Pacific Asia Journal of the Association for Information Systems

ISSN 1943-7544

Research Paper doi: 10.17705/1pais.14504 Volume 14, Issue 5 (2022)

# Exploring Factors Influencing Organizational Adoption of Artificial Intelligence (AI) in Corporate Social Responsibility (CSR) Initiatives

**Vaibhav Pai[1], Shalini Chandra[2,*]**

[1]SP Jain School of Global Management, India, vaibhavpai@gmail.com
[2,*]SP Jain School of Global Management, Singapore, shalini.chandra@spain.org

## Abstract

**Background:** *Globalization has resulted in social, economic, political, commercial, and technological integration. A social problem needs a global collaborative view to find a solution. Wide-ranging partnerships are essential to achieve developmental goals, with public and private partners pooling their resources and competencies. The private sector contributes by engaging in corporate social responsibility (CSR) initiatives. These initiatives can significantly impact by leveraging emerging technologies such as Artificial Intelligence (AI). While many support AI, some believe that AI is a threat to humanity. With mixed attitudes towards AI, its adoption in CSR is somewhat limited. This research leverages the Technology-Organization-Environment (TOE) framework to explore factors influencing AI adoption intention from an organizational perspective.*

**Method:** *The factors were identified from a thorough literature review and mapped with Carroll's CSR framework. The theorized model was tested via a sample response of 124 Indian firms.*

**Results:** *The findings of this research share insight into the influence of the nine technological, organizational, and environmental factors and dives deeper through the post-hoc analysis of the variations due to the size of the firm, public or private orientation, and industry sector.*

**Conclusions:** *Along with the contributions to literature and theory, this research study has several significant contributions to firms, AI products, service companies, AI strategists, and application developers.*

**Keywords:** Artificial Intelligence, Corporate Social Responsibility, TOE Framework, Carroll's Pyramid of CSR, Structural Equation Modelling.

This research article was submitted on July-2022 and under two revisions, accepted on September-2022.

Citation: Pai, V., & Chandra, S. (2022). Exploring Factors Influencing Organizational Adoption of Artificial Intelligence (AI) in Corporate Social Responsibility (CSR) Initiatives. *Pacific Asia Journal of the Association for Information Systems, 14*(5), 82-115. https://doi.org/10.17705/1pais.14504

## Introduction

India is the world's fifth-largest economy by nominal GDP and one of the fastest-growing countries globally ( Long & Ascent, 2020). Yet, it is engulfed by countless social issues, and poverty is still a significant challenge (Katayamadi & Wadhwa, 2019). Governments, non-government organizations, and for-profit companies work in different ways to deal with these issues (Baskaran et al., 2019; Prasad, 2020). For-profit companies and their contributions play a significant role in tackling these social and other environmental issues. Many companies have quickly identified the need and have contributed proactively to these causes through corporate social responsibility (CSR) initiatives.

CSR practices are a means through which companies can meet their consumers' expectations of shared values by presenting themselves as custodians of the environment and being ethically and socially responsible. CSR refers to organizational policies and actions focusing on many stakeholders. The outcomes beyond financial results are the triple bottom line of economic, social, and environmental performance (Aguinis, 2011). Wang et al. (2016) established a positive relationship between CSR and financial performance based on a meta-analysis of 42 studies. Similarly, Jung et al. (2022) studied the interaction effect between IT-enabled innovation and CSR on firm performance. Effective CSR initiatives by companies benefit the community, the environment, and businesses.

Notwithstanding the far-reaching benefits of CSR to companies, such as better brand recognition and customer loyalty, organizational growth, and better financial performance (KsiężaK, 2016), CSR often fails to deliver for both companies and society. Companies often measure the value generated by CSR inconclusively because of human bias in value assessment and incompetence by the managers (Naqvi, 2018). Companies may miss out on integrating CSR with their business strategies to create a competitive advantage and make their CSR programs a success (Naqvi, 2018). Companies are consistently exploring new approaches to improve the efficiency and effectiveness of their CSR programs. It has been observed that social capital generates value and benefits in an ICT intervention (Ahmed et al., 2019). Information systems enable companies to become more environmentally and socially sustainable and remain competitive (Dao & Abraham, 2021). and technology is an effective enabler in enhancing the formulation and implementation of various business and CSR initiatives (Dubickis & Gaile-Sarkane, 2021). One such emerging technology is Artificial Intelligence (AI). AI is intelligence exhibited by machines rather than humans or other animals. It is applied when a machine simulates human cognitive functions like learning and problem-solving (Russel & Norvig, 2015). In CSR, AI has the potential to optimize the CSR program for the firm by learning the business drivers and CSR goals and recommending a program strategy accordingly (Naqvi, 2018).

The upswing in artificial intelligence (AI) technology is being witnessed across varied business sectors worldwide. AI technology simulates human cognitive functions like learning and problem-solving (Russel & Norvig, 2015). Companies such as Amazon, Uber, Tesla, Google, Alibaba, and many others have transformed their business models using AI to enhance their competitive advantage (Lee et al., 2019). A global survey reported measurable benefits of up to a 20% average decrease in cost and a 10% average increase in revenue from adopting AI.

Though research on AI for sustainability is widely spread worldwide, being conducted in 112 countries (Bracarense et al., 2022), and AI is rapidly gaining relevance across industries from sales to marketing and finance to supply chain, the firm-level adoption of AI for CSR is marginal (Wang et al., 2020). McKinsey Global Institute compiled a library of about six hundred use cases of technology applications contributing to well-being. These especially involved vital societal challenges such as job security, health and equal opportunities, in which more than 60% of the cases used specific AI capabilities (Bughin et al., 2019). AI has the potential to significantly contribute to society in addressing several development issues. For example, AI is being used to help increase recycling rates and reduce ocean plastic pollution, map an individual's skill set captured through a guided assessment directly to relevant occupations, determine optimal resource allocation for electricity infrastructure in developing countries, help farmers optimize the exact amount of water needed to irrigate crops, predict and address severe acute childhood malnutrition, generate visualizations and predictions of poverty in areas without survey data, and come up with an alternative credit-scoring mechanism to make consumer lending more accessible to low-income individuals (Google AI, 2019). AI has shown to be an effective tool in crisis response to a pandemic such as COVID-19. AI helped understand the virus and accelerate drug discovery, testing and diagnosis for predicting the evolution, prevention through contact tracing and surveillance, personalised responses, recovery monitoring and improving the tools (OECD, 2020).

Despite the far-reaching capabilities of AI to go beyond human skills and overcome the common pitfalls of CSR processes by tightly integrating CSR strategy with the overall business strategy, insights into the adoption of AI for CSR from a firm's perspective have not caught enough research attention (Krkač & Bračević, 2020). Against the aforementioned backdrop of the identified research gaps, our study aims to explore and evaluate factors influencing the intention to adopt AI technology for CSR initiatives. The process by which a firm adopts and implements technological innovations is influenced by technological, organizational, and environmental contexts (Depietro et al., 1990). Our research is predicated on this significant theoretical and managerial need.

Formalizing a business plan for CSR initiatives using AI by firms would require the firm's modalities to be diverse in managerial, organizational, technological, and environmental factors. This is because a company would require an integrated ecosystem of AI with technological factors and many organizational and environmental factors for adoption (Raghunath, 2021). For example, the knowledge of the decision-makers knowledge and the social and legal issues emerging from the company's use of AI might become essential factors. Furthermore, adopting AI for CSR initiatives will largely depend on technology and CSR's integrated influence. Thus, to have a holistic understanding of the subject, the technology adoption theory needs to be modelled in an integrated fashion with the CSR theory to understand their resulting synergies and contradictions for adopting AI for CSR. Guided by this rationale, we theorize our study on the Technology-Organization-Environment (TOE) framework, an organizational-level and multi-perspective theoretical framework (Tornatzky et al., 1990), and integrate it with Carroll's Pyramid of CSR (Carroll, 2016). Thus, the key question that we examine in this study is:

*# RQ – What technological, organizational, and environmental factors are significant for adopting AI for CSR initiatives?*

While AI is gaining traction with increasing use cases in mainstream business activities and processes, AI adoption in CSR activities is still nascent. Past literature and studies have covered various factors influencing the adoption of new innovative technologies (Gökalp et al., 2022; Sohn & Kwon, 2020). However, it is crucial to explore technological, organizational, and environmental factors that play a significant role in adopting AI for CSR initiatives. It is also imperative to understand how organizations can efficiently manage these factors to develop the model and increase overall value delivery efficiently (Gökalp et al., 2022).

This study is based on the above-stated critical theoretical and practical problems associated with AI adoption for CSR initiatives. This research examines the factors influencing AI adoption for CSR initiatives with the technological, organizational, and environmental dimensions. As one of the initial studies to explore this problem, the study shares valuable and critical contributions to theory and practice.

## Theory and Hypotheses

### AI and its Adoption for Social Good

Artificial Intelligence (AI) is a machine's ability to perform cognitive functions we associate with human minds, such as perceiving, reasoning, learning, and problem-solving (Chui et al., 2018). AI has the potential to contribute to society by addressing several development issues significantly. For example, AI is used to determine optimal resource allocation for electricity infrastructure in developing countries, help farmers optimize the water for irrigating crops, and even make consumer lending more accessible to low-income by developing credit-scoring mechanisms (Google AI, 2019). AI technologies and tools play a crucial role in multiple aspects of crisis response to a pandemic such as COVID-19 (OECD, 2020). As these social challenges become more intertwined with technology-based disruptions, goals such as ending poverty, boosting shared prosperity, and building effective CSR strategies depend on harnessing the power of technologies such as AI (Strusani & Houngbonon, 2019).

### AI Adoption for CSR

Technology adoption by individuals or organizations is a well-researched topic. Prior research on technology adoption used theories such as the Technology Adoption Model (TAM) (Davis, 1989), Theory of Planned Behavior (TPB) (Ajzen, 1991), Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2016), Diffusion of Innovation (DOI) (Rogers, 2003) and the TOE framework (Tornatzky et al., 1990). However, the firm-level adoption of AI for fulfilling social goals is still in the nascent stages (Rana et al., 2014). A complex technology such as AI needs thorough consideration from multiple aspects for fulfilling social objectives such as CSR. Hence, the identification and development of the AI factors were based on a two-step process consistent with the approach developed by Zhu et al. (2006) and proposed by Venkatesh and Bala (2012). The two steps complemented each other and helped identify the factors relevant to the context of AI adoption in CSR initiatives.

First, as this research explores and evaluates factors influencing organizations' decisions to adopt AI for CSR initiatives, a thorough analysis of the literature revealed that the TOE framework offers an analytical framework for research on adopting and integrating multiple types of innovation in information technology (Chauhan et al., 2018; Oliveira & Martins, 2011). While the TOE framework helps researchers examine some broad contextual factors, the critical factors relevant to this research, adopting AI in CSR initiatives, had to be included. Hence, as the second step, the TOE framework was mapped with Carroll's theory for firm-level adoption of AI in CSR.

### Technology, Organization, and Environment (TOE) Framework for AI Adoption

TOE is an organizational-level framework adopted to understand a firm's technology adoption decisions in three contexts: technological, organizational, and environmental (Tornatzky et al., 1990), as shown in Figure 1. The *technological context* relates to internal and external technologies available to an organization, focusing on how the existing technologies within the organization and the available innovations external to the firm influence the innovation adoption process. The *organizational context* looks at the impact of firms' characteristics, such as the degree of centralization and formation, management structure, and quality of human resources, on the innovation adoption process. The external *environmental context* is the ecosystem in which an organization operates its business, such as the industry, the competition, and the regulations (Hameed & Arachchilage, 2016).

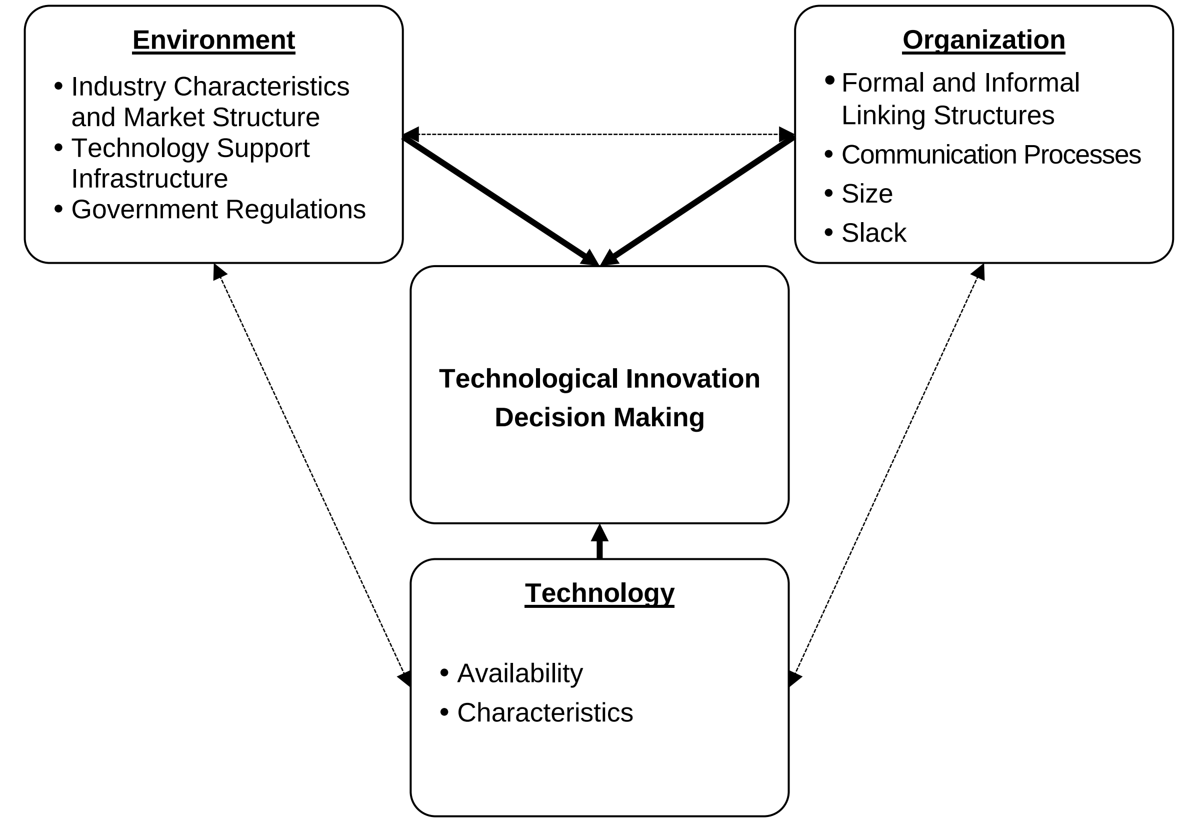



**Figure 1 – TOE Framework**

## Theoretical Framework for Firm-level Adoption of AI

The TOE framework is flexible in identifying specific factors in technology, organization, and environment contexts due to consistent empirical support, robust theoretical basis, and applicability to various information systems (IS) domains. Many studies in the recent past have used the TOE framework for technology adoption, such as augmented reality (Chandra & Kumar, 2018), big data solutions (Salleh & Janczewski, 2016) and blockchain (Clohessy et al., 2019), cloud computing (Gangwar et al., 2015), e-business (Oliveira & Martins, 2010), e-commerce (Ghobakhloo et al., 2011), enterprise resource planning (Awa & Ojiabo, 2016), e-signature (Chang et al., 2007), human resource information systems (Alam et al., 2016), information systems security (Hameed & Arachchilage, 2016), IoT (Arnold & Voigt, 2019), knowledge management systems (Wang & Wang, 2016), mobile commerce (Chau & Deng, 2018), Radio-frequency identification (RFID) (Bhattacharya & Wamba, 2015) and robotics (Pan & Pan, 2019). Furthermore, the TOE framework has been applied to study innovative technologies such as open-source applications and mobile government (Chauhan et al., 2018; Shareef et al., 2016; Ven & Verelst, 2012). The widespread use of the TOE framework to explore technological adoption motivated the use of TOE to explore AI adoption in the context of CSR initiatives by Indian firms.

Even though the TOE framework has been widely applied to several IS innovation domains, the specific factors identified within the three contexts (technological, organizational, and environmental) have varied across different studies. As the first step in this study, we identified prior IS adoption research factors, which used the TOE framework as a theoretical foundation. We also extended the list of factors identified by past research by adding new environmental factors relevant to the ecosystem in which the firm conducts its business in this context for its CSR initiatives (Tornatzky et al., 1990). Figure 2 illustrates the TOE framework-based research model for the study.

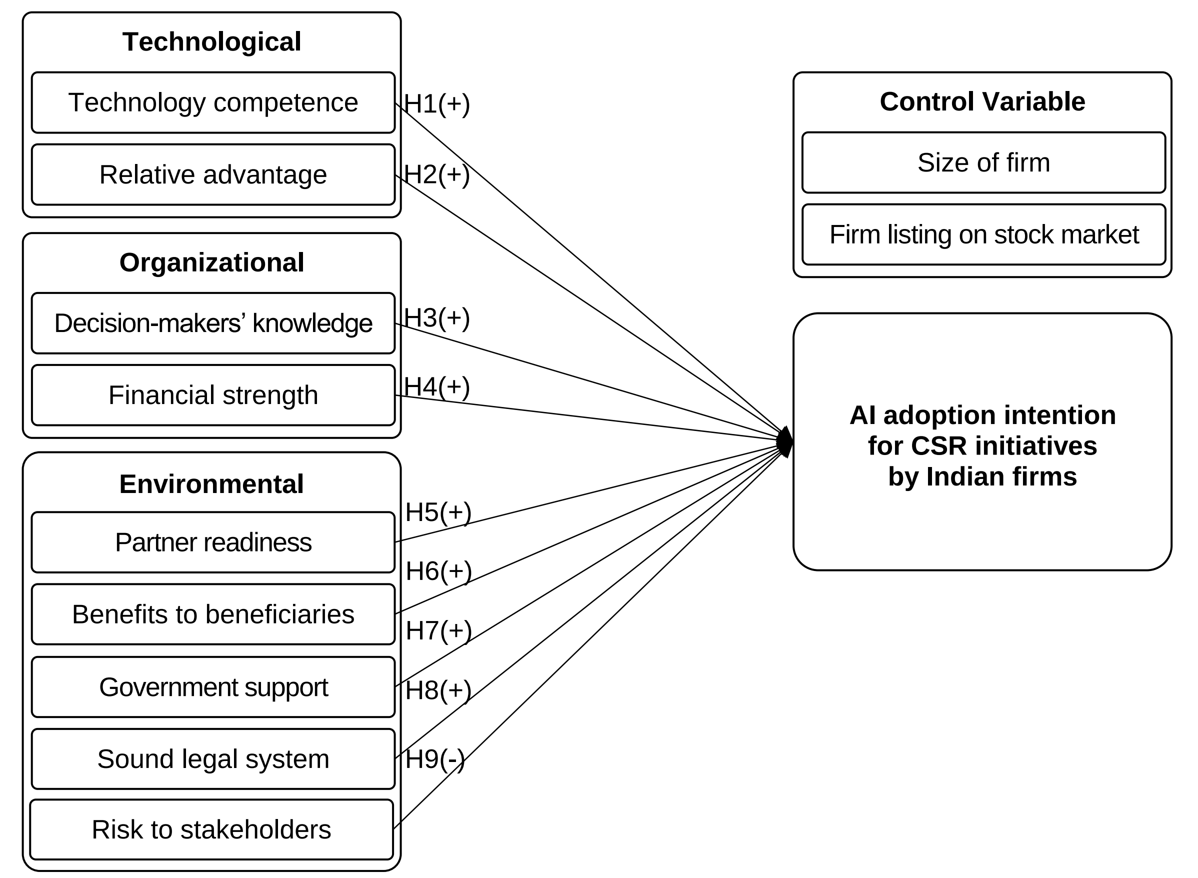



**Figure 2 – Research Model**

## *Mapping TOE and Carroll's Theory for Firm-Level Adoption of AI in CSR*

Though the TOE variables identified for this study are theoretically grounded, it is essential to note that CSR practices are distinct from other profit-driven business strategies. CSR initiatives require a company to operate ethically and sustainably and deal with its environmental and social impacts. It was necessary to harmonize the TOE variables with a CSR theory to understand the adoption of AI in the CSR context. Hence, in the second step, the theoretical relevance of the factors identified in the first step was mapped against CSR theory individually by the two independent mappers. The mappers were not informed of the expected theoretical framework. This helped us control potential bias due to theoretical knowledge about the study (Bhattacherjee & Premkumar, 2004). They were, however, briefed on the variables along with the formal definitions and illustrative examples of each TOE and Carroll's pyramid variables. Then they were asked to map the TOE variables against Carroll's pyramid of CSR. Next, we tested the reliability of the two independent mappings of variables to demonstrate agreement among the mappers. We used percentage agreement to measure whether the mappers' agreement was reliable. The two mappers agreed on nearly all the mapped variables indicating a strong agreement. After independent mappings, the two mappers collectively revisited each variable and resolved any discrepancies until they were satisfied with one consensus mapping. The details of Carroll's pyramid of CSR and the theoretical rationalization of consensus mapping of TOE variables with Carroll's pyramid of CSR are presented in the subsequent sections.

## Consensus Mapping of TOE Variables with Carroll's Pyramid of CSR

CSR is a management concept whereby companies integrate social, environmental, and economic concerns in their business operations and interactions with their stakeholders. It is generally understood to achieve a balance of economic, environmental, and social imperatives referred to as the 'triple bottom line approach' while addressing shareholders' and stakeholders' expectations (UNIDO, 2019). It is how firms integrate social, environmental, and economic concerns into their values, culture, decision-making, strategy, and operations in a transparent and accountable manner. As a result, they establish better practices within the firm, create wealth and improve society (Hohnen, 2007). The company's philanthropic responsibilities affect the community and non-profit organizations and are significantly related to employee morale (Carroll, 2016).

One of the popular constructs of CSR used in literature and practice for several decades is Carroll's four-part framework or CSR definition, depicted graphically in Figure 3 (Carroll, 2016). Carroll's four-part definition states that 'corporate social responsibility encompasses the economic, legal, ethical and discretionary (philanthropic) expectations society has of organizations at a given time (Carroll, 1979, 1991).


**Figure 3 – Carroll's Pyramid of CSR**

A stakeholder perspective needs to focus on the pyramid of CSR as a whole, not different parts. The policies, decisions, and actions should fulfill all four components' requirements. Each component addresses and affects various stakeholders in varying priorities enumerated as Economic (shareholders and employees), Legal (owners and employees), Ethical (customers and employees), and Philanthropic (community, non-profit organizations, and employees).

### Economic Responsibilities

Society views businesses as institutions that produce and sell the goods and services that society needs and desires. Companies making profits are viewed as an essential element of society by the world's economic systems. Economic responsibilities direct businesses to use financial effectiveness (such as increasing revenue, optimizing costs, suitable investments, and efficient strategies) for long-term financial success. Businesses create profits by adding value and, in the process, benefit all stakeholders, including customers, employees, and shareholders. One of the most important factors influencing the resources spent on CSR initiatives is the business's economic performance; hence, the economic responsibility is a baseline requirement.

*Technology competence* refers to an organization's technical competencies, such as information technology infrastructure and employees' capabilities to understand IT (Zhu &

Kraemer, 2005). The successful exploitation of innovations and ideas is essential for a business to bring new products and services to market, increase efficiency by improving processes and improve its economic performance (profitability). The organization's technological competence plays a significant role in exploiting and adopting new technologies such as AI and embracing innovation to fulfil economic responsibility.

*Relative advantage* is 'the degree to which an innovation is perceived as better than the idea, program, or the product it replaces' (Rogers, 2003). The nature of the innovation determines the type of relative advantage significant to the firm and can be expressed as economic profitability, social prestige, or other ways (Rogers, 2003). Hence the relative advantage of adopting AI becomes critical in fulfilling the economic responsibility of the firm.

*Financial strength* is the availability of the organization's financial resources (Chandra & Kumar, 2018). Sufficient finance enables firms to adopt the desired technology and fulfil their economic responsibility (Ghobakhloo et al., 2011).

*A partner's readiness* to deal with trading partners is an essential economic factor (Tornatzky et al., 1990). The lower costs due to the concentrated focus on pursuing development activities, cumulative time spent on the field, cost of human resources deployed, and operational efficiencies make it a better option to collaborate with implementation partners. The fixed costs are often less as the implementation partners usually try to obtain resources from multiple sources, including the government (PwC India, 2013). Their readiness in terms of adopting the technology becomes an essential factor. Thus, improving the intervention's impact by keeping the cost in check helps fulfill the business's economic responsibility.

### Legal Responsibilities

Society has established some ground rules, including laws and regulations around running a business. Firms should comply with these rules while providing goods and services to various stakeholders. Firms should fulfill their legal duties and care for their obligations to society.

*Government support* is the government's actions and efforts in promoting new technology. Government plays a vital role in improving technology adoption rates across countries (James, 2003). Companies operating in an environment with restrictive government policies have low IT adoption (Dasgupta et al., 1999). The regulations and policies around adopting AI technology and their clarity enable businesses to fulfill their legal responsibilities efficiently.

*Sound legal systems* are the policies, legalities, and business practices to ensure a smooth interaction between technology and its users (Scherer, 2015). The increase in the role of AI in the economy and society presents conceptual and practical challenges for the legal system. It raises important questions about current policies, legalities, and business practices ensuring proper applications of AI (Scherer, 2015). The impact of laws and regulations is critical in adopting new technologies (Clohessy et al., 2019; Oliveira et al., 2014). A sound legal ecosystem enables businesses to fulfill their legal responsibilities.

### Ethical Responsibilities

Businesses should perform their duties and ethically conduct their activities. Even if some activities are prohibited by society but not codified into law, it is the ethical responsibility of businesses to conduct themselves as expected by society. It expects firms to act responsibly and follow principles of moral philosophy such as rights and justice.

*Decision-makers' knowledge* is decision-makers and leaders' involvement in the investment decision by conducting mutual discussions and assessing the proposed solution (Kamal et al., 2011). One of the critical phases in innovation adoption is the involvement of the decision-


https://aisel.aisnet.org/pajais/vol14/iss5/4
DOI: 10.17705/1pais.14504

makers and leaders in the investment decision by conducting mutual discussions and assessing the proposed solution (Kamal et al., 2011). To fulfill the ethical responsibilities, it becomes essential to recognize and respect new or evolving ethical and moral norms of society, know the technology itself and consider it while adopting AI for CSR initiatives to impact the community.

*Risk to stakeholders* includes the risks of adopting new technologies (Marra et al., 2003). The inability to assess risk can result in delays in adopting technologies such as AI, thus preventing them from reaping the potential benefits (Canhoto & Clear, 2020). One of the essential expectations from businesses under ethical responsibilities is to do what is just and fair and avoid harm. So, it becomes vital to assess physical or digital risk to the stakeholders while adopting AI to fulfill ethical responsibilities.

### Philanthropic Responsibilities

Corporate philanthropy might not be an obligation in a literal sense. However, it is what society expects or desires, even if these activities are voluntary and discretionary. Companies engage in various organization-led, partner-led, or employee-led (volunteerism) initiatives to give back to society to fulfill their perceived philanthropic responsibilities.

*Benefits to beneficiaries* are the effort required by the beneficiaries to bring to the forefront the benefits of using the new technology. The more novel the technology, the more efforts are required to ensure that users understand what problems it solves (Lakhani & Iansiti, 2017). Prior study shows that emerging value-adding use cases are essential for innovation adoption (Clohessy et al., 2019). Hence it becomes necessary to assess whether adopting new technology will impact and benefit the beneficiaries fulfilling philanthropic responsibilities.

Figure 4 shows the coders' consensus mapping of the TOE variables with Carroll's CSR Pyramid. It clearly shows the relevance of identified TOE variables for AI adoption in the context of CSR. It is important to note that the CSR of business entails concurrent fulfilment of a firm's economic, legal, ethical, and philanthropic responsibilities. A CSR-driven firm should make every effort as a business to make a profit. While doing so, the firm needs to obey the law. The firm should engage in ethical practices that are fair and just. It should make all efforts to give back to society. The pyramid should be viewed as a unified whole (Carroll, 2016). Hence, the proposed variables were relevant for adopting AI for CSR initiatives.

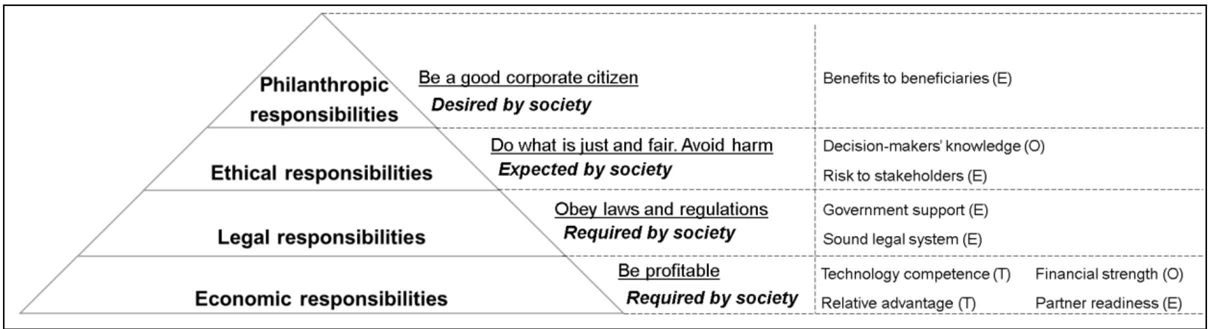



**Figure 4 – Mapping Carroll's Pyramid with the TOE Variables**

## *Hypotheses Development*

### Technological Context

The technologies and internal and external processes of the organization are covered in the technological context (Oliveira & Martins, 2011). The firm's current technology systems and those available in the market are equally important considerations for adopting emerging technology such as AI. This study proposes technology competence and relative advantage as technological factors relevant to AI adoption for CSR initiatives.

*Technological competence.* It is one of the critical factors when a firm assesses benefits generated by a particular technology (San-Martín et al., 2016). Past research shows an affirmative relationship between technology competence and adopting new technology (Junior et al., 2019). According to Rogers (2003), innovation is an idea, practice, or object perceived as new for adoption. The innovation development process consists of decisions, activities, and impacts from need or problem recognition until innovation adoption and its consequences. Firms that give importance to innovation tend to support new technology adoption (Anandarajan et al., 2002). Digitally mature companies, having AI infrastructure in terms of assets, usage, and labour, tend to be early AI adopters (Bughin et al., 2019). One of the characteristics of early AI adopters is that they use AI technology in the core activities of their businesses. In this research, we propose that organizations that explore new IS innovations, have the necessary infrastructure to support AI technology, and currently use AI in their core activities would be more inclined to adopt AI for CSR initiatives. Global technologically competent firms such as Amazon, Apple, Facebook, Google, and Microsoft have also acquired AI start-ups (Sawers, 2019). Firms like Google and Microsoft are already in the advanced stages of using AI for positive social initiatives (Google AI, 2019; Microsoft, 2019). If the firm is competent technologically, it will adopt new technologies such as AI for CSR initiatives. Hence, we hypothesize:

*H1. The technology competence of firms is positively associated with the adoption intention of AI for CSR initiatives.*

*Relative advantage.* Firms consider the relative benefits and challenges of adopting new technology such as AI. By enabling multi-tasking, AI can reduce the time taken in decision-making and performing complex tasks without incurring a high cost. AI can lend itself to diverse applications across various sectors and has also demonstrated the potential to address society's developmental challenges in healthcare, education, and inclusive banking and finance (Kathuria et al., 2020). AI has been applied to many functions, such as customer service chatbots and automatic network operation, improving the process and efficiency, lowering operation costs, increasing service quality, and improving the overall customer experience (El Khatib et al., 2019). Research has also indicated that organizational innovation practices positively impact job satisfaction (Park et al., 2016), and the relative advantage of new technologies has positively influenced adoption (Kumar et al., 2017). The nature of the innovation determines the relative advantage significant to the firm and can be expressed as economic profitability, social prestige, or other ways (Rogers, 2003). As the firms recognize AI's business and social benefits, they will invest in AI technology and willingly adopt it. Hence, we hypothesize:

*H2. The relative advantage of AI is positively associated with the adoption intention for CSR initiatives.*

### Organizational Context

The organizational context refers to the firm's attributes that enable or hinder the adoption and implementation of the innovation (Oliveira et al., 2014). It is the resources available to aid the adoption of an innovation (Lippert & Govindarajulu, 2006). This study explores decision-makers knowledge and financial strength as critical organizational factors.

*Decision-makers Knowledge.* It is one of the essential phases in innovation adoption. The adoption decision needs to evaluate the proposed ideas from a technical, financial, and strategic perspective (Hameed & Arachchilage, 2019).


https://aisel.aisnet.org/pajais/vol14/iss5/4
DOI: 10.17705/1pais.14504

Access to the literature and relevant resources is essential to help make an informed decision to adopt AI for CSR initiatives. The better the decision-makers' knowledge and innovativeness, the better the firm's chances of adopting new technology (Lin & Lee, 2005). Decision-makers' knowledge about innovative technologies such as AI and their benefits to CSR initiatives is critical. Hence, we hypothesize:

*H3. The decision-makers' knowledge of AI is positively associated with the adoption intention of AI for CSR initiatives.*

*Financial Strength*. While organizational resources such as human capital, infrastructure, and information are essential for nurturing innovation, organizations' financial strength is critical in fostering innovation and implementing new processes, products, or services (Chandra & Kumar, 2018). For a decision to adopt an emerging technology such as blockchain, a study confirmed that the availability of financial and human resources and access to IT infrastructure has a positive influence (Clohessy et al., 2019).

The financial resources needed to adopt robots, artificial intelligence, and service automation (RAISA) would involve the acquisition, installation, maintenance costs, specialist hiring, and staff training costs, among other expenses, depending on the type of applications (Ivanov & Webster, 2017). Sufficient finance enables firms to adopt the desired technology (Ghobakhloo et al., 2011). Financial strength has become one of the critical factors for the adoption of AI for CSR initiatives. Hence, we hypothesize:

*H4. The firm's financial strength is positively associated with the adoption intention of AI for CSR initiatives.*

### Environmental Context

The environmental context refers to the ecosystem in which a firm conducts its business and includes attributes such as customers, competition, and vendors. The environmental context also presents restrictions and prospects for technological innovation and adoption (Chandra & Kumar, 2018). This study focuses on adopting AI in the context of CSR. Hence, the environmental factors considered are partner readiness, benefits to beneficiaries, government support, legal environment, and risk to stakeholders.

*Partner Readiness.* Dealing with trading partners is considered an essential factor in the environmental context (Tornatzky et al., 1990). To operationalize the institutional mechanism and leverage intellectual and financial resources investment, firms choose one option to work with external entities or implementation partners (for example, non-government organizations [NGOs]) to achieve their CSR goals and vision. The benefits of working with implementation partners include their experience and knowledge of the sector or issue the firm has decided to focus on. The lower costs due to the concentrated focus on pursuing development activities, cumulative time spent on the field, the cost of human resources deployed, and operational efficiencies make it a better option to collaborate with partners. The fixed costs are often less as implementation partners usually try to get resources from multiple sources, including the government (PwC India, 2013).

Many companies working from a stewardship orientation provide information on their CSR activities and involve NGOs in monitoring them and improving their CSR policy (Nijhof et al., 2008). Lack of trading partner readiness inhibits innovation adoption (Zhu et al., 2003). Various phases involve partners, such as project planning, execution, progress monitoring, and reporting. It becomes important to consider their understanding of AI technology, whether they think it positively impacts the common goals, and check if they are open to adopting AI technology. Hence, we hypothesize:

*H5. Partner readiness is positively associated with the adoption intention of AI for CSR initiatives.*

*Benefits to Beneficiaries*. The more novel the technology is, the more effort is required to ensure users understand what problems it solves (Lakhani & Iansiti, 2017). Prior study shows that emerging value-adding use cases are essential for innovation adoption (Clohessy et al., 2019).

While many successful AI use cases for social good are emerging (Google, 2019), companies that overcame initial obstacles have successfully implemented a proof of concept. However, they face challenges integrating AI components into the existing system landscape (MHP, 2019). It becomes crucial to look at what the practitioners think about the impact and scaling of AI for solving some social issues and evaluate inhibition in direct interaction of the AI technology with the beneficiaries in some cases. Hence, we hypothesize:

*H6. Benefits to beneficiaries are positively associated with AI's adoption intention for CSR initiatives.*

*Government Support.* Government plays a vital role in improving technology adoption rates across countries (James, 2003). Evaluating the government's actions and their impact on the technological environment is crucial. Williamson (1980) summarized two ways government could affect innovation diffusion, one of which is taking specific action on increasing or decreasing the payoffs through tax or other measures, and the second is by altering the climate in which they are received.

Government intervention is needed to effectively adapt and carry forward the AI revolution to promote AI adoption. Governments, with their instrumentalities, are trying to adopt proactive measures to accelerate AI adoption in multiple processes at different levels. NITI Aayog, the GOI policy think tank, has planned to focus on five sectors that would significantly benefit AI in solving societal issues – agriculture, education, healthcare, smart cities and infrastructure, smart mobility, and transportation (NITI Aayog, 2018). How the government's policies actively enable AI implementation, protect the interests of AI users, and its involvement in technology usage impacts the adoption decision needs to be seen. Companies operating in an environment with restrictive government policies have low IT adoption (Dasgupta et al., 1999). Hence, we hypothesize:

*H7. Government support is positively associated with the adoption intention of AI for CSR initiatives.*

*Sound Legal System.* Technologies such as AI bring continuous interaction between intelligent devices and people, resulting in a vast amount of stored and processed data impacting our daily lives in various aspects (Magrani, 2019). This increase in AI's role in the economy and society presents conceptual and practical challenges for the legal system. It raises important questions about current policies, legalities, and business practices ensuring proper AI applications (Scherer, 2015). In 2017, a robot named Sofia positioned itself as a woman was granted Saudi Arabian citizenship. The same year, Japan provided a residence permit under a special regulation to Shibuya Mirai, a chatbot. In both cases, robot status action contradicts the current national legal norms (Atabekov & Yastrebov, 2018).

In India, the law currently applicable to AI is the Information Technology Act 2000, covering various aspects, including cyber offences. The Information Technology Rules 2011 concentrate on implementing and maintaining security and sensitive personal data (Kumari, 2019). In its policy discussion paper, NITI Aayog (2018) suggested a framework related to a negligence test for damages caused by AI software requiring self-regulation by the stakeholders, safe harbours to insulate or limit liability, and apportionment of damages to bear


https://aisel.aisnet.org/pajais/vol14/iss5/4
DOI: 10.17705/1pais.14504

the proportionate liability and actual harm requirements. One of the legal system's critical stakeholders, the law firms, are already using AI tools for various activities and is now using AI to build new tools (Walters, 2019).

It is crucial to evaluate how the current legal guidelines and framework around the use of AI impact the adoption of AI for CSR initiatives from a CSR practitioner's perspective. The effects of laws and regulations are critical in adopting new technologies (Clohessy et al., 2019; Oliveira et al., 2014). Hence, we hypothesize:

*H8. A sound legal system is positively associated with the adoption intention of AI for CSR initiatives.*

*Risk to Stakeholders.* Risk plays a vital role in adopting new technologies (Marra et al., 2003). Various companies transform technology risk functions to drive value, predict risks and adapt to the dynamics and speed of change. According to the KPMG survey (Lageschulte et al., 2018) of 200 senior IT risk management executives, 66% of respondents adopted AI technology after assessing the potential risks. Research has also shown that perceived risks negatively influence the intention to use new technology (Prakash & Das, 2020; Tripathi & Mishra, 2019).

Risks spanning the complete life cycle of an AI application, from its conception to usage to monitoring, can result in unintended consequences for individuals, organizations, and societies. The types of digital or physical risks can potentially impact (i) individuals' privacy and reputation, financial health, equity, and fair treatment, (ii) organizations' financial performance, legal and compliance, and reputational integrity, and (iii) society's economic and political stability and infrastructure integrity (Cheatham et al., 2019).

The inability to assess the risk can result in delays in adopting technologies such as AI, thus preventing them from reaping the potential benefits (Canhoto & Clear, 2020). The identification of potential risks can have a negative effect on the adoption intention of AI for CSR initiatives. Hence, we hypothesize:

*H9. The risk to stakeholders is negatively associated with the adoption intention of AI for CSR initiatives.*

## Method

### *Data Collection*

To test the research model in Figure 2, we first developed a survey instrument (with items on a five-point Likert scale ranging from strongly disagree to strongly agree). We identified and adapted appropriate measures from the existing literature, where psychometric properties have already been established (see Appendix A). We conducted a pilot study to test the preliminary questionnaire with 36 respondents with a technological or academic background.

Following the pilot study, we modified and refined the questionnaire and then evaluated the hypothesized relationships developed from the model. The targeted respondents comprised CSR practitioners and professionals such as the head of the CSR division, CSR managers, senior management, and executives with CSR responsibilities from Indian organizations spending significant resources and actively involved in CSR initiatives. Such organizations were identified, regardless of whether they used AI applications for CSR. While pre-screening, fulfilling this requirement was the qualifying criteria for the survey respondents.

Each shortlisted participant was chosen through LinkedIn based on parameters such as the designation or title, projects they have worked on, educational qualifications, and relevant industry experience. The potential respondents were updated about the criteria, and a check question in the survey to verify this element was included. Every profile was viewed through a lens of how they could contribute to the research. As the survey focused on organization-level adoption, it was ensured that professionals from different organizations were approached across the agriculture, manufacturing, and services sector. The sector-wise Indian GDP is composed of agriculture, manufacturing, and services (Ministry of Statistics and Programme Implementation, 2021). Hence the sectors were grouped as services and non-services representing agriculture and manufacturing. In services, we ensure a good representation of technological and non-technological companies. The study was conducted from June to September 2020 period.

The research questionnaire was shared with 663 prospective participants. Subsequently, responses from 144 participants were received with a 21.72% response rate. After a thorough evaluation, 124 responses were finalized for data analysis. We used ADANCO, a composite-based structural equation modelling (SEM) technique, for the data analysis. Our research model had 11 paths, including the control variables. Hence, 124 responses fulfilled the popular rule of thumb for robust SEM estimations, which suggests using a minimum sample size of ten times the maximum number of paths aiming at any construct (Barclay et al., 1995).

## Demographics and Study Variables

The study was conducted in India based on the research objective, and participants from Indian companies or Indian entities of multinational companies were approached. Demographic information about the organization's size, which sector they belonged to (agriculture, manufacturing, and services), the age of the firm, and whether the organization was listed on the stock exchange was sought from the respondents. Table 1 shows the demographic profile of the organizations of the respondents.

**Table 1 – Demographic profile of the respondent organizations**

| **Size** *(# employees)* | ***n*** | **Listed** *(Stock Exchange)* | ***n*** |
|---|---|---|---|
| < 10,000 | 74 | Yes | 80 |
| > 10,000 | 50 | No | 44 |
| **N** | **124** | **N** | **124** |
| | | | |
| **Sector** *(Industry)* | ***n*** | **Age of firm** *(Years)* | ***n*** |
| Agriculture & Manufacturing | 60 | < 20 | 35 |
| Services | 64 | > 20 | 89 |
| **N** | **124** | **N** | **124** |

## Common Method Bias

As the data on all the variables for this research were self-reported and collected through the same questionnaire during the same period with a cross-sectional research design, we wanted to ensure that the study did not have any systematic bias influences. We used appropriate instrument design and data collection procedures, as Podsakoff et al. (2003) suggested. We also performed Harman's one-factor test in SPSS to test for any possibility of common method bias (Podsakoff & Organ, 1986). The test requires conducting an exploratory factor analysis on all the measures used in the research, based on the assumption that if common method bias exists, a single factor or a general factor accounting for the majority of the covariance among the measures will emerge (Podsakoff et al., 2003). Accordingly, we examined the factor structure solution emerging from an exploratory factor analysis of all the research variables to examine the number of factors necessary to account for the variance in the variables. The test indicated that nine major factors accounted for 70.65% of the variance, and the first (largest) factor did not account for a majority of the variance (23.36%). Because neither one single factor emerged that accounted for the majority of the variance in the model nor one factor accounted for more than 50% of the variance, we conclude that common method bias is not a significant problem with the data (Podsakoff et al., 2003; Srivastava & Chandra, 2018).

### *Control Variables*

Because the dependent variable may be influenced by factors other than those in the hypothesized model, we incorporated relevant control variables in the research model to better understand the variance explained by the predictor variables. The control variables are certain firms' characteristics that might influence the adoption of AI technology for CSR initiatives. This research includes two control variables, the firm’s size and listing status, that may influence the adoption of AI for CSR initiatives.

The size of the firm may influence its technology adoption. Previous research on technology adoption has shown that firm size has influenced technology adoption (Chiu et al., 2017; Garrison et al., 2015). Furthermore, the influence of a firm's listing status on the stock exchange (listed or unlisted) needs to be controlled. This is because past studies have shown that it is easier to support CSR initiatives with 'other people's money (Goergen et al., 2019). Listed firms are more likely to commit to CSR if the managers have some independence to direct organizational resources to enhance their image or brand (Ioannou & Serafeim, 2015). Hence, the firm's size and listing were considered control variables in this study.

## Analysis and Results

For the data analysis, we used ADANCO v 2.1.1, user-friendly software for composite-based SEM and confirmatory composite analysis (Henseler & Dijkstra, 2014; Henseler et al., 2016; Ziggers & Henseler, 2016). It offers the advantage of implementing several limited-information estimators, such as partial least squares (PLS) path modelling or ordinary least squares (OLS) regression based on sum scores (Henseler & Dijkstra, 2014). Using ADANCO for PLS path modelling offers the advantage of assessing the construct reliability and validity using the measurement model, verifying the model fit via overall goodness-of-fit tests, and using the structural model for hypothesis testing (Henseler et al., 2016; Ziggers & Henseler, 2016). Following the recommended two-stage analytical procedure (Anderson & Gerbing, 1988; Hair et al., 1998), we first evaluated the measurement model and examined the structural relationships in the second stage

### *Measurement Model*

The relationship between the constructs and their indicators is specified in the measurement model (Henseler & Dijkstra, 2017). We tested three types of validity: content, convergent, and discriminant. Content validity assesses whether the chosen measures appropriately capture the complete domain of the construct (Straub et al., 2004). We examined content validity by checking for consistency between the measurement items and the existing literature. This was done at the stage of designing the questionnaire. Convergent validity checks that the indicators for a construct are more correlated with one another than with the indicators of another construct (Petter et al., 2007). Convergent validity was exhibited as factor analysis showed a strong correlation between each item and its corresponding construct. We also tested for convergent validity by examining the composite reliability (CR) and average variance extracted (AVE: the ratio of the construct variance to the total variance among indicators) for the indicators (Hair et al., 1998). 0.70 is the suggested CR threshold for reliable measurement

(Chin, 1998). As seen in Table 2, the CR values ranged from 0.91 to 0.79. AVE was satisfactory, with values ranging from 0.77 to 0.56, thus fulfilling the threshold criterion of 0.50 (Fornell & Larcker, 1981). The high Cronbach's alpha (CA) values, ranging from 0.85 to 0.65, confirm the reliability of the scales for all the constructs. The values of 0.6 to 0.7 are acceptable, while 0.7 to 0.9 are considered satisfactory (Hair Jr et al., 2016).

**Table 2 – Descriptives, CR, CA, AVE**

| Construct | MN | SD | CR | CA | AVE |
|---|---|---|---|---|---|
| TC | 3.65 | 0.95 | 0.91 | 0.85 | 0.77 |
| RA | 4.06 | 0.62 | 0.88 | 0.81 | 0.64 |
| DK | 3.40 | 0.85 | 0.86 | 0.76 | 0.67 |
| FS | 2.81 | 0.78 | 0.79 | 0.65 | 0.56 |
| PR | 2.98 | 0.71 | 0.84 | 0.74 | 0.64 |
| BB | 3.65 | 0.72 | 0.87 | 0.79 | 0.7 |
| GT | 3.01 | 0.69 | 0.81 | 0.67 | 0.59 |
| LW | 2.82 | 0.66 | 0.86 | 0.76 | 0.67 |
| RK | 2.85 | 0.71 | 0.83 | 0.67 | 0.72 |
| AI | 3.42 | 0.73 | 0.83 | 0.68 | 0.61 |

*Notes: TC: Technology competence; RA: Relative advantage; DK: Decision-makers' knowledge; FS: Financial strength; PR: Partner readiness; BB: Benefit to beneficiaries; GT: Government support; LW: Sound legal system; RK: Risk to stakeholders; AI: Adoption Intention. MN: Mean; SD: Standard Deviation; CR: Composite Reliability; CA: Cronbach Alpha; AVE: Average Variance Extracted*

We verified the discriminant validity of the constructs by checking the square root of the AVE, as recommended by Fornell and Larcker (1981). The values of the square root of the AVEs (shown on the diagonal in the shaded cells of Table 3) are all greater than the corresponding inter construct correlations (the off-diagonal entries in Table 3), exhibiting satisfactory discriminant validity.

We also examined the cross-loadings of the items on other constructs, which were relatively low, indicating discriminant validity. Further, we also checked for the heterotrait-monotrait (HTMT) ratio criterion recommended for variance-based SEM models to establish discriminant validity (Hair et al., 2019; Henseler et al., 2015). HTMT is the average of the Heterotrait-Heteromethod correlations (i.e., the correlations of indicators across constructs measuring different phenomena) relative to the average of the Monotrait-Heteromethod correlations (i.e., the correlations of indicators within the same construct) (Ashrafi et al., 2019). The HTMT should be significantly lesser than one (ideally less than 0.85) to discriminate between two factors (Henseler et al., 2015). In this study, HTMT ratios for all pairs were less than 0.85, fulfilling the HTMT criterion for discriminant validity.

**Table 3 - Correlations**

| Construct | TC | RA | DK | FS | PR | BB | GT | LW | RK | AI |
|---|---|---|---|---|---|---|---|---|---|---|
| TC | **0.877** | | | | | | | | | |
| RA | 0.329** | **0.800** | | | | | | | | |
| DK | 0.352** | 0.258** | **0.819** | | | | | | | |
| FS | 0.128 | 0.226* | 0.225* | **0.748** | | | | | | |
| PR | 0.234** | 0.224* | 0.413** | .053 | **0.800** | | | | | |
| BB | 0.215* | 0.522** | 0.185* | .211* | 0.211* | **0.837** | | | | |
| GT | 0.042 | 0.074 | 0.173 | .048 | 0.166 | 0.201* | **0.768** | | | |
| LW | 0.005 | 0.186* | 0.211* | .294** | 0.253** | 0.312** | 0.410** | **0.819** | | |
| RK | -0.019 | 0.078 | -0.087 | .209* | -0.150 | 0.038 | 0.085 | 0.063 | **0.849** | |
| AI | 0.258** | 0.440** | 0.408** | .298** | 0.466** | 0.461** | 0.185* | 0.271** | 0.077 | **0.781** |

*Notes: TC: Technology competence; RA: Relative advantage; DK: Decision-makers' knowledge; FS: Financial strength; PR: Partner readiness; BB: Benefit to beneficiaries; GT: Government support; LW: Sound legal system; RK: Risk to stakeholders; AI: Adoption Intention. The numbers highlighted in bold on the diagonal represent the square roots of the AVE*
**p<0.05; **p<0.01*

Furthermore, we tested for multicollinearity problems by checking the variance inflation factor (VIF) values. The analysis of VIF values for all our constructs confirms they are within the tolerance limit of 1 to 5, and hence multicollinearity does not exist in the model (Daoud, 2017). Together, our results indicate a satisfactory measurement model paving the way for subsequent structural model analysis.

### Model Fit

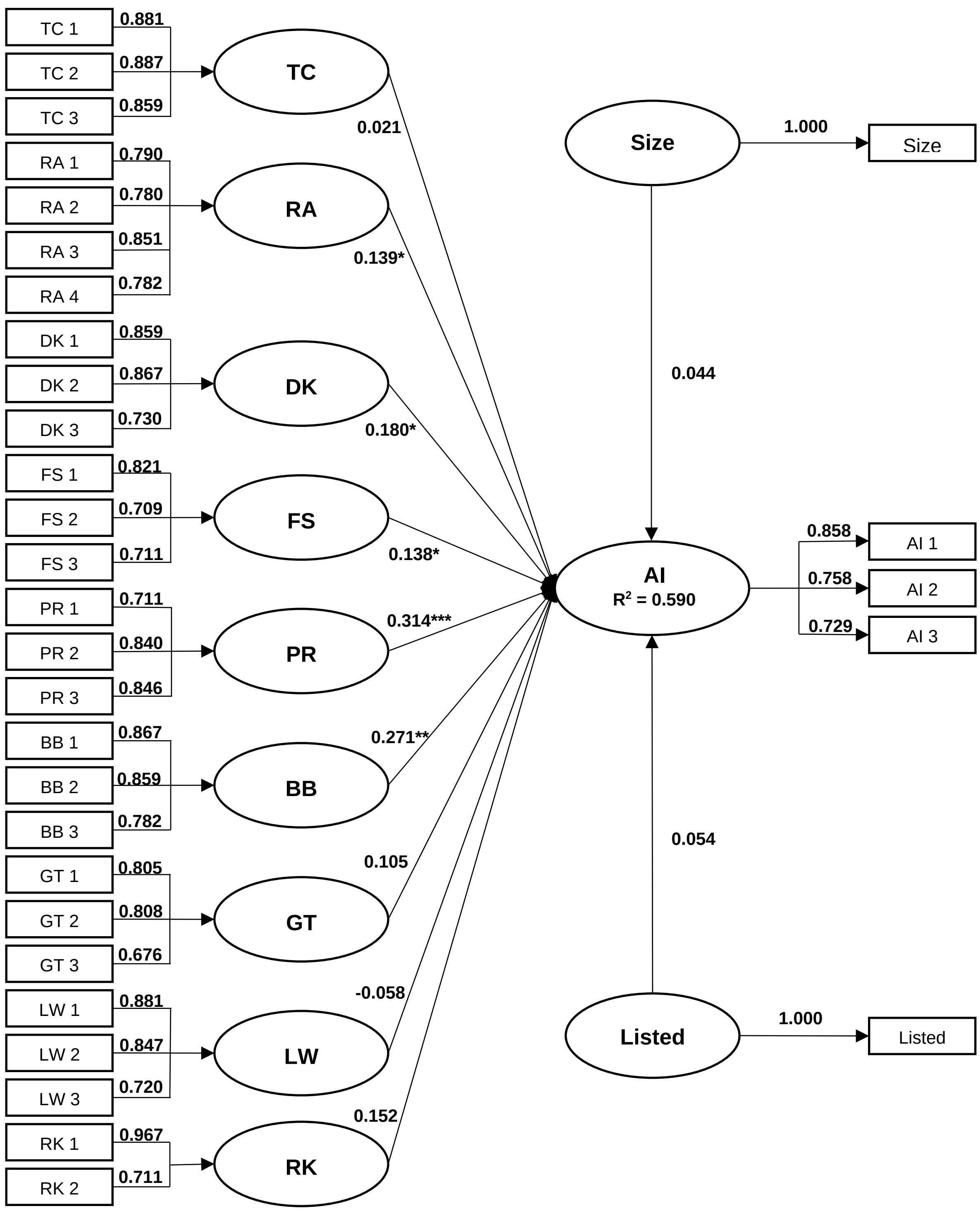
Before testing the hypothesized model, we first tested model fit by using the absolute measure of fit - Standardized Root Mean Square Residual (SRMR). Standardized Root Mean Square Residual (SRMR), a measure of the mean absolute value of the covariance residuals, is defined as the difference between the observed correlation and the model implied correlation matrix. It measures discrepancies between observed and expected correlations as a model fit criterion and is used to avoid model misspecification. The SRMR for this model was 0.08. SRMR value of 0.08 for the model less than 0.1 indicated a good fit (Henseler et al., 2015).

Next, we tested for the model fit using the d_ULS (i.e., the squared Euclidean distance) and d_G (i.e., the geodesic distance). They represent two ways to compute the discrepancy between the empirical covariance matrix and the covariance matrix implied by the composite factor model (Dijkstra & Henseler, 2015). We compared their original d_ULS (d_ULS=4.07; confidence interval: 2.05~4.20) and d_G (d_G=1.40; confidence interval: 1.15~1.71) values against the confidence interval created from the sampling distribution. The upper bound of the confidence interval was larger than the original value of the exact d_ULS and d_G fit criteria, indicating that the model had a "good fit".

### Structural Model

Once the construct measures were confirmed as reliable and valid, the structural model results were assessed by examining the model's predictive capabilities and the relationship between the constructs. A bootstrapping procedure was used, and the statistical significance of the hypothesized relationships was estimated by bootstrapping. It enabled all structural path coefficients to compute the t and p values. Figure 5 shows the structural model with path coefficients.

According to Cohen (1988), $R^2$ values for dependent latent variables are assessed as 0.26 (substantial), 0.13 (moderate), 0.02 (weak) and according to Chin (1998) the suggested $R^2$ values are 0.67 (substantial), 0.33 (moderate) and 0.19 (weak). The high variance of 59% explained in this study shows the robustness of the AI adoption model.




*Notes: TC: Technology competence; RA: Relative advantage; DK: Decision-makers' knowledge; FS: Financial strength; PR: Partner readiness; BB: Benefit to beneficiaries; GT: Government support; LW: Sound legal system; RK: Risk to stakeholders; AI: Adoption Intention*
*C -Complete. S - Small, L - Large, M - Manufacturing, S - Service, LS - Listed on the stock exchange, US - Not listed on the stock exchange.*

**Figure 5 – Structural Model**

Technology competence and its relationship with the adoption intention of AI for CSR initiatives proved insignificant (β = 0.02, t = 0.32, $p > 0.10$), thereby refuting hypothesis H1. The adoption intention of AI for CSR initiatives proved to have a significant relationship with the relative advantage possibly gained by implementing AI technology for CSR initiatives (β = 0.14, t = 1.75, $p < 0.05$), thereby confirming the positive association hypothesized in H2. Decision-makers knowledge (considered under the organizational context) and its relationship with the adoption intention of AI for CSR initiatives proved to be significant (β = 0.18, t = 2.20, $p < 0.05$), thereby suggesting the positive association hypothesized in H3. The firm's financial strength and its relationship with the adoption intention of AI for CSR initiatives proved to be significant (β = 0.14, t = 1.92, $p < 0.05$), establishing the positive association hypothesized in H4. Partner readiness and its relationship with the adoption intention of AI for CSR initiatives proved significant (β = 0.31, t = 4.64, $p < 0.01$), establishing a strong positive association hypothesized in H5. Benefits to beneficiaries were considered under the environmental context, and its relationship proved significant with the adoption intention of AI for CSR initiatives (β = 0.27, t = 3.41, $p < 0.01$), thereby establishing a strong positive association hypothesized in H6. Government support, the antecedent considered under the environmental context, had a significant relationship with the adoption intention of AI for CSR initiatives (β = 0.10, t = 1.48, $p < 0.10$), thereby establishing a positive association hypothesized in H7. The sound legal system was one of the antecedents considered under the environmental context. Its relationship with the adoption intention of AI for CSR initiatives proved insignificant (β = -0.06, t = -0.7, $p > 0.10$), thereby refuting hypothesis H8. Risk to stakeholders was the final antecedent that passed the validity test. Its relationship with the adoption intention of AI for CSR initiatives shows a significant relationship (β = 0.15, t = 1.99, $p < 0.05$), establishing the negative association hypothesized in H9. The control variables, the firm's size and whether it is listed on the stock exchange, did not indicate a significant association with AI adoption intention.

## Post Hoc Analysis

Once the analysis was complete, the data was revisited and checked for multi-group analysis. This was done primarily to understand the differences among various demographic groups and draw richer insights from the data. The groups were categorized for the size (small, large) of firms, whether they are listed on the stock exchange (listed, not listed), and the sector they belong to (manufacturing and services). Once the construct measures were found to be reliable and valid, the structural model results were assessed by examining the model's predictive capabilities and the relationship between the constructs for these different groups. The firm's age group did not fulfill the reliability and validity criteria. Table 4 shows that the CA and AVE values were satisfactory for multi-group analysis. Furthermore, the high $R^2$ values indicate that the variance explained by the proposed variables in the sub-groups was significant, as all VIF values were less than 5, and there were no significant multicollinearity problems (Srivastava & Chandra, 2018).

**Table 4 – Multi-group analysis – Cronbach's Alpha (CA), Average Variance Extracted (AVE) and R2**

| Var | C (124) (Complete) | | S (74) (Small) | | L (50) (Large) | | M (60) (Manufacturing) | | S (64) (Services) | | LS (80) (Listed) | | US (44) (Not Listed) | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | CR | AVE | CR | AVE | CR | AVE | CR | AVE | CR | AVE | CR | AVE | CR | AVE |
| TC | 0.85 | 0.77 | 0.83 | 0.75 | 0.85 | 0.75 | 0.86 | 0.78 | 0.83 | 0.74 | 0.87 | 0.79 | 0.81 | 0.72 |
| RA | 0.81 | 0.64 | 0.85 | 0.69 | 0.74 | 0.56 | 0.79 | 0.62 | 0.83 | 0.67 | 0.82 | 0.65 | 0.81 | 0.64 |
| DK | 0.76 | 0.67 | 0.79 | 0.69 | 0.72 | 0.64 | 0.70 | 0.62 | 0.82 | 0.73 | 0.72 | 0.64 | 0.79 | 0.70 |
| FS | 0.65 | 0.56 | 0.62 | 0.52 | 0.61 | 0.53 | 0.67 | 0.55 | 0.62 | 0.56 | 0.66 | 0.57 | 0.66 | 0.58 |
| PR | 0.74 | 0.64 | 0.69 | 0.60 | 0.80 | 0.71 | 0.79 | 0.70 | 0.66 | 0.52 | 0.73 | 0.63 | 0.76 | 0.66 |
| BB | 0.79 | 0.70 | 0.79 | 0.71 | 0.78 | 0.69 | 0.81 | 0.72 | 0.77 | 0.68 | 0.75 | 0.67 | 0.83 | 0.75 |
| GT | 0.67 | 0.59 | 0.68 | 0.61 | 0.67 | 0.46 | 0.61 | 0.51 | 0.70 | 0.62 | 0.69 | 0.59 | 0.65 | 0.58 |
| LW | 0.76 | 0.67 | 0.82 | 0.73 | 0.64 | 0.56 | 0.75 | 0.67 | 0.76 | 0.63 | 0.75 | 0.67 | 0.77 | 0.30 |
| RK | 0.67 | 0.72 | 0.71 | 0.77 | 0.61 | 0.68 | 0.62 | 0.67 | 0.73 | 0.75 | 0.68 | 0.72 | 0.68 | 0.75 |
| AI | 0.68 | 0.61 | 0.68 | 0.62 | 0.67 | 0.61 | 0.73 | 0.65 | 0.63 | 0.58 | 0.66 | 0.60 | 0.69 | 0.61 |
| $R^2$ | 0.59 | | 0.59 | | 0.67 | | 0.67 | | 0.59 | | 0.57 | | 0.65 | |

*Notes: TC: Technology competence; RA: Relative advantage; DK: Decision-makers' knowledge; FS: Financial strength; PR: Partner readiness; BB: Benefit to beneficiaries; GT: Government support; LW: Sound legal system; RK: Risk to stakeholders; AI: Adoption Intention*
*C -Complete. S - Small, L - Large, M - Manufacturing, S - Service, LS - Listed on the stock exchange, US - Not listed on the stock exchange.*

After verifying the validity and reliability of the various demographic groups, we conducted a multi-group analysis to dig deeper into the influence of the variables on each of the demographic groups. The results presented in Table 5 gave us interesting insights discussed in the next section.

**Table 5 - Multi-group analysis – Total Effect Inference**

| Effect | C (124) (Complete) | | S (74) (Small) | | L (50) (Large) | | M (60) (Manufacturing) | | S (64) (Services) | | LS (80) (Listed) | | US (44) (Not Listed) | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | t | p | t | p | t | p | t | p | t | p | t | p | t | p |
| TC → AI | 0.32 | 0.37 | 0.45 | 0.33 | -0.26 | 0.40 | 0.92 | 0.18 | 0.14 | 0.45 | 0.04 | 0.48 | 0.86 | 0.19 |
| RA → AI | 1.75 | 0.04 | 2.51 | 0.01 | -0.23 | 0.41 | 1.46 | 0.07 | 0.72 | 0.24 | 1.38 | 0.08 | 0.98 | 0.16 |
| DK → AI | 2.20 | 0.01 | 1.69 | 0.05 | 1.20 | 0.12 | 0.52 | 0.30 | 2.23 | 0.01 | 1.23 | 0.11 | 1.75 | 0.04 |
| FS → AI | 1.92 | 0.03 | 1.35 | 0.09 | 0.29 | 0.39 | 1.21 | 0.11 | 1.01 | 0.16 | 2.04 | 0.02 | 0.63 | 0.26 |
| PR → AI | 4.64 | 0.00 | 2.89 | 0.00 | 2.59 | 0.00 | 3.94 | 0.00 | 2.36 | 0.01 | 2.20 | 0.01 | 2.32 | 0.01 |
| BB → AI | 3.41 | 0.00 | 0.79 | 0.21 | 3.79 | 0.00 | 0.94 | 0.17 | 3.11 | 0.00 | 2.67 | 0.00 | 1.84 | 0.03 |
| GT → AI | 1.48 | 0.07 | 1.15 | 0.13 | 0.59 | 0.28 | -0.02 | 0.49 | 1.76 | 0.04 | 1.55 | 0.06 | 0.32 | 0.37 |
| LW → AI | -0.70 | 0.24 | -0.09 | 0.46 | -0.97 | 0.17 | 1.05 | 0.15 | -1.51 | 0.07 | -0.37 | 0.36 | 0.70 | 0.24 |
| RK → AI | 1.99 | 0.02 | 1.70 | 0.04 | 1.82 | 0.03 | 1.44 | 0.07 | 1.65 | 0.05 | 1.01 | 0.08 | 1.17 | 0.12 |

*Notes: TC: Technology competence; RA: Relative advantage; DK: Decision-makers' knowledge; FS: Financial strength; PR: Partner readiness; BB: Benefit to beneficiaries; GT: Government support; LW: Sound legal system; RK: Risk to stakeholders; AI: Adoption Intention*
*C -Complete. S - Small, L - Large, M - Manufacturing, S - Service, LS - Listed on the stock exchange, US - Not listed on the stock exchange.*

## Discussion

### *Discussion of Structural Model Results*

This study showed that technology competence does not significantly impact AI adoption intention for CSR initiatives. This finding is inconsistent with earlier studies concerning other technologies (Chandra & Kumar, 2018; Martins et al., 2016; Wang & Wang, 2016). A plausible explanation is that the latest technology architecture and models shift the infrastructure and technical needs to the supplier or external teams, reducing the need for AI competencies within


https://aisel.aisnet.org/pajais/vol14/iss5/4
DOI: 10.17705/1pais.14504

the CSR team or the firm's internal ecosystem. AI applications can also be perceived as intuitive with less need for technical expertise.

The findings showed that the relative advantage of using AI for CSR initiatives significantly impacts the AI adoption intention for CSR initiatives. One of the essential objectives of any firm investing in new technology is to save costs by bringing efficiencies. It has been proven that AI helps firms improve processes and efficiency, lower operation costs, and improve overall service quality or products resulting in enhanced customer experiences (Bughin et al., 2019; NITI Aayog, 2018).

In line with past studies that have shown that the employees with decision-making authority on technology adoption, if equipped with knowledge about the technology and its potential impact, have a significant influence on the adoption of technologies (Alam et al., 2016; Chandra & Kumar, 2018). This antecedent showed a strong relationship with the adoption intention of AI for CSR initiatives.

For any technological innovation, a firm's financial strength is crucial, including the financial resources that determine its availability of human capital and IT infrastructure resources. Studies have found that financial strength significantly influences innovation in a firm (Chandra & Kumar, 2018; Clohessy et al., 2019; Ghobakhloo et al., 2011). This study found that the firm's financial strength is significant for AI adoption intention, even in CSR initiatives.

One of the options firms choose to achieve their CSR goals is to partner with external entities such as NGOs (implementation partners). There are multiple benefits of working with partners and, on many occasions, dealing with them for various resources, including technology adoption or integration, becomes one of the crucial factors in the environmental context (Lin & Lin, 2008; PwC India, 2013; Zhu et al., 2003). This study's findings re-emphasized that partners' readiness influences innovation adoption.

Value-adding use cases are one of the most important determinants of innovation adoption and evaluating the benefits any technology can provide becomes significantly essential. One of the most critical elements in the CSR context is addressing the core social issue or the problem. If the technology can help resolve these issues and benefit the actual beneficiaries of these social interventions, it becomes easy to adopt such emerging technologies (Clohessy et al., 2019; Google, 2019; Lakhani & Iansiti, 2017; MHP, 2019). This study's findings show a strong relationship between benefits to beneficiaries and the adoption intention of AI for CSR initiatives.

Organizations can engage more with innovative technologies such as AI if the government provides a platform and a conducive environment for such innovations. This study confirms that government support positively influences a firm's AI adoption intention for CSR initiatives.

With AI's increased use and role in the economy and society, current policies, rules, and legalities have become significantly important. A sound legal system becomes critical for the adoption of new technologies. This factor showed a non-significant relationship with the dependent variable, the adoption intention of AI for CSR initiatives. One possible explanation could be that development of the legal framework is still in the embryonic stage (NITI Aayog, 2018). The response from the CSR practitioners illustrates the insignificance of this factor on AI adoption intention for CSR initiatives.

The inability to assess the risk can result in delays in adopting technologies such as AI, thus preventing them from reaping the potential benefits (Canhoto & Clear, 2020). The potential risk of adopting new technologies impacts the adoption intention, and the findings of this study re-emphasize this even in the context of CSR initiatives.

## Discussion of Post-hoc Analysis

For multi-group analysis, the groups were categorized for the size (small, large) of firms, if listed on the stock exchange (listed, not listed), and the sector they belong to (manufacturing and services). In some cases, the analysis showed contradicting results.

The relative advantage, decision-makers' knowledge, and financial strength factors were significant in small firms but insignificant in large firms. While the benefits to beneficiaries factor were significant in large firms, it was insignificant in small firms.

The decision-makers' knowledge, benefits to beneficiaries, government support, and sound legal system factors were significant in firms in the services sector. Still, they were insignificant in the manufacturing sector firms. While relative advantage was insignificant in the services sector, it was significant in manufacturing sector firms.

The relative advantage, financial strength, and government support factors were significant in firms listed on the stock exchange. However, they were insignificant in private firms not listed on the stock exchange. The decision-makers knowledge factor was significant in unlisted firms but insignificant in the listed firms.

Indications are that firms can behave differently based on their characteristics. It is suggested that future researchers dive deeper into these aspects when studying the AI adoption intention for CSR initiatives.

## Implications

### Theoretical Implications

The study offers several theoretical implications.

*First*, AI research in CSR is scarce and mainly focused on the technological advancement of AI. While technological elements are essential, acceptance and adoption of AI are equally critical. This research expands our understanding of IS by exploring the organizational endorsement and this emerging technology adoption in the CSR context. Accordingly, this study contributes to integrating AI and CSR by setting the foundation for future research.

*Second*, well-established adoption theories such as TAM and DOI have been studied extensively. This is one of the first studies to use the TOE framework for an AI adoption model and suggest the critical role of technological, organizational, and environmental contexts for AI in CSR initiatives. This model can be extended for future research studies on the firm's innovation adoption intention. This study expands the literature and will help increase future researchers' interest in focusing on AI adoption and implementation in CSR initiatives.

*Third*, this study focuses on adopting technology from the organization's perspective and how future research can explore the organizational view of new technology adoption.

*Fourth*, the research explores various factors that can impact the adoption intentions of AI technology in CSR initiatives. The extension of literature on multiple factors presents a framework with the theoretical basis to understand the antecedents of AI adoption intention for CSR initiatives. These characteristics can be focused on in detail with rigour, and the list can be further expanded.

*Fifth*, this research mapped Carroll's theory with the TOE model and can be referred to while researching the intersection of social theories and technology.

*Sixth*, this research contributes a validated research framework for AI adoption intention in the CSR context. The model and the framework can be utilized to study the adoption of other emerging technologies, such as blockchain, for CSR.

## Practical Implications

Along with the contributions to literature and theory, this research study has several important contributions to firms, AI products, service companies, and technologists.

*First*, several technology applications are resolving vital societal challenges related to, for example, health, food security, and climate action. While there are upcoming use cases for AI solving societal issues, the potential is not tapped to the fullest, and this research study is predicated on that gap. AI technology can be harnessed to solve many day-to-day practical challenges such as garbage and waste management, guided individual skill assessment, and water-use optimization to irrigate crops. Various AI companies and start-ups can work in these areas and develop multiple tools and applications. This study focuses on the significance and importance of AI technology and the factors that should be considered for easy adoption, and considering the study has been done in India, it contributes to research and development in Asia Pacific Region.

*Second*, the study concentrates on critical factors that drive AI adoption in CSR initiatives and direct the AI product companies, start-ups, practitioners, and technologists to consider these vital factors while designing and developing solutions for better value creation. AI technology has its peculiarity in complexity and the efforts needed to implement and integrate it with the existing structure and business ecosystem. Previous studies have focused on the perceived usefulness of the technology, while this research study emphasizes the importance of the firm's organizational characteristics and environmental support. This must be thoroughly studied in the future from the relevance and value creation perspectives.

*Third,* the study highlights that AI companies and vendors must understand the customers' intent and readiness to adopt AI technologies. After understanding the nuances, they can develop the right product and create relevant demand. AI companies should demonstrate how beneficiaries can significantly profit from this technology and how they can genuinely make a real, meaningful, and scalable impact.

*Fourth*, the research emphasizes that the organization's decision-makers knowledge plays a vital role in adopting and implementing AI technology. Suppose decision-makers are exposed to the literature, studies, demonstrations, and relevant artefacts related to technology use cases such as AI in the CSR context. In that case, it will encourage the adoption to accomplish the intended goals.

The results generally highlight that inter-organizational characteristics are essential in guiding new technology adoption intentions. Firms, AI start-ups and companies, and the subject matter experts must consider the technological, organizational, and environmental contexts. It is essential to have a clear vision and participation from all stakeholders to generate the intended outcome and benefits of adopting AI technology for their CSR initiatives.

## *Limitations and Scope for Future Research*

This research study makes significant contributions to understanding AI adoption for CSR initiatives from the firm's perspective; however, there are a few limitations.

*First*, evaluating the factors influencing the AI adoption for CSR initiatives from a firm's perspective is a new research area in information systems. The analysis and implications were drawn from data and inputs collected through a survey targeted at potential AI technology adopters. Hence, the generalization of the study results can be potentially regarded as a research issue. While the study highlights important variables influencing the adoption intention of AI for CSR, more research is needed in this area to identify further dimensions.

*Second*, this research has identified and studied several critical factors influencing the AI adoption intention for CSR initiatives. However, AI technology is evolving rapidly, and many additional factors might be discovered to enhance the model. For example, future studies should focus on changing aspects which may pose a risk to AI adoption, such as AI as a black box and algorithmic biases in AI. Future research should minimise these biases through training, testing, and validating AI. This would ensure that results don't produce bias due to algorithms or data sets.

Furthermore, because data scientists and data labellers are diverse, there is a need to establish strict guidelines for data handling. These guidelines may include rules for data labelling, bringing together multiple source inputs to assure data variety, analysing data regularly, keeping records of errors, taking help from domain experts to review collected and annotated data, and implementing multi-pass annotation. Future research may consider factors pertaining to the usage of Google's What-if Tool or IBM's AI Fairness 360 Open-Source Toolkit to examine and inspect AI models. Such evolving factors may be critical for AI adoption.

*Third*, this research focused only on Indian firms. Future studies can be conducted on this research subject in various countries or geographies with different socio-economic and regulatory environments to get deeper insights into how those factors influence the outcome.

*Fourth*, the research study was cross-sectional, and views, understanding, and intentions were captured at a single point in time. This understanding is subject to change as respondents are exposed to technology and become acquainted with it. Future research can focus on developing a dynamic model to predict intentions and perceptions over time.

This study highlights that, along with technological factors, the organizational and environmental elements play an essential role in influencing the adoption intentions of technology such as AI. Hence, firms, AI companies, start-ups, technologists, and industry professionals must consider these three contexts and align that with a clear vision and strategy to add real value and highly scalable impact.

## Acknowledgments

We would like to thank Arumugam Seetharaman, Dhrupad Mathur, Koilakuntla Maddulety for their participation and support in this research. We would also like to thank the anonymous reviewers for their constructive feedback on previous versions of the manuscript.

## References

Aguinis, H. (2011). Organizational responsibility: Doing good and doing well. In S. Zedeck (Ed.), *APA Handbook of Industrial and Organizational Psychology, vol 3, Maintaining, Expanding, and Contracting the Organization* (pp. 855-879). American Psychological Association.

Ahmed, Z., Kumar, V., Kumar, U., & Eryilmaz, E. (2019). Social capital and ICT intervention: A holistic model of value. *Pacific Asia Journal of the Association for Information Systems*, *11*(4), 44-74.

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179-211.

Alam, M. G. R., Masum, A. K. M., Beh, L.S., & Hong, C. S. (2016). Critical factors influencing decision to adopt Human Resource Information System (HRIS) in hospitals. *PloS One*, *11*(8), 1-22.

Alarie, B., Niblett, A., & Yoon, A. H. (2018). How artificial intelligence will affect the practice of law. *University of Toronto Law Journal*, *68*(supplement 1), 106-124.

Anandarajan, M., Igbaria, M., & Anakwe, U. P. (2002). IT acceptance in a less-developed country: A motivational factor perspective. *International Journal of Information Management*, *22*(1), 47-65.

Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modeling in practice: A review and recommended two-step approach. *Psychological Bulletin*, *103*(3), 411-423.

Ashrafi, A., Ravasan, A. Z., Trkman, P., & Afshari, S. (2019). The role of business analytics capabilities in bolstering firms' agility and performance. *International Journal of Information Management, 47*, 1-15.

Arnold, C., & Voigt, K. I. (2019). Determinants of industrial internet of things adoption in German manufacturing companies. *International Journal of Innovation and Technology Management*, *16*(06), 1950038.

Atabekov, A., & Yastrebov, O. (2018). Legal status of artificial intelligence across countries: Legislation on the move. *European Research Studies Journal*, *21*(4), 773-782.

Awa, H. O., & Ojiabo, O. U. (2016). A model of adoption determinants of ERP within TOE framework. *Information Technology & People*, *29*(4), 901-930.

Barclay, D. W., Higgins, C. A., & Thompson, R. (1995). The partial least squares approach to causal modeling: Personal computer adoption and use as illustration. *Technology Studies, 2*(2), 285-309

Baskaran, A., Chandran,, V. G. R., & Ng, B. K. (2019). Inclusive entrepreneurship, innovation and sustainable growth: Role of business incubators, academia and social enterprises in Asia. *Science, Technology and Society*, *24*(3), 385-400.

Bhattacharya, M., & Wamba, S. F. (2015). A conceptual framework of RFID adoption in retail using TOE framework. *International Journal of Technology Diffusion*, 6(1), 1-32.

Bhattacherjee, A., & Premkumar, G. (2004). Understanding changes in belief and attitude toward information technology usage: A theoretical model and longitudinal test. *MIS Quarterly*, *28*(2), 229-254.

Bracarense, N., Bawack, R. E., Fosso Wamba, S., & Carillo, K. D. A. (2022). Artificial intelligence and sustainability: A bibliometric analysis and future research directions. *Pacific Asia Journal of the Association for Information Systems*, *14*(2), 136-159.

Bughin, J., Hazan, E., Allas, T., Hjart, K., Manyika, J., Sjatil, P. E., & Shigina, I. (2019, May 15). *'Tech for Good': Using technology to smooth disruption and improve well-being*.

McKinsey & Company. https://www.mckinsey.com/featured-insights/future-of-work/tech-for-good-using-technology-to-smooth-disruption-and-improve-well-being

Canhoto, A. I., & Clear, F. (2020). Artificial intelligence and machine learning as business tools: A framework for diagnosing value destruction potential. *Business Horizons*, *63*(2), 183-193.

Cao, Q., Baker, J., Wetherbe, J., & Gu, V. (2012). Organizational adoption of innovation: Identifying factors that influence RFID adoption in the healthcare industry. In *European Conference on Information Systems (ECIS)*, Barcelona, Spain.

Carroll, A. B. (1979). A three-dimensional conceptual model of corporate performance. *Academy of Management Review*, *4*(4), 497-505.

Carroll, A. B. (1991). The pyramid of corporate social responsibility: Toward the moral management of organizational stakeholders. *Business Horizons*, *34*(4), 39-48.

Carroll, A. B. (2016). Carroll's pyramid of CSR: Taking another look. *International Journal of Corporate Social Responsibility*, *1*(1), 1-8.

Chandra, S., & Kumar, K. N. (2018). Exploring factors influencing organizational adoption of augmented reality in e-commerce: Empirical analysis using technology-organization-environment model. *Journal of Electronic Commerce Research*, *19*(3), 237-265.

Chang, I. C., Hwang, H. G., Hung, M. C., Lin, M. H., & Yen, D. C. (2007). Factors affecting the adoption of electronic signature: Executives' perspective of hospital information department. *Decision Support Systems*, *44*(1), 350-359.

Chau, N. T., & Deng, H. (2018). Critical determinants for mobile commerce adoption in Vietnamese SMEs: A conceptual framework. *Procedia Computer Science*, *138*, 433-440.

Chauhan, S., Jaiswal, M., Rai, S., Motiwalla, L., & Pipino, L. (2018). Determinants of adoption for open-source office applications: A plural investigation. *Information Systems Management*, *35*(2), 80-97.

Cheatham, B., Javanmardian, K., & Samandari, H. (2019). Confronting the risks of artificial intelligence. *McKinsey Quarterly, 2*, 1-9.

Chen, Y., Yin, Y., Browne, G. J., & Li, D. (2019). Adoption of building information modeling in Chinese construction industry: The technology-organization-environment framework. *Engineering, Construction and Architectural Management*, *26*(9), 1878-1898.

Chin, W. W. (1998). The partial least squares approach to structural equation modeling. *Modern Methods for Business Research*, *295*(2), 295-336.

Chiu, C. Y., Chen, S., & Chen, C. L. (2017). An integrated perspective of TOE framework and innovation diffusion in broadband mobile applications adoption by enterprises. *International Journal of Management, Economics and Social Sciences*, *6*(1), 14-39.

Chong, A. Y. L., & Chan, F. T. (2012). Structural equation modeling for multi-stage analysis on Radio Frequency Identification (RFID) diffusion in the health care industry. *Expert Systems with Applications*, *39*(10), 8645-8654.

Chui, M., Kamalnath, V., & McCarthy, B. (2018). An Executives Guide to AI, McKinsey Analytics. *Retrieved August, 24, 2018.*

Clohessy, T., Acton, T., & Rogers, N. (2019). Blockchain adoption: Technological, organisational and environmental considerations. In H. Treiblmaier, R. Beck (Eds.), *Business transformation through blockchain* (pp. 47-76). Palgrave Macmillan, Cham.

Cohen, J. (1988). *Statistical Power Analysis for the Behavioral Sciences* (2nd ed.). Hillsdale: Lawrence Erlbaum Associates.

Dao, V. T., & Abraham, T. (2021). An Empirical Examination of the Use of IS-enabled Sustainability Initiatives Across the Integrated Sustainability Framework. *Pacific Asia Journal of the Association for Information Systems*, *13*(3), 57-85.

Daoud, J. I. (2017, December). Multicollinearity and regression analysis. In *Journal of Physics: Conference Series* (Vol. 949, No. 1, p. 012009). IOP Publishing.

Dasgupta, S., Agarwal, D., Ioannidis, A., & Gopalakrishnan, S. (1999). Determinants of information technology adoption: An extension of existing models to firms in a developing country. *Journal of Global Information Management*, *7*(3), 30-40.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319-340.

Depietro, R., Wiarda, E., & Fleischer, M. (1990). The context for change: Organization, technology and environment. *The processes of Technological Innovation*, *199*(0), 151-175.

Dijkstra, T. K., & Henseler, J. (2015). Consistent partial least squares path modeling. *MIS Quarterly*, *39*(2), 297-316.

Dubickis, M., & Gaile-Sarkane, E. (2021). Factors influencing technology transfer in companies at emerging economies. *Science, Technology and Society*, *26*(2), 242-271.

El Khatib, M. M., Al-Nakeeb, A., & Ahmed, G. (2019). Integration of cloud computing with artificial intelligence and Its impact on telecom sector—A case study. *iBusiness*, *11*, 1-10.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39-50.

Gangwar, H., Date, H., & Ramaswamy, R. (2015). Understanding determinants of cloud computing adoption using an integrated TAM-TOE model. *Journal of Enterprise Information Management*, *28*(1), 107-130.

Garrison, G., Wakefield, R. L., & Kim, S. (2015). The effects of IT capabilities and delivery model on cloud computing success and firm performance for cloud supported processes and operations. *International Journal of Information Management*, *35*(4), 377-393.

Ghobakhloo, M., Arias-Aranda, D., & Benitez-Amado, J. (2011). Adoption of e-commerce applications in SMEs. *Industrial Management & Data Systems*, *111*(8), 1238-1269.

Goergen, M., Chahine, S., Wood, G., & Brewster, C. (2019). The relationship between public listing, context, multi-nationality and internal CSR. *Journal of Corporate Finance*, *57*, 122-141.

Gökalp, E., Gökalp, M. O., & Çoban, S. (2022). Blockchain-based supply chain management: Understanding the determinants of adoption in the context of organizations. *Information Systems Management*, *39*(2), 100-121.

Google. (2019). *Accelerating social good with artificial intelligence: Insights from the Google AI Impact Challenge*. Google. https://services.google.com/fh/files/misc/accelerating_social_good_with_artificial_intelligence_google_ai_impact_challenge.pdf

Google AI. (2019). *Applying AI to some of the world's biggest challenges*. Goole AI. https://ai.google/social-good/

Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (1998). *Multivariate Data Analysis*. Upper Saddle River, NJ: Prentice hall.

Hair, J. F., Sarstedt, M., & Ringle, C. M. (2019). Rethinking some of the rethinking of partial least squares. *European Journal of Marketing*, *53*(4), 566-584.

Hair Jr, J., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2016). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*. Sage Publications.

Hameed, M. A., & Arachchilage, N. A. G. (2019). A conceptual model for the organizational adoption of information system security innovations. In R. Joshi & B. Gupta (Eds.), *Security, Privacy, and Forensics Issues in Big Data* (pp. 317-339). IGI Global.

Hameed, M. A., & Arachchilage, N. A. G. (2016). A model for the adoption process of information system security innovations in organisations: A theoretical perspective. *The 27th Australasian Conference on Information Systems*, Wollongong, Australia.

Henseler, J., & Dijkstra, T. (2017). *Adanco 2.0.1 User Manual*. Composite Modeling GmbH & Co.

Henseler, J., & Dijkstra, T. K. (2014). *ADANCO 1.0. Kleve: composite modeling*. www.compositemodeling.com

Henseler, J., Hubona, G., & Ray, P. A. (2016). Using PLS path modeling in new technology research: Updated guidelines. *Industrial Management & Data Systems, 116*(1), 2-20.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115-135.

Hohnen, P. (2007). *Corporate Social Responsibility: An Implementation Guide for Business*. International Institute for Sustainable Development.

Long, A., & Ascent, D. (2020). World economic outlook. *International Monetary Fund*.

Ioannou, I., & Serafeim, G. (2015). The impact of corporate social responsibility on investment recommendations: Analysts' perceptions and shifting institutional logics. *Strategic Management Journal*, *36*(7), 1053-1081.

Ivanov, S. H., & Webster, C. (2017). Adoption of robots, artificial intelligence and service automation by travel, tourism and hospitality companies – a cost-benefit analysis. In I*nternational Scientific Conference "Contemporary tourism – traditions and innovations"*.

James, J. (2003). *Bridging the Global Digital Divide*. Edward Elgar Publishing.

Jeon, B. N., Han, K. S., & Lee, M. J. (2006). Determining factors for the adoption of e-business: the case of SMEs in Korea. *Applied Economics*, *38*(16), 1905-1916.

Jung, M., Eom, M. T., & Yayla, A. (2022). Investigating the interaction effect between IT-enabled innovation and corporate social responsibility on firm performance. *Information Systems Management*, 1-20.

Junior, C. H., Oliveira, T., & Yanaze, M. (2019). The adoption stages (evaluation, adoption, and routinisation) of ERP systems with business analytics functionality in the context of farms. *Computers and Electronics in Agriculture*, *156*, 334-348.

Kamal, M., Weerakkody, V., & Irani, Z. (2011). Analyzing the role of stakeholders in the adoption of technology integration solutions in UK local government: An exploratory study. *Government Information Quarterly*, *28*(2), 200-210.

Katayamadi, R., & Wadhwa, D. (2019, January 9). *Half of the world's poor live in just 5 countries*. Data Blog. https://blogs.worldbank.org/opendata/half-world-s-poor-live-just-5-countries

Kathuria, R., Kedia, M., & Kapilavai, S. (2020). *Implications of AI on the Indian Economy*. Indian Council for Research on International Economic Relations (ICRIER).

Khan, M. J., & Mahmood, S. (2018). Assessing the determinants of adopting component-based development in a global context: A client-vendor analysis. *IEEE Access*, *6*, 79060-79073.

Lageschulte, P., Westbrook, R., Mehta, V., Nagaraj, K., Galvan, J., & Mouli,P.(2018), *Disruption is the new norm*. KPMG International.

Krkač, K., & Bračević, I. (2020). Artificial Intelligence and Social Responsibility. In D. Crowther & S. Seifi (Eds.), *The Palgrave Handbook of Corporate Social Responsibility* (pp. 1-23). Palgrave Macmillan.

KsiężaK, P. (2016). The benefits from CSR for a company and society. *Journal of Corporate Responsibility and Leadership*, *3*(4), 53-65.

Kumar, D., Samalia, H. V., & Verma, P. (2017). Factors influencing cloud computing adoption by Small and Medium-Sized Enterprises (SMEs) In India. *Pacific Asia Journal of the Association for Information Systems*, *9*(3), 25-48.

Kumari, T. S. (2020, July). Artificial Intelligence and the Law. *In Advances in Computational and Bio-Engineering: Proceeding of the International Conference on Computational and Bio Engineering, 2019*, *Volume 2* (Vol. 16, p. 169). Springer Nature.

Lai, H. M., Lin, I. C., & Tseng, L. T. (2014). High-level managers' considerations for RFID adoption in hospitals: An empirical study in Taiwan. *Journal of Medical Systems*, *38*(2), 1-17.

Lakhani, K. R., & Iansiti, M. (2017). The truth about blockchain. *Harvard Business Review*, *95*(1), 119-127.

Lee, J., Suh, T., Roy, D., & Baucus, M. (2019). Emerging technology and business model innovation: The case of artificial intelligence. *Journal of Open Innovation: Technology, Market, and Complexity*, *5*(3), 44.

Lin, H. F., & Lin, S. M. (2008). Determinants of e-business diffusion: A test of the technology diffusion perspective. *Technovation*, *28*(3), 135-145.

Lin, H. F., & Lee, G. G. (2005). Impact of organizational learning and knowledge management factors on e-business adoption. *Management Decision*, *43*(2), 171-188.

Lippert, S. K., & Govindarajulu, C. (2006). Technological, organizational, and environmental antecedents to web services adoption. *Communications of the IIMA*, *6*(1), 147-160.

Magrani, E. (2019). New perspectives on ethics and the laws of artificial intelligence. *Internet Policy Review*, *8*(3), 1-19.

Makridakis, S. (2017). The forthcoming Artificial Intelligence (AI) revolution: Its impact on society and firms. *Futures*, *90*, 46-60.

Marra, M., Pannell, D. J., & Ghadim, A. A. (2003). The economics of risk, uncertainty and learning in the adoption of new agricultural technologies: where are we on the learning curve? *Agricultural Systems*, *75*(2-3), 215-234.

Martins, R., Oliveira, T., & Thomas, M. A. (2016). An empirical analysis to assess the determinants of SaaS diffusion in firms. *Computers in Human behavior*, *62*, 19-33.

Mehr, H., Ash, H., & Fellow, D. (2017). Artificial intelligence for citizen services and government. *Ash Cent. Democr. Gov. Innov. Harvard Kennedy Sch., no. August, 1-12.* MHP. (2019). *A.I.dea Book - Use Cases and Trends in Artificial Intelligence*. MHP.

Microsoft. (2019). *Using AI for Good with Microsoft AI*. Microsoft. https://www.microsoft.com/en-us/ai/ai-for-good

Ministry of Statistics and Programme Implementation. (2021, Jun 17). *Sector-wise GDP of India*. Statistics Times. https://statisticstimes.com/economy/country/india-gdp-sectorwise.php#:~:text=According%20to%20CIA%20Fackbook%2C%20sector,larger%20producer%20of%20agriculture%20products.

Naqvi, A. (2018, Jan 18). *How AI and robotics can transform CSR*. Reuters. https://www.reutersevents.com/sustainability/how-ai-and-robotics-can-transform-csr

Nijhof, A., de Bruijn, T., & Honders, H. (2008). Partnerships for corporate social responsibility: A review of concepts and strategic options. *Management Decision*, *46*(1), 152-167.

NITI Aayog. (2018). *National Strategy for Artificial Intelligence*. NITI Aayog.

OECD. (2020, April 23). *Using artificial intelligence to help combat COVID-19*. OECD. https://www.oecd.org/coronavirus/policy-responses/using-artificial-intelligence-to-help-combat-covid-19-ae4c5c21/

Oliveira, T., & Martins, M. F. (2010). Firms patterns of e-business adoption: Evidence for the European Union-27. *Electronic Journal of Information Systems Evaluation*, *13*(1), 47-56.

Oliveira, T., & Martins, M. F. (2011). Literature review of information technology adoption models at firm level. *Electronic Journal of Information Systems Evaluation*, *14*(1), 110-121.

Oliveira, T., Thomas, M., & Espadanal, M. (2014). Assessing the determinants of cloud computing adoption: An analysis of the manufacturing and services sectors. *Information & Management*, *51*(5), 497-510.

Pan, M., & Pan, W. (2019). Determinants of adoption of robotics in precast concrete production for buildings. *Journal of Management in Engineering*, *35*(5), 1-13.

Park, S., Tseng, Y., & Kim, S. (2016). The impact of innovation on job satisfaction: Evidence from US federal agencies. *Asian Social Science*, *12*(1), 274-286.

Petter, S., Straub, D., & Rai, A. (2007). Specifying formative constructs in information systems research. *MIS Quarterly, 31*(4), 623-656.

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: a critical review of the literature and recommended remedies. *Journal of Applied Psychology*, *88*(5), 879-903.

Podsakoff, P. M., & Organ, D. W. (1986). Self-reports in organizational research: Problems and prospects. *Journal of Management*, *12*(4), 531-544.

Prakash, A. V., & Das, S. (2020). Intelligent conversational agents in mental healthcare services: A thematic analysis of user perceptions. *Pacific Asia Journal of the Association for Information Systems*, *12*(2), 1-34.

Prasad, C. S. (2020). Constructing alternative socio-technical worlds: Re-imagining RRI through SRI in India. *Science, Technology and Society*, *25*(2), 291-307.

PwC India. (2013). Handbook on Corporate Social Responsibility in India. *See http://www. mca. gov. in/SearchableActs/Schedule7. htm. Accessed September, 10, 2017.*

Raghunath, N. (2021). Technological adoption as a social process in food centres in Singapore. *Science, Technology and Society*, *26*(3), 375-391.

Rana, N. P., Weerakkody, V., Dwivedi, Y. K., & Piercy, N. C. (2014). Profiling existing research on social innovation in the public sector. *Information Systems Management*, *31*(3), 259-273.

Rogers, E. M. (2003). *Diffusion of Innovations*. Free Press.

Russel, S., & Norvig, P. (2015). *Artificial Intelligence - A Modern Approach*. (3rd ed.). Uttar Pradesh, India: Pearson India Education Services Pvt. Ltd.

Salleh, K. A., & Janczewski, L. (2016). Adoption of big data solutions: A study on its security determinants using Sec-TOE Framework. In *International Conference on Information Resources Management (CONF-IRM)*, Cape Town, South Africa.

San-Martín, S., Jiménez, N. H., & López-Catalán, B. (2016). The firms benefits of mobile CRM from the relationship marketing approach and the TOE model. *Spanish Journal of Marketing-ESIC*, *20*(1), 18-29.

Sawers, P. (2019, December 23). *How the 'big 5' bolstered their AI through acquisitions in 2019*. Venture Beat. https://venturebeat.com/2019/12/23/how-the-big-5-bolstered-their-ai-through-acquisitions-in-2019/

Scherer, M. U. (2015). Regulating artificial intelligence systems: Risks, challenges, competencies, and strategies. *Harvard Journal of Law & Technology*, *29*(2), 353-400.

Schillewaert, N., Ahearne, M. J., Frambach, R. T., & Moenaert, R. K. (2005). The adoption of information technology in the sales force. *Industrial Marketing Management*, *34*(4), 323-336.

Shareef, M. A., Dwivedi, Y. K., Laumer, S., & Archer, N. (2016). Citizens' adoption behavior of mobile government (mGov): A cross-cultural study. *Information Systems Management*, *33*(3), 268-283.

Shiau, W. L., Hsu, P. Y., & Wang, J. Z. (2009). Development of measures to assess the ERP adoption of small and medium enterprises. *Journal of Enterprise Information Management*, *22*(1/2), 99-118.

Soares-Aguiar, A., & Palma-dos-Reis, A. (2008). Why do firms adopt e-procurement systems? Using logistic regression to empirically test a conceptual model. *IEEE Transactions on Engineering Management*, *55*(1), 120-133.

Sohn, K., & Kwon, O. (2020). Technology acceptance theories and factors influencing artificial Intelligence-based intelligent products. *Telematics and Informatics*, *47*, 101324.

Srivastava, S. C., & Chandra, S. (2018). Social presence in virtual world collaboration: An uncertainty reduction perspective using a mixed methods approach. *MIS Quarterly*, *42*(3), 779-804.

Straub, D., Boudreau, M. C., & Gefen, D. (2004). Validation guidelines for IS positivist research. *Communications of the Association for Information systems*, *13*(1), 380-427.

Strusani, D., & Houngbonon, G. V. (2019). *The role of artificial intelligence in supporting development in emerging markets.* International Finance Corporation, Washington, DC. https://openknowledge.worldbank.org/handle/10986/32365

Teo, T. S., Ranganathan, C., & Dhaliwal, J. (2006). Key dimensions of inhibitors for the deployment of web-based business-to-business electronic commerce. *IEEE Transactions on Engineering Management*, *53*(3), 395-411.

Thong, J. Y. (1999). An integrated model of information systems adoption in small businesses. *Journal of Management Information Systems*, *15*(4), 187-214.

Tornatzky, L. G., Fleischer, M., & Chakrabarti, A. K. (1990). *Processes of technological innovation*. Lexington Books.

Tripathi, S., & Mishra, V. (2019). Determinants of cloud computing adoption: A comparative study. *Pacific Asia Journal of the Association for Information Systems*, *11*(3), 28-54.

UNIDO. (2019, January 29). *What is CSR?* . UNIDO. https://www.unido.org/our-focus/advancing-economic-competitiveness/competitive-trade-capacities-and-corporate-responsibility/corporate-social-responsibility-market-integration/what-csr

Ven, K., & Verelst, J. (2012). A qualitative study on the organizational adoption of open source server software. *Information Systems Management*, *29*(3), 170-187.

Venkatesh, V., & Bala, H. (2012). Adoption and impacts of interorganizational business process standards: Role of partnering synergy. *Information Systems Research*, *23*(4), 1131-1157.

Venkatesh, V., Thong, J. Y., & Xu, X. (2016). Unified theory of acceptance and use of technology: A synthesis and the road ahead. *Journal of the Association for Information Systems*, *17*(5), 328-376.

Walters, E. (2019, May 21). *Nothing Artificial About It: How Law Firms (Really) Use AI in Practice.* Medium. https://medium.com/@ejwalters/nothing-artificial-about-it-how-law-firms-really-use-ai-in-practice-f793947b6f94

Wang, Q., Dou, J., & Jia, S. (2016). A meta-analytic review of corporate social responsibility and corporate financial performance: The moderating effect of contextual factors. *Business & Society*, *55*(8), 1083-1121.

Wang, Y. M., & Wang, Y. C. (2016). Determinants of firms' knowledge management system implementation: An empirical study. *Computers in Human Behavior*, *64*, 829-842.

Wang, Y., Xiong, M., & Olya, H. (2020). Toward an understanding of responsible artificial intelligence practices. In *Proceedings of the 53rd Hawaii International Conference on System Sciences*, Hawaii, USA.

Williamson, O. E. (1980). *Organizational Innovation: The Transaction Cost Approach*. University of Pennsylvania, Center for the Study of Organizational Innovation.

Xu, W., Ou, P., & Fan, W. (2017). Antecedents of ERP assimilation and its impact on ERP value: A TOE-based model and empirical test. *Information Systems Frontiers*, *19*(1), 13-30.

Zhang, H., & Xiao, J. (2017). Assimilation of social media in local government: an examination of key drivers. *The Electronic Library, 35*(3), 427-444.

Zhu, K., Kraemer, K., & Xu, S. (2002). A cross-country study of electronic business adoption using the technology-organization-environment framework. In *International Conference on Information Systems.*

Zhu, K., Kraemer, K., & Xu, S. (2003). Electronic business adoption by European firms: a cross-country assessment of the facilitators and inhibitors. *European Journal of Information Systems*, *12*(4), 251-268.

Zhu, K., & Kraemer, K. L. (2005). Post-adoption variations in usage and value of e-business by organizations: Cross-country evidence from the retail industry. *Information Systems Research*, *16*(1), 61-84.

Zhu, K., Kraemer, K. L., & Dedrick, J. (2004). Information technology payoff in e-business environments: An international perspective on value creation of e-business in the financial services industry. *Journal of Management Information Systems*, *21*(1), 17-54.

Zhu, K., Kraemer, K. L., & Xu, S. (2006). The process of innovation assimilation by firms in different countries: a technology diffusion perspective on e-business. *Management Science*, *52*(10), 1557-1576.

Ziggers, G. W., & Henseler, J. (2016). The reinforcing effect of a firm's customer orientation and supply-base orientation on performance. *Industrial Marketing Management*, *52*, 18-26.

# Appendix A

**Table 6 - Measurement Items and Sources**

| Construct | Adapted Source, Reference | Indicator | Items |
|---|---|---|---|
| Technology Competence | Khan & Mahmood (2018), Wang & Wang (2016), Zhang & Xiao (2017), Zhu et al. (2002) | TC 1 | My organization explores new IS innovations available in the market (such as AI). |
| | | TC 2 | My organization has the infrastructure to support AI technology /applications. |
| | | TC 3 | My organization currently uses various AI tools /applications. |
| Relative Advantage | Chen et al. (2019), Chong & Chan (2012), Martins et al. (2016), Shiau et al. (2009) | RA 1 | Technology innovations such as AI technology will provide better returns. |
| | | RA 2 | AI will help in the betterment of my organization's processes. |
| | | RA 3 | AI will help improve the impact of the interventions created for beneficiaries. |
| | | RA 4 | AI use will instill a better sense of accomplishment for the teams working on the CSR projects. |
| Decision-makers Knowledge | Chandra & Kumar (2018), Jeon et al. (2006), Thong (1999) | DK 1 | The decision-makers have the expertise and adequate knowledge about innovative technologies. |
| | | DK 2 | The decision-makers understand the benefits of using AI in CSR initiatives. |
| | | DK 3 | The decision-makers have access to all the resources to make appropriate decisions. |
| Financial Strength | Cao et al. (2012), Lai et al. (2014), Xu et al. (2017) | FS 1 | My organization can absorb the cost of implementing technology such as AI for CSR initiatives. |
| | | FS 2 | The cost of implementing and maintaining AI technology may deter my organization's adoption of AI for CSR. |
| | | FS 3 | The cost of training employees for AI applications/tools may deter my organization's adoption of AI for CSR. |
| Partner Readiness | Awa & Ojiabo (2016), Soares-Aguiar & Palma-dos-Reis (2008), Zhu et al. (2003) | PR 1 | My organization's CSR implementation partners know how to use AI technology/applications. |
| | | PR 2 | My organization's CSR implementation partners think AI technology can positively impact the common objectives and goals. |
| | | PR 3 | My organization's CSR implementation partners will be open to adopting AI technology/applications. |
| Benefits to Beneficiaries | Makridakis (2017), Schillewaert et al. (2005), Zhu & Kraemer (2005) | BB 1 | I believe AI can solve many social issues faced by the beneficiaries of our CSR initiatives. |
| | | BB 2 | I believe that the beneficiaries will not object to using AI to solve their issues. |
| | | BB 3 | I believe that the number of beneficiaries reached can be greater with the use of AI technology. |
| Government Support | Chiu et al. (2017), Mehr et al. (2017), Zhu et al. (2004) | GR 1 | The government is active in enabling AI technology implementation. |
| | | GR 2 | Current regulations are sufficient to protect the interests of AI technology users. |
| | | GR 3 | The government is using AI technologies for various projects and initiatives. |
| Sound Legal System | Alarie et al. (2018), Scherer (2015), Teo et al. (2006) | LW 1 | I believe that the legal framework & guidelines for AI applications are in place. |
| | | LW 2 | I believe that many stakeholders/legal consultants/lawyers can comprehend AI technology applications and their impact. |

## About the Authors

**Vaibhav Pai** is a management professional with 18 years of experience across multiple businesses and geographies. Currently, he is working as Chief Operating Officer at BOND.AI (US-headquartered, conversational AI-powered, Financial Wellness Platform). He was a founding member of Transaction Square, a leading Business, Tax, and Regulatory Advisory firm. He spent more than a decade with CMS group of companies as a part of the CEO’s office where he worked with the senior leadership team in developing, coordinating, and implementing various corporate initiatives for organisational growth and excellence. As a member of the promoters’ family office, he worked with many large Investment Banks, Private Equity and Professional Services firms on multiple projects. His experience and key strengths include Business Planning, Strategic Planning, Start-up investments, and execution of complex projects including Mergers and acquisitions. His research interests include technology adoption, new emerging technologies, and CSR.

**Shalini Chandra** is an Associate Professor at S P Jain School of Global Management, Singapore. Prior to joining S P Jain, she has worked as Research Fellow at Nanyang Technological University (NTU) Singapore and holds a Ph.D. from the same university. Her research has been published in several international refereed journals such as MIS Quarterly (MISQ), Journal of the Association for Information Systems (JAIS), Information Systems Journal (ISJ), European Journal of Information Systems (EJIS), and Communications of the AIS (CAIS), Technological Forecasting and Social Change (TFSC) among others. She has also presented her work at several top-tier conferences in Information Systems such as International Conference on Information Systems (ICIS), Academy of Management (AOM), Pacific Asia Conference on Information Systems (PACIS), and, Americas Conference on Information Systems (AMCIS), and at top-tier communication conferences such as International Communication Association (ICA). She currently serves as an Associate Editor at the European Journal of Information Systems. Her research interests include technology enabled innovation and new collaborative technologies, adoption and acceptance of new technologies, dark side of technology and social media.