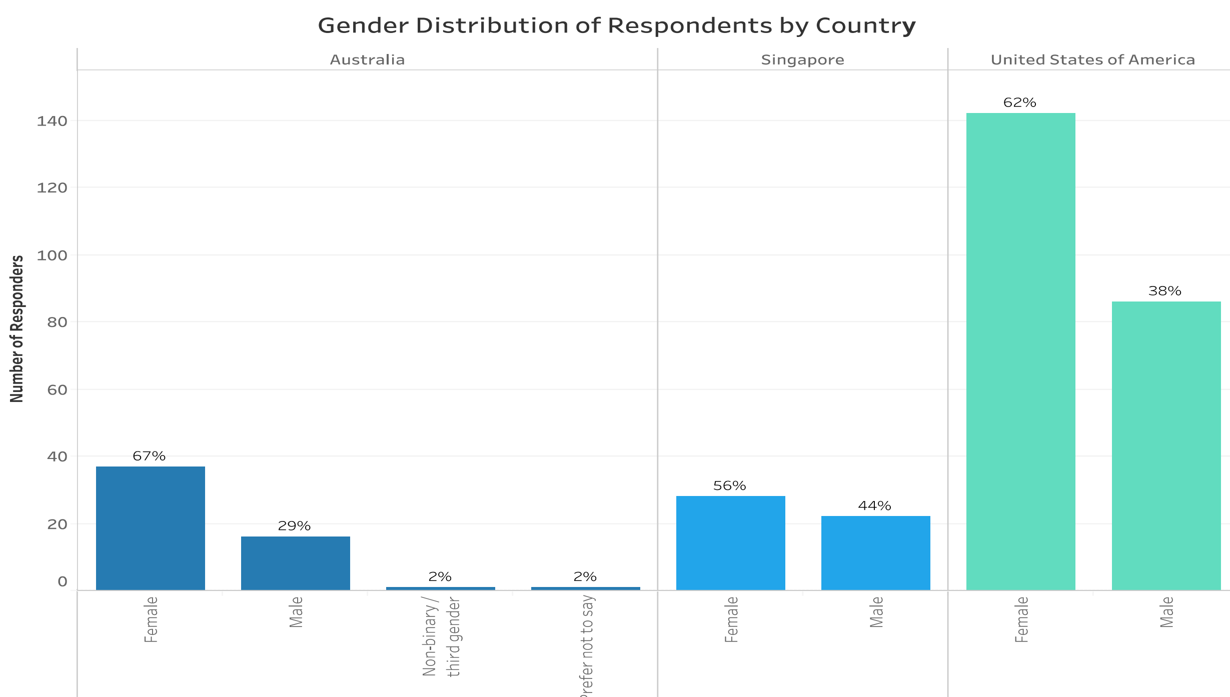
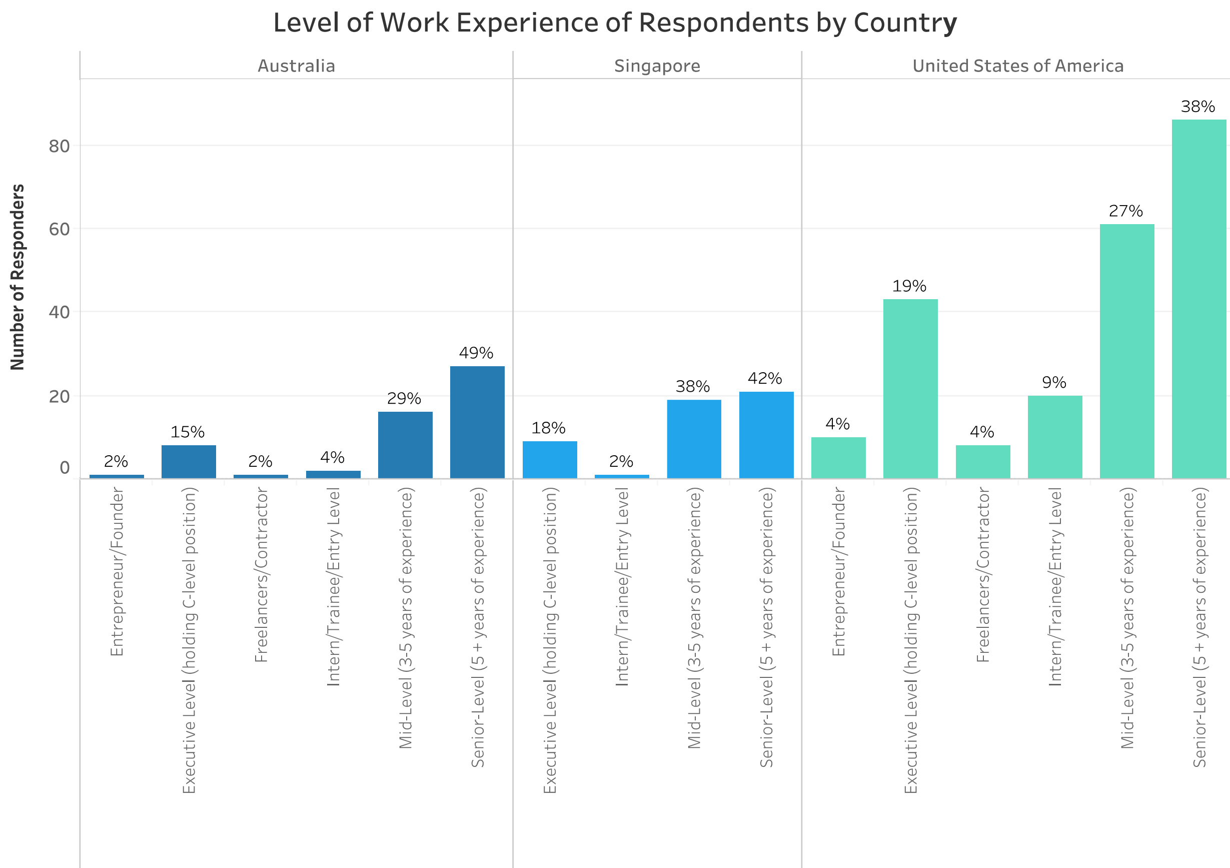
Administration
Customer Service
Data Science and AI
Finance/Accounting
Human Resources
Information Technology
Marketing
Operations and logistics
Others
Sales


Gender Distribution of Respondents by Country
Australia
Singapore
United States of America
Number of Responders
140
120
100
80
60
40
20
0
67%
29%
2%
2%
56%
44%
62%
38%
Female
Male
Non-binary / third gender
Prefer not to say


Level of Work Experience of Respondents by Country
Australia
Singapore
United States of America
Number of Responders
0
20
40
60
80
2%
15%
2%
4%
29%
49%
18%
2%
38%
42%
4%
19%
4%
9%
27%
38%
Entrepreneur/Founder
Executive Level (holding C-level position)
Freelancers/Contractor
Intern/Trainee/Entry Level
Mid-Level (3-5 years of experience)
Senior-Level (5 + years of experience)

11.2 Appendix B: Interview Questions included in the Qualitative study.

Link to the Questions in the Quantitative Survey :

//smusg.au1.qualtrics.com/jfe/preview/previewId/6be1a987-50b9-41e3-a946-8fa46e3766e8/SV_ag6HAY6Fj3otLgO?Q_CHL=preview&Q_SurveyVersionID=current

Table 37 Interview Questions

Can you share your experiences or observations regarding the use of AI technologies within our organization?
How do you perceive the role of AI in your daily work tasks and responsibilities?
In your opinion, what does ethical deployment of AI mean in the context of our organization?
Can you recall any specific instances where AI was deployed unethically, or where ethical considerations were particularly important?
What are your thoughts on the impact of AI ethics on employee engagement? Do you think it affects how employees feel about their work or the organization as a whole?
How well do you think our organization communicates its AI ethics principles to employees? Have you received any training or information regarding this?
Can you describe any positive or negative experiences related to AI ethics within the organization that have affected your engagement or motivation?
What, in your view, are the key ethical considerations that should be taken into account when deploying AI in the workplace?
Have you ever had concerns about how AI may impact your job security or career prospects? How do you think these concerns relate to AI ethics?
Are there specific suggestions or recommendations you would like to make regarding the ethical deployment of AI in our organization to improve employee engagement?
How do you think AI ethics align with the organization's overall values and culture?
Can you provide examples of any initiatives or practices within the organization that promote ethical AI deployment and employee engagement?
How do you perceive the organization's commitment to addressing ethical concerns related to AI, and how does it affect your trust in the organization?
Are there any other thoughts or experiences related to AI ethics and employee engagement that you would like to share?

11.3 Appendix C: More details about results from Hypothesis 5

11.3.1 Hypothesis 5a)

Moderation analysis was conducted using SPSS's PROCESS macro (Hayes, 2013). The interaction between Responsible AI and CSR was significant ($b = -.0753$, $SE = .0343$, $t = -2.1972$, $p < .05$), indicating that the relationship between Responsible AI and Technology Acceptance Index was moderated by CSR. The simple slope of Responsible AI on Technology Acceptance Index was significant at all levels of CSR ($b = .5033$, $SE = .0477$, $t = 10.5402$, $p <$

.001), (b = .4521 , SE = 0379, t = 11.9372 , p > .05). and (b = .4010, SE = .0409, t = 9.8060 , p < .001)

11.3.2 Hypothesis 5b)

Moderation analysis was conducted using SPSS's PROCESS macro (Hayes, 2013). The interaction between Responsible AI and CSR was significant (b = -.1428 , SE = .0704 , t = --2.0276 , p < .05), indicating that the relationship between Responsible AI and Technology Adoption Intention is moderated by CSR. The simple slope of Responsible AI on AI Adoption Intention was significant at all levels of CSR (b = .6320, SE = .0981, t = 6.4426 , p < .001), (b = .5351 , SE = .0778, t = 6.8759 , p < .001). and (b = .4381, SE = .0840 , t = 5.2147 , p < .001)

Figure 24 The interaction between Responsible AI and CSR in predicting Technology Acceptance Index was found to be significant (b = -0.0753, SE = 0.0343, t = -2.1972, p = 0.0287).

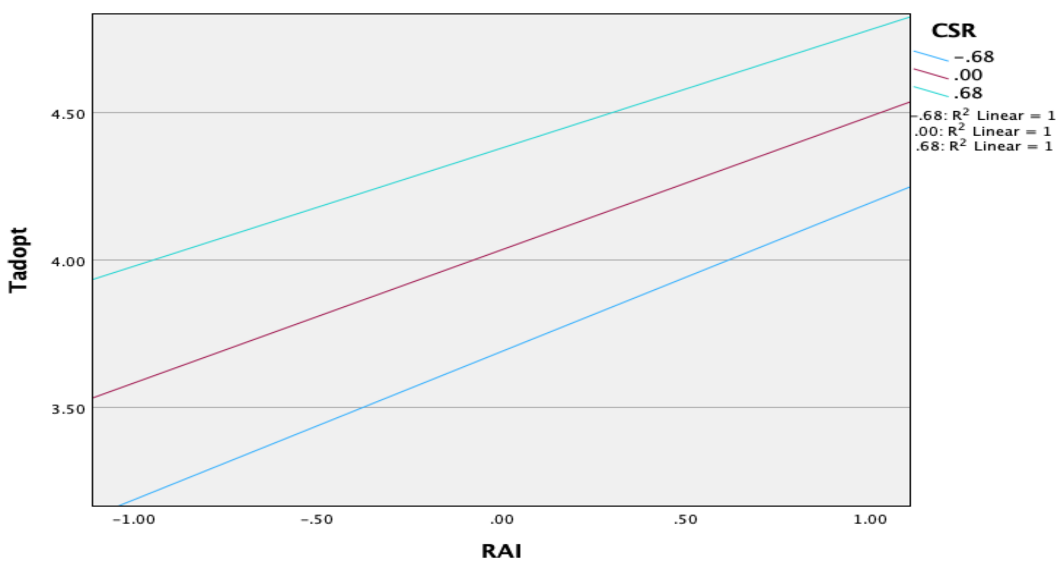
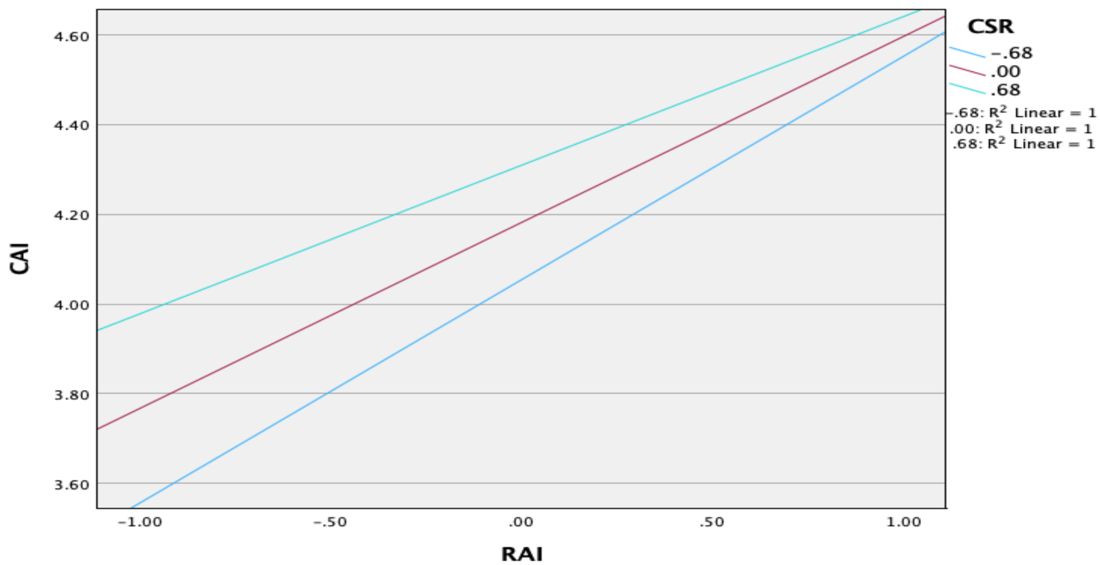


Figure 25 The interaction between RAI and CSR predicting CAI was found to be not significant at 5% level of confidence (b = -0.1228, SE = 0.0705, t = -1.7431, p = 0.0822).



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