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Understanding Organizations' Artificial Intelligence Journey: A Qualitative Approach

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Abstract

Background: *With growth in Artificial Intelligence (AI) adoption, challenges and hurdles are also becoming evident. Organizations implementing AI are challenged to find ways to leverage AI to produce optimum results and benefits for the organization. Understanding other organizations' AI implementation journeys will help them start and implement AI. By understanding the different facets of AI implementation, they can strategize AI to gain business value. Though several studies have examined AI adoption, there are few studies on how firms implement it. We close this gap by studying AI adoption and implementations in various firms.*

Method: *Using a qualitative approach of semi-structured interviews, we studied twenty global organizations of various sizes that have implemented AI.*

Results: *The study categorizes the results into four major themes – facilitators, barriers, trends, and strategies for implementing AI. Our study reinforces the relevance of the TOE framework and Roger's DOI theory in studying AI adoption. Organizational factors such as top management support, strategic roadmap, availability of skilled resources, and corporate culture influenced AI adoption. Their lack of data or poor data quality is a primary challenge. The privacy laws concerning data, as well as regulatory bottlenecks, further exacerbate this problem. We also identified and mapped the standard AI implementations to their AI technologies. We found that most of them exploit AI's image and natural language processing capabilities to automate their processes. Regarding implementation, firms work with partners to obtain customer data and use federated learning.*

Conclusion: *Understanding firms' AI implementation journey will help us promote further adoption and experimentation. Organizations can identify areas where they can leverage AI to enhance value, prepare themselves for the future, start and proceed with AI implementation efforts and overcome barriers they might encounter.*

Keywords: AI Adoption, AI Implementation, AI Adoption Framework, AI Strategies.

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Introduction

Artificial Intelligence (AI) is a hot topic of discussion these days, both in the industry and research communities. A 2020 International Data Corporation (IDC) survey[1] of more than 2,000 Information Technology and business decision-makers confirms that AI adoption is growing worldwide. McKinsey reports[2] that AI adoption is growing and improving firms' bottom lines. However, with increasing AI adoption, challenges and hurdles are also surfacing. A recent Gartner survey[3] shows that scaling AI is a challenge, and organizations struggle to move AI from the pilot to the production stage. The report states, "*Organizations still struggle to connect the algorithms they are building to a business value proposition, which makes it difficult for IT and business leadership to justify the investment required to operationalize models.*"

Several scholars have examined AI adoption from various perspectives using different approaches. Most of them have examined the factors influencing AI adoption using survey methods in specific application areas, such as smart manufacturing (Ghobakhloo & Ching, 2019; Kinkel et al., 2022), cancer genomics (Xu et al., 2019), robotics (Latikka et al., 2019; Song & Kim, 2022), smart homes (Shin et al., 2018), virtual assistants (Hu et al., 2022; McLean & Osei-Frimpong, 2019), autonomous vehicles (Adnan et al., 2018), and big data analytics (Baig et al., 2019; Yu et al., 2022). A few other studies have used a qualitative interview-based approach to examine AI adoption. For example, Song and Kim (2022) investigated the factors influencing human-robot interaction. Jang et al. (2021) explored managers' perceptions of chatbots to help understand the adoption and forecast of financial chatbots. Sun and Medaglia (2019) examined the challenges of IBM Watson in the public healthcare ecosystem. Similarly, Verma and Bhattacharyya (2017) examined big data analytics in emerging economies using semi-structured interviews of twenty-two organizations in India. A few studies also investigated AI's risks and ethical dimensions (Mirbabaie et al., 2022; Zhang et al., 2022). Other approaches based on netnography and thematic analysis of publicly available user reviews have been used to study factors influencing AI adoption. For example, Prakash and Das (2020) used this approach to study users' decisions to adopt mental healthcare conversational agents. Thus, the factors affecting AI adoption are well-researched.

Several studies have also examined challenges and issues in AI adoption. For example, Dwivedi et al. (2021), for example, highlight significant opportunities, realistic assessment of impact, and AI challenges through experts' collective insight. They group AI challenges into several categories: data, technological, social, economic, ethical, political, legal and policy, organizational and managerial. Other papers discuss the current situation and future opportunities in specific application areas. For example, Bracarense et al. (2022) did this for AI and sustainability using a literature review. One of the most significant challenges AI poses in front of organizations is the need for adequate data for training and issues related to data quality, security, governance, and regulatory approvals. Data integration and preparation take almost one-third of the time of AI implementation. There are also some potential ethical, legal, and social impacts and risks brought in by AI (Mirbabaie et al., 2022).

Although AI adoption has been studied from different perspectives and approaches in various application areas, we find a prominent need to examine how organizations implement AI (Kinkel et al., 2022). Particularly in the academic discourse, there has been less focus on AI's organizational integration and impacts (Nguyen et al., 2022). Not many studies comprehensively inform us about the state of AI implementation in organizations, given the unique challenges and issues posed by AI. What strategies do they take to implement AI, and what benefits do they derive from it?

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[1] https://www.idc.com/getdoc.jsp?containerId=prUS48870422, Accessed Dec. 20, 2022
[2] https://www.mckinsey.com/business-functions/quantumblack/our-insights/global-survey-the-state-of-ai-in-2021
[3] https://www.gartner.com/en/newsroom/press-releases/2022-08-22-gartner-survey-reveals-80-percent-of-executives-think-automation-can-be-applied-to-any-business-decision

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The objective of this study is, therefore, to examine firms' AI journey. Specifically, this study addresses the following: *What is the current research on AI adoption and challenges? Given AI's unique challenges, how are firms implementing AI within the organization?* To answer the first research question, we conduct a systematic literature review. Using the literature review, we elucidate individual and organizational-level AI adoption factors. The organizational level factors have been mapped to the Technology-Organization-Environment framework. These help organizations understand the AI challenges that may influence its implementation. To answer the second research question, we interview CXOs/Senior level managers from twenty different organizations to understand their AI use journey. This helps us know how to promote further AI use in organizations. Organizations can identify areas where they can leverage AI to enhance value, prepare themselves for the future, start and proceed with AI implementation efforts and overcome the barriers.

Literature Review and Theoretical Framework

John McCarthy, an American computer and cognitive scientist from Stanford University, introduced the term "Artificial Intelligence" in 1955 (Gurkaynak et al., 2016). He defined it as '*the science and engineering of making intelligent machines, especially brilliant computer programs.*' However, AI has numerous applications and is a broad concept ranging from intelligent assistants in our phones to future technologies that may cause a paradigm shift in our understanding of life. It tries to simulate human intelligence in machines. The European Commission's High-Level Expert Group on AI (AI-HLEG) defines AI as "*systems that display intelligent behavior by analyzing their environment and taking actions – with some degree of autonomy – to achieve specific goals. AI-based systems can be purely software-based, acting in the virtual world (e.g., voice assistants, image analysis software, search engines, speech and face recognition systems), or AI can be embedded in hardware devices (e.g., advanced robots, autonomous cars, drone or Internet of Things applications)*"[4]. We follow this definition of AI in our study. AI has applications in numerous areas, such as robots (Do et al., 2018), virtual assistants (McLean & Osei-Frimpong, 2019), and chatbots that use natural language processing (NLP) and speech recognition properties. AI finds applications even in the medical (Toh et al., 2019) and agriculture fields (Sabzi et al., 2018).

We used two approaches for conducting the literature review. First, we conducted a content analysis of the existing literature on AI adoption to answer the first research question. We searched for articles on Science Direct and EBSCOHost using different combinations of the following keywords: "Artificial Intelligence adoption," "AI adoption," "AI adoption theories," and "AI determinants & challenges" by applying the Boolean operators AND/OR to collect as many articles as possible. We did not limit our analysis to any period or domain. Second, we collected papers by reviewing the citations of the articles obtained through the first approach. We used its basic and advanced search features to find relevant journal articles. We examined and reviewed the papers in detail. The initial search gave us over 100 journal articles. These articles were then manually scanned for their content. We eliminated some articles which did not specifically deal with AI adoption. After the manual screening process, we were left with 53 articles. Even though this paper is about the AI adoption journey of organizations, we did not eliminate papers that talked about AI adoption at the individual level for the literature review section. The individual-level AI adoption factors will help organizations to understand what they should do to improve consumer adoption intention of their AI implementation products and services. It will be useful to understand the barriers to AI adoption at the individual consumer level and to know about the apprehensions they might have in using AI products. The organization can use this information and address the concerns while designing and implementing AI. Figure 1 presents the application area-wise distribution of the journal articles.

[4] https://ec.europa.eu/futurium/en/system/files/ged/ai_hleg_definition_of_ai_18_december_1.pdf

About 13% of the studies were in the application area of service encounters and delivery, 11% in manufacturing, procurement, and supply chain applications, 11% in tools in medical and healthcare, 9.5% in the application area of voice assistants, and 7.5% in big data analytics. Around 15% of the articles deal with ethical issues associated with AI, and 36% deal with AI adoption at the individual level.

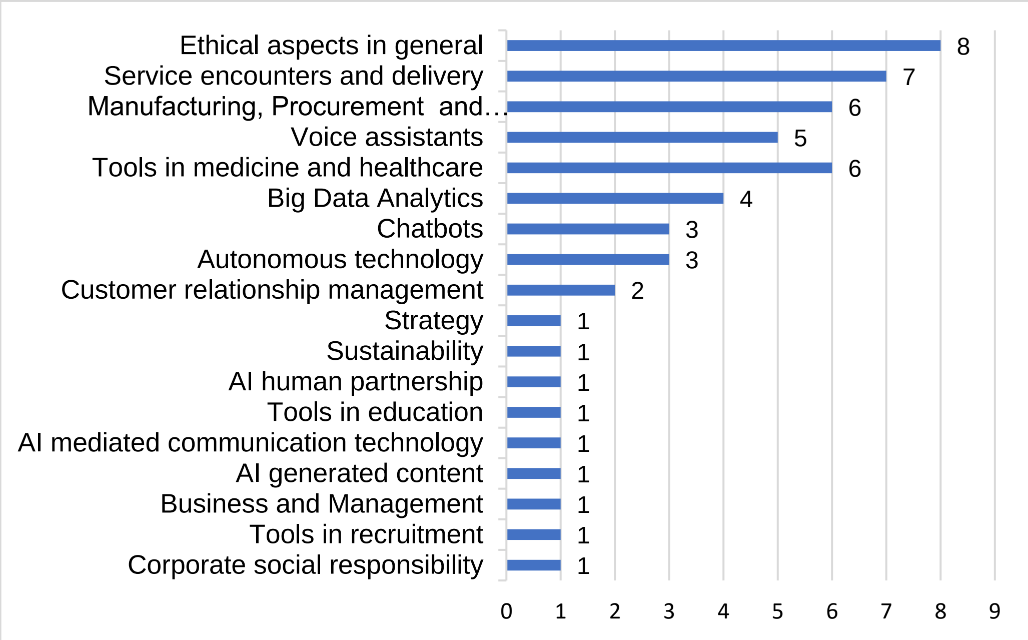

Figure 1 – Application Area-Wise Distribution of the Articles

Table 1 summarizes the literature review and lists factors influencing AI adoption in various application areas, along with the research focus and the methodology. The details in Table 1 will be helpful for organizations when they are implementing AI.

At the individual level, the articles mainly deal with factors influencing AI adoption in the application areas of service encounters and delivery, voice assistants, autonomous technology, education, AI-mediated communication technology, AI-generated content, and recruitment. At the organizational level, the articles mainly deal with factors influencing AI adoption in manufacturing, procurement and supply chain, medicine and healthcare, big data analytics, chatbots, customer relationship management, strategy, sustainability, AI human partnership, and business and management.

Even though the literature review gives a good picture of the factors influencing AI adoption at the individual and organizational level for various application areas, we do not restrict our study to any specific application area. We examine firms' AI adoption journey in general. The literature review, however, does not inform us about AI implementation in organizations. It is important to know whether the firms can approach AI adoption like any other technology adoption or treat it differently. Therefore, we studied organizations that have adopted AI to understand their AI journey; strategies adopted for implementation; value created from the implementation, and the hurdles encountered.

Table 1 – Literature Review

Author(s)	Methodology	Research Focus	Application Area	Factors influencing Adoption
Song and Kim (2022)	The survey, interview, video clip simulation	Facilitators and barriers to adoption	Service encounters and delivery	At the individual level – Social influence, hedonic motivation, effort expectancy, trust, anthropomorphism, perceived empathy and interaction quality, performance efficacy, familiarity, robot use self-efficacy, perceived service risk, and robot-service fit. Usefulness, social capability, and appearance affect Human-Robot interaction.
Chi et al. (2021)	Literature review, interview, focus group study	Development and validation of AI adoption scale		
Chuah et al. (2021)	Survey	Facilitators and barriers to adoption		
Pelau et al. (2021)	Survey	Facilitators and barriers to adoption		
Chen et al. (2021)	Survey	Facilitators and barriers to adoption		
Gursoy et al. (2019)	Survey	Facilitators and barriers to adoption		
Lu et al. (2019)	Survey	Development and validation of AI adoption scale		
Kinkel et al. (2022)	Survey	Facilitators and barriers to adoption	Manufacturing, procurement, and supply chain applications	At the organizational level - Organizational factors included strategic road mapping, R&D intensity, suitable alignment of organizational politics, innovation of business models by focusing on agile customer co-creation, data-driven delivery operations, and scalable ecosystem integration. Technological factors included perceived compatibility, existing IT infrastructure, previous AI exposure, digital skills, dedicated approach to data management, use of advanced software packages, skilled employees, training programs, critical AI capabilities viz data pipeline, algorithm development, and AI democratization. Other factors included environmental pressures, implementation costs, and the complexity of the company's products.
Sjödin et al. (2021)	Case study	How to innovate business models to scale AI		
Allal-Chérif et al. (2021)	Case study	Use and impact of AI		
Jha et al. (2020)	Interview	Facilitators and barriers to adoption		
Ghobakhloo and Ching (2019)	Survey	Facilitators and barriers to adoption		
Mahroof (2019)	Case Study	Facilitators and barriers to adoption		

Table 1 – Literature Review

Author(s)	Methodology	Research Focus	Application Area	Factors influencing Adoption
Hu et al. (2022)	Survey	Facilitators and barriers to adoption	Voice assistants	At the individual level – Utilitarian benefits, symbolic benefits, perceived benefits, and hedonic benefits. Social attractiveness, performance expectancy, effort expectancy, price value, perceived anthropomorphism, trust, perceived usefulness, perceived social pressure, reliability, accuracy, perceived power, trust in technology and service provider, the trade-off between privacy risks and benefits,
Vimalkumar et al. (2021)	Survey	Privacy concerns about AI		
Fernandes and Oliveira (2021)	Survey	Facilitators and barriers to adoption		
Prakash and Das (2020)	Netnography	Facilitators and barriers to adoption		
McLean and Osei-Frimpong (2019)	Survey	Facilitators and barriers to adoption		
Khanijahani et al. (2022)	Literature review	Facilitators and barriers to adoption	Tools used in medicine and healthcare	At the organizational level – Environmental factors included the presence of an ecosystem of key players in technology, research, radiology, regulatory bodies, and data regulation to ensure privacy. Technological factors included minimizing bias in training data and ensuring the data set has no inherent biases. Organizational factors included making individuals and organizations responsible and accountable, having ethical frameworks to build trust, and training. Psychosocial factors, such as perceived ease of use or usefulness, performance or effort expectancy, social influence, and trust. Technological challenges are algorithmic transparency, reproducibility, real-world assessment, lack of trust towards AI-based decisions, unethical use of shared data, black box algorithms, and perceived threat to autonomy.
Liu and Tao (2022)	Survey	Facilitators and barriers to adoption		
Sogani et al. (2020)	Editorial review	Facilitators and barriers to adoption		
Toh et al. (2019)	Literature review	Facilitators and barriers to adoption		
Sun and Medaglia (2019)	Interview	Facilitators and barriers to adoption		
Xu et al. (2019)	Literature review	Facilitators and barriers to adoption		
Yu et al. (2022)	Survey	Facilitators and barriers to adoption	Big Data Analytics	At the organizational level - Organizational factors such as top management support, support of other decision-makers, managers, and organizational knowledge related to BIG DATA ANALYTICS, and organizational expectations. Technological factors such as compatibility with existing systems, data environment, collection of high volumes of data, use of cloud services to manage the data, technology readiness, and data quality. Environmental factors such as governmental pressure on senior management, pressure to be competitive, stronger, and clearer privacy and governance.
El-Haddadeh et al. (2021)	Survey	Facilitators and barriers to adoption		
Wright et al. (2019)	Case study	Use and impact of AI		
Verma and Bhattacharyya (2017)	Interview	Facilitators and barriers to adoption		

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Table 1 – Literature Review

Author(s)	Methodology	Research Focus	Application Area	Factors influencing Adoption
Jiang et al. (2022)	Survey	Customer satisfaction and social media engagement	Chatbots	At the organizational level – Organizational challenges were related to a lack of organizational capability, organizational resistance, technological immaturity, extensive investment, and strict government regulations.
Zhu et al. (2022)	Survey	Facilitators and barriers to adoption		
Jang et al. (2021)	Interview	Facilitators and barriers to adoption		
Simpson et al. (2019)	Simulation	Facilitators and barriers to adoption	Autonomous technology	At the individual level – Coefficient of imitation-observability, coefficient of innovation-compatibility, relative advantage, trust towards technology, the rate at which autonomous technology improves over time, status and environment consciousness, disability, age, gender, income, and education. Challenges were related to the influence of ethical implications on trust. Perceived risk, perceived concerns, perceived dread, lack of accountability, system failure, privacy concerns, deprivation from the joy of driving, and loss of driving skills.
Cunningham et al. (2019)	Survey	Facilitators and barriers to adoption		
Adnan et al. (2018)	Literature review	Risks and ethical dimensions of AI		
Chatterjee et al. (2022)	Survey	Use and impact of AI	Customer relationship management	At the organizational level – Organizational factors such as organizational agility and leadership support. Technological challenges related to technology turbulence.
Chatterjee et al. (2020)	Literature review	Facilitators and barriers to adoption		
Li et al. (2021)	Data from CSMAR DB and annual reports	Facilitators and barriers to adoption	Strategy	At the organizational level – Organizational factors such as the interplay of CIO presence with board knowledge heterogeneity (e.g., educational diversity, R&D experience, experience with AI orientation) shapes the formation of AI orientation.
Bracarense et al. (2022)	Literature review	The current state of affairs and future opportunities	Sustainability	At the organizational level – Organizational challenges include motivating interaction between machines and experts, lack of understanding of how cyberattacks may be produced in this area, and complexity of measurement.
Wu et al. (2020)	Survey	Facilitators and barriers to adoption	AI-generated content	At an individual level – Subjects were more critical of the AI- than the human-generated content.

Table 1 – Literature Review

Author(s)	Methodology	Research Focus	Application Area	Factors influencing Adoption
Chowdhury et al. (2022)	Survey	Facilitators and barriers to adoption	AI human partnership	At the organizational level – Organizational factors such as knowledge sharing within the organizations, AI skills, AI understanding, and AI job clarity influence trust in AI
Kim et al. (2022)	Online experiment	Facilitators and barriers to adoption	Tools in education	At the individual level – Greater credibility of an AI instructor with a humanlike voice than those with a machinelike voice. Social presence mediates the relationship between the voice and the perceived credibility of the AI instructor.
Goldenthal et al. (2021)	Survey	Facilitators and barriers to adoption	AI-mediated communication technology	At an individual level – Challenges include age, accents, slurred speech, different styles, and dialects. Not equally accessible to all users based on device access, internet access, and the cost of the device, internet, and AI-MC services. Privacy and biases are other barriers.
Cubric (2020)	Tertiary study	Facilitators and barriers to adoption	Business and Management	At the organizational level – Relative advantages include increased productivity, reduced cost, customer satisfaction, accuracy, help with decision-making, predictions, and well-being. Technological Challenges included the high cost of labeling data, support infrastructure, data unavailability, and lack of trust and safety.
Van Esch et al. (2019)	Survey	Facilitators and barriers to adoption	Tools in recruitment	At the individual level – Technology use motivation, the novelty of AI. Barriers include use anxiety.
Pai and Chandra (2022)	Survey	Facilitators and barriers to adoption	Corporate social responsibility (CSR)	At the organizational level – Factors depended on the firm size, sector, and other characteristics, but the following factors played a role. Organizational factors included the technology competence of firms, relative advantage, decision-maker's knowledge of AI, firm's financial strength, partner readiness, and benefits to beneficiaries. Environmental factors included Government support and a sound legal system. Challenges included risk to stakeholders.

Table 1 – Literature Review

Author(s)	Methodology	Research Focus	Application Area	Factors influencing Adoption
Mirbabaie et al. (2022)	Literature review	Risks and ethical dimensions of AI	Ethical aspects, in general	At the organizational level – Ethical challenges include harmful and unintended consequences during AI implementation and use in organizations and potentially ethical, legal, and social impacts and risks brought in by AI. Technological challenges included data bias, dataset shift, adversarial attack, and out-of-domain data and model-related risks such as model bias, model misspecification, and model prediction uncertainty. AI adoption fosters the creation of a type of psychological contract, which they termed "Alienational." Technological solutions include explainable AI that helps decision-makers understand and scrutinize machine-learned decisions. Addressing ethical concerns included fulfilling beneficence, non-maleficence, justice, and autonomy to build trust. Fairness, accountability, and transparency are important factors. Achieve fairness through augmented human–ML partnership, which may balance with automation under the right circumstances.
Zhang et al. (2022)	None	Risks and ethical dimensions of AI		
Ågerfalk et al. (2021)	Professional development workshop	Use and impact of AI		
Dwivedi et al. (2021)	None	Facilitators and barriers to adoption		
Braganza et al. (2021)	Survey	Risks and ethical dimensions of AI		
Teodorescu et al. (2021)	None	Risks and ethical dimensions of AI		
Moreira et al. (2021)	None	Risks and ethical dimensions of AI		
Shin and Park (2019)	Survey	Risks and ethical dimensions of AI		

Looking at some recent works on AI adoption, we find that organizations have used extensive digitization to transform themselves because of the pandemic, but there have been many obstacles. It is not enough to simply invest in the latest technology. AI should support firms' business strategies and include social impact measures in their success stories (Tarhini et al., 2022). Pai and Chandra (2022) explored factors influencing organizational adoption of AI in corporate social responsibility initiatives using the TOE framework and found that the relative advantage gained by AI implementation was significant in small firms, for firms listed on the stock exchange, and in the manufacturing sector. Government support and sound legal systems significantly influenced AI adoption in the services sector. In a recent study investigating the determinants of big data analytics, TOE was used as one of the theoretical foundations of the study, and technology readiness, high data quality, organizational expectations, and knowledge of analytics positively influenced managers' use of big data analytics in decision-making (Yu et al., 2022). In another study investigating factors for e-marketplace adoption by small and medium-sized enterprises, trust, security, privacy, top management support, and stakeholder support, followed by government support, emerged as strong factors. Structure, characteristics, processes, and resources are the different dimensions of organizations that influence the adoption of digital work. Top management support, organizational culture and readiness, social influence, and mimetic and normative pressure played important roles in adopting digital work (Wibowo et al., 2022).

Theoretical Background

Most of the factors noted in Table 1 can be categorized at the organizational level using the TOE framework (Figure 2).

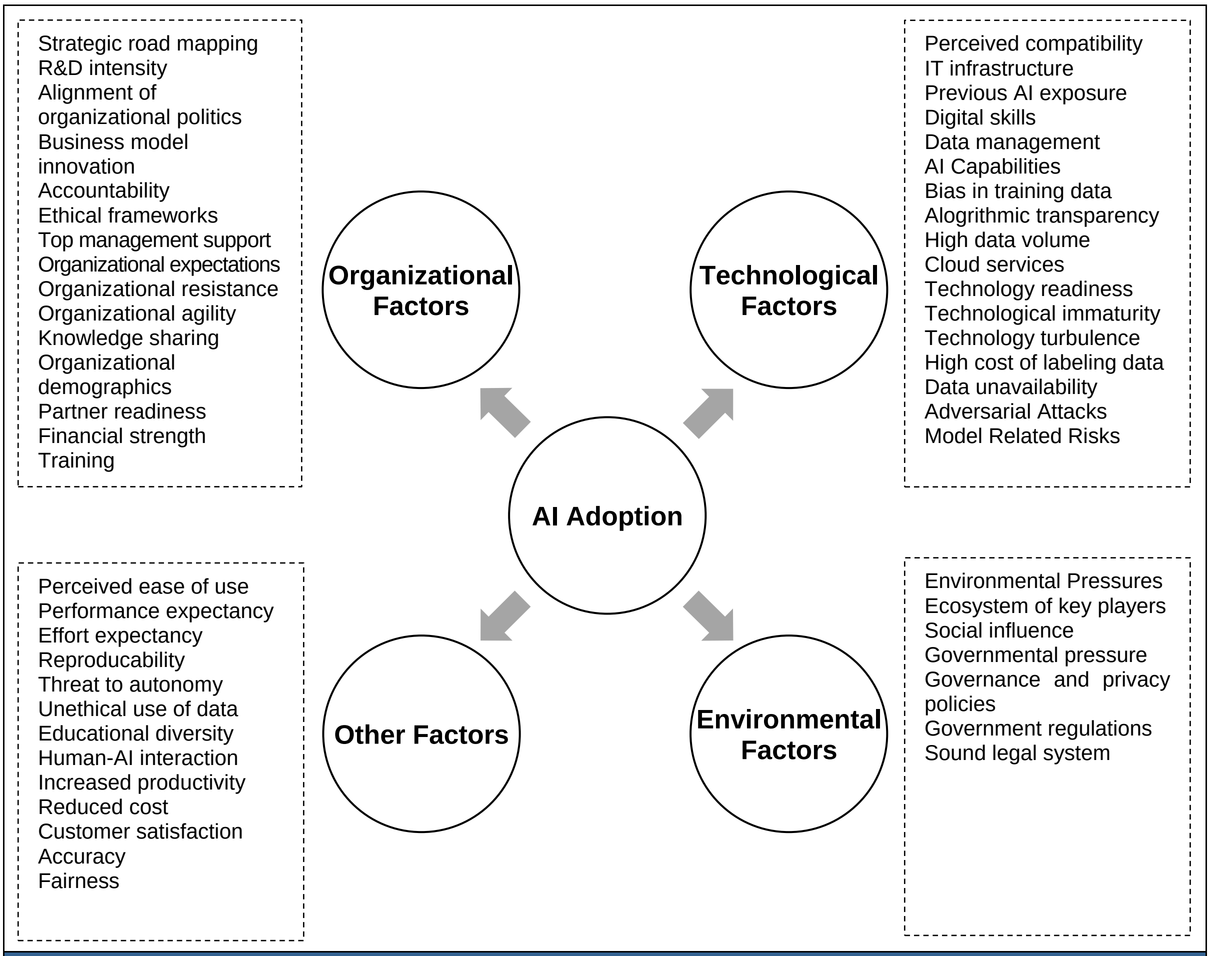

Figure 2 – Mapping Factors from Literature Review with TOE Framework

Outside the TOE context, there are other factors. Factors such as increased productivity, reduced cost, customer satisfaction, accuracy, help with decision making, well-being, reproducibility and benefits may be categorized as relative advantage. Relative advantage is one of Rogers (1983) innovation attributes. So, we see that most of the factors influencing AI adoption can be explained using the TOE framework and Rogers' innovation attributes. Hence, we use it as the overarching framework to guide our research. Threat to autonomy, unethical use of data, risk to stakeholders, harmful and unintended consequences, fairness, ethical, legal and social impacts may be categorized as ethical concerns of AI. We intend to study the ethical concerns of AI in a subsequent study.

The two prominent adoption models at the firm level used in information systems literature are the technology-organization-environment (TOE) framework and the diffusion of innovations (DOI) theory (Oliveira & Martins, 2011; Tornatzky & Klein, 1982). The other theories used to study technology adoption are the technology acceptance model (TAM) (Davis, 1989), the theory of planned behavior (TPB) (Ajzen, 1991), and the unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003). However, these theories generally examine adoption at the individual level. Since AI is an emerging technology and organizations are starting to adopt it, we use the TOE theory to examine its adoption in organizations.

The technology-organization-environment (TOE) framework explains the adoption and integration of various types of technological innovation in an organization. It is an organizational-level framework that can be used to examine technological innovation. It identifies three aspects of an organization, namely the technology, the organization, and the environment, which influence the process by which the organization adopts and implements a technological innovation (Oliveira & Martins, 2011). Research has used the TOE framework widely for understanding technology adoption, such as for understanding CRM adoption stages (Cruz-Jesus et al., 2019), SaaS adoption (Oliveira et al., 2019), technology adoption for big data analytics, and in the manufacturing sector as well.

We combine TOE with DOI theory to obtain richer insights into the phenomena. The DOI theory explains the rate at which new technology and ideas diffuse in organizations and how and why they spread. Rogers (1983) proposed five attributes of innovation that determine the adoption rate: relative advantage, compatibility, complexity, trialability, and observability. Based on DOI theory at the firm level (Rogers, 1995), innovativeness is related to independent variables such as individual (leader) characteristics and organizational structural characteristics (Oliveira & Martins, 2011). Scholars have widely used DOI for examining technology adoption, including mobile cloud computing adoption (Carreiro & Oliveira, 2019), technology adoption in the financial markets (Chakravarty & Dubinsky, 2005), and big data analytics (Lai et al., 2018).

Rogers' innovation attributes, relative advantage, complexity, and compatibility can be considered technological factors influencing adoption. The firm-level individual (leader) and internal organizational structural characteristics can be considered organizational factors. Many previous studies have combined Roger's innovation attributes with the technological factors influencing the adoption (Low et al., 2011; Wang et al., 2010). The combined DOI and TOE framework is presented in Figure 3.

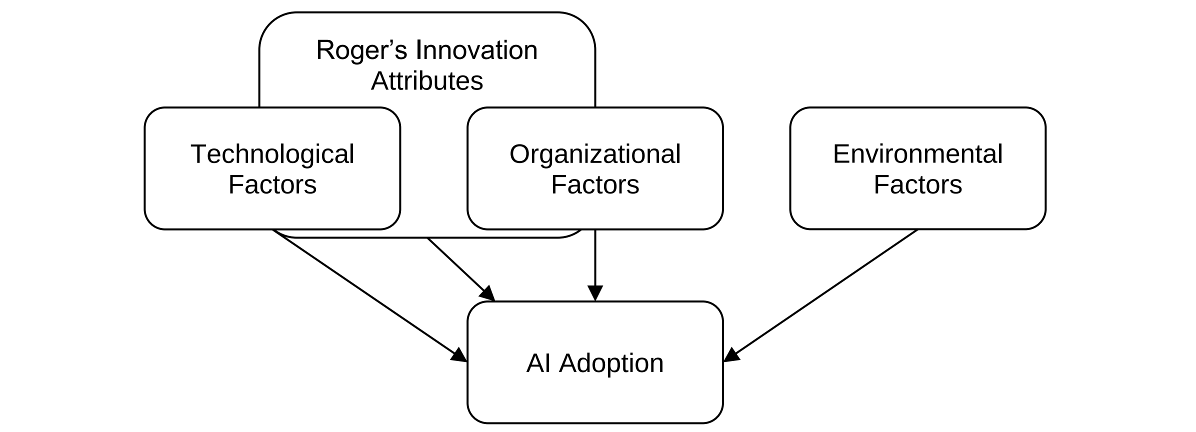

Figure 3 – Framework Combining TOE and DOI

Research Methodology

Research Design

We used a qualitative approach to understand AI adoption and implementation in organizations thoroughly. An organization is an economic entity that is socially and legally recognized (Swanson, 2007). The study was conducted towards the end of 2020. First, we prepared a list of industry professionals working in the AI domain using our primary and secondary contacts. They were then sent emails and contacted via telephone to understand if they were suitable candidates to share insights about AI implementation in their organizations. We finalized a list of twenty experts who had implemented AI in their organizations. Since these professionals were all experts in their fields, we could gain enough information and insights by interviewing them. These interviews may be considered key informant interviews as all the interviewees had firsthand knowledge of the topic and had access to detailed information. A smaller number of key informants is generally sufficient in achieving theoretical saturation. We used 20 key informant interview participants who were all senior management personnel within their organizations. We used a semi-structured interview format to gain different perspectives on AI adoption. This could not have been done using a survey. We interviewed nine participants in early 2021 who agreed to the interview. The rest of the eleven participants agreed only to the survey initially. They were later interviewed towards the end of 2021 after they agreed to the same. We also collected secondary data from newsletters and company website articles to ensure the consistency and reliability of our dataset.

Table 2 presents a summary of these organizations sorted by their annual revenue. These organizations belong to different industries. Eleven of these were from India, and the rest nine were from the United States of America. However, most of these organizations had a global presence. Using the definition of small and midsize business as given by Gartner[5], we categorized six organizations with revenue less than 50 million USD as small (CS-4, CS-7, CS-8, CS-14, CS-16, and CS-18); organizations with revenues between 50 million and 1 billion USD as mid-side (CS-3); and those above 1 billion USD as large (the remaining thirteen organizations).

[5] https://www.gartner.com/en/information-technology/glossary/smbs-small-and-midsize-businesses

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Table 2 – Summary of the Organizations Studied

Code	Industry/Vertical	Designation	Home region of the interviewee	Employees	Annual revenue (Million USD)
CS-7	Transportation – payment	COO	India	<20	< 1
CS-8	Health Care – computer vision	CEO	India	<20	< 1
CS-18	Technology startup-IoT	Co-founder	India	5-9	< 1
CS-14	IT Services- drones	CEO	India	20-49	1 – 10
CS-16	IT Services- AI/NLP solutions	Product strategist	USA	20-49	1 – 10
CS-4	IT Services	Senior Architect	USA	20-49	10–50
CS-3	IT Services	Business development	India	>10,000	100-500
CS-1	IT Services-consulting	Accounts manager	India	>20,000	1000-2000
CS-19	IT services	Sales manager	USA	>10,000	1000-2000
CS-10	Telecommunications	Hardware designer	USA	>10,000	2000-5000
CS-12	IT Services- business process	Data science team lead	India	>50,000	2000 - 5000
CS-13	Health care services	Analytics director	USA	>10,000	2000 - 5000
CS-6	IT Services – digital solutions	Business unit head	India	>2000	2000 - 5000
CS-9	IT Services – IT infrastructure	Engineering head	USA	>7000	5000 -10000
CS-11	Computers - wireless chip	Chip designer	USA	>10,000	5000-10000
CS-5	Computers-semiconductors	Principal Engineer	India	>30,000	5000-10000
CS-2	IT Services	Automation lead	India	>100,000	5000-10000
CS-15	Finance- personal investing	Analytics leader	USA	>50,000	10000 – 30000
CS-20	Health insurance	Director of AI	USA	>50,000	100,000
CS-17	Business technology	Product Manager	India	>100,000	>100,000

These twenty organizations covered various sectors, namely health care services (1 small and one large), IT services (3 small, one mid-size, and six large), technology (1 small and one large), computers and electronics (2 large), transportation (1 small), finance (1 large), health insurance (1 large), and telecommunications (1 large). Figure 4 shows the industry-wide distribution of these organizations.

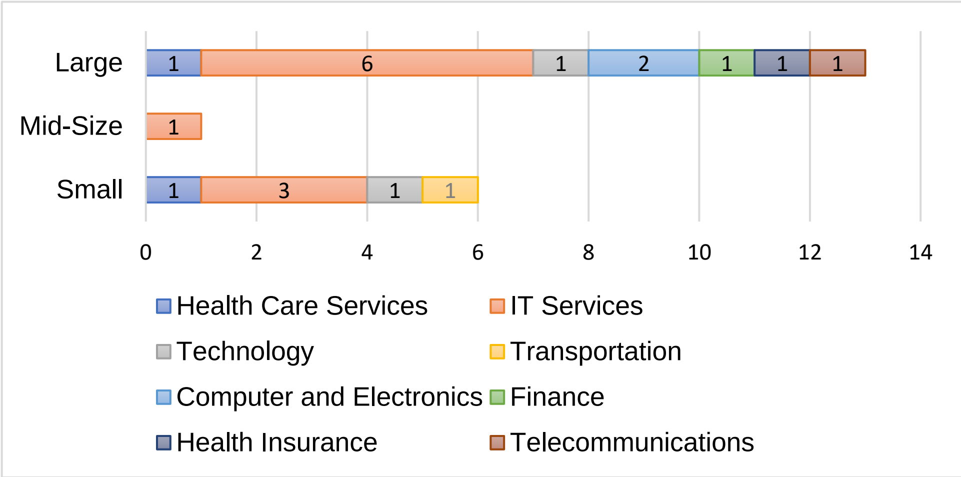

Figure 4 – Industry Wise Distribution of Organizations

We collected data from these organizations using semi-structured interviews. The guiding questions for these semi-structured interviews are presented in Appendix 1. We interviewed senior management personnel from these organizations, including the CEO, CTO, COO, technical heads, AI product owner, business development heads, directors of analytics, account managers, and senior architects. All interviewees were between the age of 30 and 50. 80% of the interviewees were male. We asked questions regarding the AI capability and the AI products implemented in the organization. We also asked several questions regarding AI adoption, platforms, algorithms, trends, and business strategies. We interrogated them on the details of AI implementations in their organization, the strategy and details of their business model, the AI trends, and the factors that facilitated/hindered AI adoption. Each interview lasted for about 90 minutes. The interviews were audio-recorded and transcribed. The audio-recorded interviews enabled repeated revisiting of the data to check for emerging themes and ensure we were true to the data collected.

Data Coding

We coded all the interviews using NVivo12 software. Using NVivo, we analyzed the interviews and identified AI implementation themes relevant to our study. One author developed the initial set of codes by doing line-by-line coding using NVivo 12. The author used an open coding process. A total of 70 initial codes emerged. The second author performed coding consistency checks to ensure the credibility of the codes. The authors further rationalized this set by removing duplicates and merging codes in consultation with each other (Atkinson, 2002). A total of 65 rationalized codes were obtained. We looked for common patterns and defined them as categories/themes. The rationalized codes were then assigned to these categories/themes in NVivo 12. The research question and the interview questionnaire were kept in mind while creating the themes. We then reviewed and refined the themes. We had to merge some of these themes, and 11 final themes emerged from these codes. Appendix 2 shows a few samples of coding. There was a total of 35 rationalized codes for the AI implementation theme.

To check the reliability of the coding, another coder from the research team helped re-code the data using the codes and themes generated above. This was also done in NVivo 12. We then compared the codes in the software. This gave us Cohen's Kappa for all the codes and the source data. We then did an unweighted average of these values and obtained an average value of 0.82 for Cohen's Kappa. The literature has used Cohen's kappa to test agreement between raters (Rau & Shih, 2021). With a value of 0.82, the strength of the agreement is almost perfect (Landis & Koch, 1977). This helped remove the bias in the interpretation of the interview text. We also used secondary data from newsletters and company website articles to ensure the consistency of our dataset.

Data Analysis and Findings

We identified various factors that influence AI adoption based on the transcribed records. We categorized all these factors using the framework presented in Figure 2. We organized the findings regarding facilitators of AI adoption, Barriers to AI adoption, Trends in AI implementation, and Strategies for deriving business value from AI.

Facilitators of AI adoption

Table 3 presents the details. Among the facilitating factors, relative advantage received over 120 mentions, including saved time, increased convenience, 24X7 availability, aid in decision-making, and increased productivity. Both small and large organizations gave comparable importance to relative advantage. Organizational factors featured second in the list with a total of 80 mentions. These included top management support, strategic roadmap, availability of skilled resources, and organizational culture and priorities. Large organizations give more importance to organizational factors compared to small organizations. Next was compatibility factors (such as compatibility with existing business processes, technologies, and user expectations), which had 70 mentions. Both small and large organizations gave comparable importance to compatibility factors. Environmental facilitating factors (such as competitive pressure and the industry they belonged to) had 30 mentions. Both small and large organizations gave comparable importance to environmental facilitating factors.

Table 3 – Factors Facilitating AI Adoption

TOE / DOI Attributes	Factors	Quotes/Remarks
Relative Advantage	Saves time, is convenient, increases productivity, improves performance, assists in decision making, lowers cost, is available 24X7, converts information into knowledge, reduces risk, and facilitates use in hostile environments.	CS-1: "An AI application has been developed for in-house use which has facial recognition features. This is used by the Help Desk for authentication and authorization of employees who work remotely and who have, for example, lost their RSA token or have forgotten passwords, etc. This had been especially useful during the time of the Covid-19 crisis when everyone in the organization was working from home. The company also uses AI in Pharmacovigilance to drastically reduce the time to process a case safety report." CS-2: "AI has played an important role in making the Call Center Operations more efficient. It has improved call resolution with a reduction of over 75% in the resolution time. The AI integration with the ticketing systems has helped lower operating costs. We also have an AI application for retail fraud detection, resulting in a 50% reduction in resources."
Compatibility	Existing business processes, user expectations, prevailing technology, seamless adoption, user attitude, and behavior.	CS-3: "There is a right combination of cloud and AI/ML as the cloud platforms offer ready-made algorithms. With greater acceptance of the cloud, the use of AI/ML has increased." With greater acceptance of cloud technologies, the clients also welcome using AI/ML in combination with the cloud. Cloud providers provide fully managed end-to-end AI services that help organizations accelerate AI adoption.

Table 3 – Factors Facilitating AI Adoption

TOE / DOI Attributes	Factors	Quotes/Remarks
Trialability	A culture that encourages innovation, a culture that rewards experimentation, availability of a free version of a product to try, availability of training, and hackathons.	CS-16: "Many ML, NLP software, cloud platforms for analytics, and chatbots are available in the market for a free trial."
Observability	An ability to make a side-by-side comparison, a collaboration between teams, and a good understanding of the system.	CS-17: "Collaboration between teams and training helped us understand the benefits of AI, and that helped with diffusion within the organization."
Other Technological factors	Use of deep learning algorithms and high accuracy	CS-8: "The AI product uses deep learning technology trained using millions of CT scans and proprietary AI algorithms, and the accuracy is very high. The product helps doctors to deliver personalized treatment much faster. The deep learning algorithm improved radiologists' sensitivity by around 20%." CS-13: "We have solutions for medical billing and coding, which over 1000 hospitals use. This is trained on large datasets of medical terminologies and has very good accuracy."
Organizational Factors	Top Management support, strategic roadmap, skilled resources, organizational culture & priorities, formal training programs, and financial readiness.	CS-13: "AI training, support from the leaders and the top management, business model and strategy has helped with AI adoption."
Environmental Factors	Competitive pressure, industry, government policies.	CS-20: "The covid 19 crisis helped accelerate AI adoption." CS-4: "Peer competitive pressure has driven us towards AI adoption."

Barriers to AI adoption

We also identified several barriers to AI adoption from the interviews (Table 4). Amongst the barriers, technological factors/complexity had a total of 70 mentions, including 13 mentions of data complexity, 12 mentions of data unavailability, 11 mentions of data security and quality, and ten mentions of complex and black-box algorithms. Large organizations emphasized complexities acting as barriers more than small organizations. The top organizational barriers were resistance to change, resource constraints, fear of failure, and infrastructure issues. Privacy and security laws, lack of regulatory bodies in some countries, getting regulatory approvals in other countries, and addressing ethical concerns were the top environmental barriers to AI adoption.

Table 4 – Barriers to AI Adoption

TOE/DOI Attributes	Factors	Quotes/Remarks
Technological Factors / Complexity	Data complexity, data unavailability, data security, data quality, complex algorithms, black-box algorithms.	CS-3: "There are challenges in selling AI solutions as the clients are concerned about data privacy issues and skeptical about data sharing. It is impossible to train the system in dummy data if clients are unwilling to share real data." CS-4: "The challenge, however, has been getting the customer data due to privacy laws and regulatory bottlenecks. The clients are concerned about legal implications when they are asked to share data for training the AI model. The insurance companies, for example, might want customer data related to the prescription medicines that the customers take to predict the right premium, which is not available due to privacy laws." CS-8: "Some challenges we have faced are getting the data for training due to data privacy issues. Hospitals have their own ethics committee which regulate the sharing of data."
Organizational Factors	Resistance to change, resource constraints, fear of failure, infrastructure issues, misalignment between business and technology, and financial issues.	CS-1: "There is growing urgency to develop the skills and scale in the AI domain. However, balancing that with business as usual and other priorities has been a challenge. That clashes with the AI initiatives because of resource allocation, strategic focus/prioritization, etc." CS-3 "Because AI has helped with process automation, there is increased resistance to AI adoption due to fear of job loss. Earlier automation replaced jobs that were repetitive, predictable, and routine. Still, with AI, jobs where humans had a definite advantage, such as decision-making, problem-solving, and interactions, are at risk."
Environmental Factors	Privacy and security laws, lack of regulatory bodies, regulatory approvals, government regulation and policies, transparency, accountability, and other ethical concerns	CS-8: "There is no robust legal framework in India and a regulatory body to enforce compliance for the AI medical devices, so the companies sometimes spend a huge amount of money trying to get US and European approvals. Some of the challenges we have faced in getting the data for training are due to data privacy issues. Hospitals have their own ethics committee which regulate the sharing of data." CS-4: "When FDA approval is required, there are challenges related to continually learning, improving, and changing algorithms."

Trends in AI Implementation

We identified three prominent trends from the firm's AI implementations. These are as follows:

The first prominent trend we observed was that organizations started moving from the initial exploratory phase to the implementation phase.

> "Initially, most of the clients were in the exploratory phase as far as AI technology is concerned. They were experimenting to see which AI tools to invest in. Now, they have narrowed down and have settled on the AI tools to use." [CS-1].

The second prominent trend was moving from robotic process automation to intelligent automation.

> "The trend has been to move from automating repetitive manual processes a few years ago to intelligent automation using ML now." [CS-2].

> "The trend that we have seen in the past few years in financial institutes is that they had initially experimented with robotic process automation and are now moving to use AI mostly in their back-office operations and low-impact interactions" [CS-3].

The third prominent trend we observed was that organizations moved from merely collecting data to extracting knowledge from data.

> "Earlier on, the clients were focused on collecting data. Now they have the data and are trying to find out what to do with it, how to use the data to extract intelligence out of it, how to use data to improve efficiencies and productivity, how to use data to personalize their customer experience, and how to have conversations with their clients." [CS-4].

Strategies for Deriving Business Value from AI

Several firms attempted to map AI use cases with customer needs. They also examined how to derive business value from AI. We observed several strategies that companies adopted for deriving business value from AI.

Inhouse innovation labs: Some firms developed in-house innovation labs for AI and ML research for developing numerous prototypes [CS-1, CS-2]. They use these labs to experiment with AI. Innovation labs help identify, explore, and launch new business models. They also help promote innovation, integrate with existing systems, create prototypes, etc. One of the barriers to AI adoption is balancing the needs of the new technology with business as usual and other priorities [CS-1]. The innovation labs thus play an important role in driving innovation and supporting the core business units that demand innovative products and services. This can only be achieved through support from top management and core business managers. They can start with incremental digitization and proceed to radical innovations (Sund et al., 2021).

Conducting workshops for clients: Some firms conducted workshops to sensitize clients about AI's use and benefits (such as increased productivity and reduced headcount) by identifying different use cases and creating prototypes. Their primary focus was on different degrees of process automation for their clients, where they formulated possible AI business cases and showed the ROI [CS-1, CS-4]. The IT services companies often felt that their clients who started with AI were doubtful and apprehensive about AI implementations. They were aware of the technology and experts in their domain but did not have sufficient knowledge and skills to implement AI. The workshops created a collaborative learning environment, saved time, and helped communicate with multiple stakeholders for a successful outcome. The project goals, scope, and roadmap were the outcome of such workshops.

Working with partners: Most firms partnered with other firms depending upon their AI requirements. They sometimes sold their partner's products and technology solutions to clients and worked with them on their AI implementations [CS-2, CS-3, CS-4, CS-6]. The sales teams often used AI/ML to communicate with their clients. For example, CS-3 partnered with several organizations, such as Amazon, Azure, IBM, Snowflake, Salesforce, Hotspot, etc., to resell their products and technology solutions by integrating them with AI. CS-4 partnered with retail clients to develop AI-based marketing solutions using MS Azure and Cortana Intelligence Suite. We often found a triangular partnership among companies providing infrastructure and computational services, AI development companies, and companies providing business knowledge and domain expertise. CS-5, for example, partnered with firms to deliver infrastructure that approached it for AI solutions. CS-8 partnered with Intel and Amazon for Infrastructure and cloud solutions. They planned to venture into using the AI radiology solution

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in other areas in the future. Similarly, CS-20 partnered with hospitals to collect the data required. Partnerships or alliances helped firms scale the AI growth curve faster.

Federated Learning: This is another way to build AI capabilities. For example, in the case of self-driving cars, most of the processing is done on edge (i.e., on the device). CS-5 provides a platform for scalable embedded processing for edge computing. Their strategy is to use the intelligence at the edge to complement intelligence in the cloud – a form of a new federated learning model. Edge computing helps with data privacy and efficient bandwidth use, a facilitator for semiconductor and wireless chip provider companies. As AI plays an important role in time-sensitive applications such as self-driving cars, remote surgeries, cybersecurity, etc., edge AI is useful in such cases and helps with latency, security, and privacy (Mwase et al., 2022).

Leverage Customer data: Some firms also leverage customer data [CS-3]. IT Services companies usually have clients in different domains and already have access to their data. This makes it easier to work with them on the AI/ML implementations. This emerges as a standard strategy for implementing AI as it helps overcome data-related barriers to AI adoption.

Mapping the AI implementation to the AI technology

We identified the initial and final state of the applications before and after AI implementation, along with the use cases. Table 5 presents how different organizations implemented AI technology. This can help organizations recognize how they can leverage AI technology.

Table 5 – Mapping the AI Capability/Service Implemented to the AI Properties

Use case	AI technologies used	Initial state to final state	Remarks
Financial services back-office process automation, supply chain optimization, fraud detection, and processing of KYC documents	Pattern recognition, NLP, and image processing	Change from Rule-based robotic process automation to Intelligent process automation	The most common AI implementation was process automation. Cloud service providers often provide the required hardware and infrastructure, support many machine learning frameworks, and make it easy for developers to create and train models with less effort, cost, and expertise. They also provide specialized services for text and image processing.
The helpdesk uses an AI-based facial recognition system.	Facial recognition	Change from traditional authentication and authorization of employees to using facial recognition at the helpdesk	However, there are some ethical concerns raised by facial recognition technology, such as racial discrimination, bias, and privacy issues, that organizations need to be aware of and take steps to address. The organizations were aware of the issues and had some knowledge and skills to address the issues but did not have any organization-wide standards for addressing the concerns.

Table 5 – Mapping the AI Capability/Service Implemented to the AI Properties

Use case	AI technologies used	Initial state to final state	Remarks
Processing chat transcripts, images, log data, and restaurant customer feedback data.	Data mining	Change from manual extraction of knowledge to automatic knowledge creation and management	AI models need proper data for training, and the presence of such data facilitates AI adoption. Clients are often unwilling to share real data owing to privacy issues, and it is impossible to train the AI models using dummy data (CS-3). Thus, data complexity, unavailability, security, quality issues, and complex black-box algorithms are some barriers to AI adoption.
Drug safety related to the collection, detection, assessment, monitoring, and prevention of adverse effects	NLP and image processing	Change from manual data entry and assessment for pharmacovigilance to using AI for interpretation	AI optimizes pharmacovigilance processes to reduce the time to process a case safety report drastically
AI-powered voice chatbots with conversational features for sales interactions, an intelligent chatbot for customer service that initiates the conversation and answers queries on loans and credit based on one's transaction history, and AI chatbots and virtual assistants for new parents to help them in their post-natal journeys	NLP and text processing	Change from rule-based chatbots to AI-based chatbots	The barriers faced by the organizations included trust issues that the chatbot users had with the chatbots. The organizations overcame these to some extent by making the chatbots more consistent and offering a personalized experience to the users.
Trade finance and payment finance	NLP and image processing	Change from traditional trade finance to AI-based intelligent decision-making for trade finance based on intelligent document processing	AI helps in automating routine decisions. AI has the tremendous capacity to process and analyze vast amounts of data and extract knowledge and insight and can, therefore, aid managers in decision-making. For example, CS-3 has an AI-based solution framework for trade finance which involves several documents (such as bill of lading, letter of credit, invoice, and insurance documents). It takes several important decisions based on these documents, such as determining whether a particular transaction is viable. AI is trained on past data to arrive at the current decision.

Table 5 – Mapping the AI Capability/Service Implemented to the AI Properties			
Use case	AI technologies used	Initial state to final state	Remarks
Customer data segmentation for finding the right product mix	Data mining, clustering	Change from limited customer segmentation based on a few metrics to improved customer and market segmentation with more personalization using AI.	The challenge is getting customer data due to privacy laws, regulatory bottlenecks, and legal implications
Device implementation (such as chips and microcontrollers for AVs) and a development environment with neural network compilers and libraries for self-driving cars. Location-based vehicle tracking and payment solutions for truck operators.	Edge computing: Deep learning toolkit that provides deep learning algorithms for vision processors for object detection and classification	Change from sending data to the cloud for data processing for AI to AI at the edge	In self-driving cars, there is not enough time to send data to the cloud for processing. Therefore, most of the processing must be done on edge/device. Edge computing helps with data privacy and makes efficient use of bandwidth. The greater acceptability of edge computing facilitates AI adoption faster due to alleviating security and privacy issues.
AI product that helps with the early diagnosis of lung cancer and quantifies emphysema and fibrosis	Deep learning technology trained using millions of (Computed tomography) CT scans and proprietary AI algorithms for high accuracy	Change from manual interpretation of radiology reports to classification of radiology images using computer vision for early diagnosis and faster treatment.	Since there is no robust legal framework in India and no regulatory body to enforce AI medical devices' compliance, the AI product was validated based on many clinical validation studies and published findings in reputed journals. The regulatory bodies do an in-depth analysis to determine the credibility and accuracy of algorithms used for medical purposes (Benjamens et al., 2020). The presence of legal and regulatory frameworks will facilitate firms to adopt AI.
Detect anomalous behavior during production.	Deep learning-based computer vision	Change from regular manufacturing sector maintenance to prescriptive maintenance using AI image-based quality control	Predictive analytics in manufacturing helps lower costs, reduces unplanned downtime, and optimizes machinery performance.

Discussion and Implications

A valid question facing many managers is how to use AI in their organizations. By understanding the AI trend and strategies adopted by other organizations that have implemented AI successfully, they can understand what it takes to start and progress on their own AI adoption journeys. This study examined the current state of AI adoption and implementation in organizations. We interviewed key informants from twenty organizations that have implemented/developed AI solutions. We summarize the findings of our study in Figure 5 along the four broad themes: facilitators of AI adoption, barriers to AI adoption, AI trends, and AI capability-building strategy.

Facilitators	• The relative advantage of AI such as saved time, increased convenience, 24X7 availability, and increased productivity. Unique advantages, such as the use of AI in hostile environments and as an aid in decision-making. • Compatibility with existing infrastructure, such as integration with the cloud, facilitates the adoption of AI • An organizational culture that rewards innovation, top management support, skilled resources, and a clear strategic roadmap • Availability of the proper training data • Acceptability of edge computing
Barriers	• Data complexity, unavailability, lack of security, poor data quality, complex algorithms, black-box algorithms, and addressing ethical concerns • Resistance to change, fear of failure, infrastructure issues, and misalignment between business and technology. • Privacy and security laws, lack of regulatory bodies, regulatory approvals, regulations, and policies.
Trends	• Initially, experimented with different AI tools in the exploratory phases. Later, narrowed down to AI tools and technology that could be used. • Move from automating repetitive manual processes to intelligent automation using machine learning. • The initial focus was on collecting data. Now, the focus is on extracting intelligence, improving efficiency and productivity, and personalization using AI.
AI Capability Building	• Work with partners. • Federated business model-Intelligence at the edge to complement intelligence in the cloud. • Leverage the customer data that they already have and use it for AI. • Have in-house innovation labs and conduct workshops for clients for use case identification

Figure 5 – Different Aspects of AI Adoption and Implementation

Among the facilitating factors, organizational factors feature second on the list. Apart from the factors mentioned in Figure 5, factors such as organizational agility, suitable alignment of organizational politics, financial readiness, organizational culture & priorities, and AI training programs facilitate AI adoption. Some organizational barriers include a lack of organizational capability, organizational resistance, unavailability of infrastructure, misalignment between business and technology, resource constraints, resistance to change, and fear of failure. Organizations can achieve AI adoption if they take steps to overcome these barriers. Compatibility with existing systems, infrastructure, prevailing technology, and data environment also feature in the list of facilitating factors. Some organizations partner with cloud service providers who offer ready-made algorithms and manage end-to-end AI services to accelerate AI adoption. They also provide specialized services for text and image processing. Partnering makes it easy for firms to create and train models with less effort, cost, and expertise.

We also examined the AI implementation journey of the interviewed organizations. We found that data collection is the initial step in an organization's AI adoption journey. Data plays a

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crucial role in AI adoption. Data quality, data security, and data complexity are all essential factors that affect AI. Also, there are challenges in getting the required data due to privacy laws and legal implications. Some of these issues are common to other technologies, but organizations now need large volumes of reliable training data for AI. Some organizations enter partnerships to obtain the required data. In some cases, edge computing helps resolve data privacy, security, and latency issues and thus improves response time.

We can conjecture that organizations may be apprehensive about using AI due to inadequate knowledge and skills. To address this apprehension, organizations build innovation labs, which help them identify, explore, and launch new business models, explore new ideas, create prototypes, identify use cases, and sometimes work in partnership with other consulting firms. Doing so also helps them learn collaboratively, work on business cases, and calculate the expected ROI from AI. Among the facilitating factors, relative advantage topped the list. So, once the organization understands the relative advantage of AI implementation, it might feel more confident embarking on the AI adoption journey.

A noticeable trend in organizations was moving from robotic process automation to intelligent automation using AI. Since AI helps with process automation, it faces resistance from people who fear possible job loss. Earlier, automation replaced jobs that were repetitive, predictable, and routine. But with AI, even jobs where humans have a definite advantage are at risk. Using the right human-AI partnership may help alleviate this fear to facilitate AI adoption.

As presented in the literature review, there are also some potential ethical, legal, and social impacts and risks brought in by AI. From the study, we also find that there are some ethical concerns raised by facial recognition technology, such as racial discrimination and bias and privacy issues, that organizations need to be aware of and take steps to address. Presence of an ecosystem of key players in technology, research, and regulatory bodies, regulation of data to ensure privacy, minimizing bias in training data, making individuals and leaders responsible and accountable, and having ethical frameworks to build trust might be some of the actions that organizations can take to address the ethical issues. Fairness, accountability, transparency, fulfillment of beneficence, and justice help in building trust. In one case, the AI medical product was validated based on many clinical validation studies.

Implications for Research and Practice

Our study makes an incremental contribution to theory and practice toward understanding the AI implementation journey in organizations. Regarding contribution to theory, first, literature studying the current state of AI implementation is scarce. Our analysis captures empirical data from organizations of different sizes, market capitalizations, and sectors. Secondly, this study finds that the TOE framework and Roger's DOI theory encompass many factors influencing AI adoption. Hence the findings of our study reinforce the relevance of the TOE framework and Roger's DOI theory in studying AI adoption. We found that most of the AI implementation factors lie within those proposed by the TOE framework and Roger's DOI theory. Thus, we can use these two theories for examining AI implementation within organizations. However, AI also poses other challenges that do not lie within the purview of these two theories. For example, the availability of training data is one of the factors. Most of the time, firms do not have adequate data to train the AI engine. And even if the data is available, it is usually biased. If the past data contains biases in any form, the AI engine based on such past data will also produce biased results.

Regarding practice, first, this study informs scholars of the current state of AI implementation in organizations. The managers can use this information while implementing AI in the organizations by understanding the barriers they face in their AI implementation journey and being prepared to overcome them. At the same time, they could examine the facilitating factors and strategize their AI adoption accordingly. The paper can serve as a quick guide for researchers and managers to understand different AI adoption facets. Secondly, this study helps managers and organizations understand and formulate AI adoption strategies. Knowing the AI trends and implementation strategies followed by other organizations will help managers venturing into AI make better decisions regarding their long-term innovation strategies.

Implications for Asia-Pacific

We found a few specific implications for Asian countries. First, data availability is an important issue for firms in Asia. There are no strict privacy laws and legal implications, and ethical committees in hospitals and organizations manage data access. In contrast, severe legal implications and privacy laws in the US restrict data sharing and make it difficult to get data for training. Secondly, as there is no robust legal framework in India and no regulatory body to enforce AI medical devices' compliance, firms validate AI products based on many clinical validation studies and findings published in reputed journals. The companies otherwise have to spend considerable money trying to get US and European approvals. The regulatory bodies do an in-depth analysis to determine the credibility and accuracy of algorithms used for medical purposes (Benjamens et al., 2020). Their lack seriously undermines the proper use of AI in the Asian region. Third, firms lack a systematic approach to addressing AI biases in Asian countries. The organization using facial recognition technology in India said they were aware of bias-related issues and had some knowledge and skills to address them. However, they did not have any organization-wide standards for addressing the concerns. Respondents mentioned bias only when specifically nudged. This implies that the bias in training data is not so much of an issue. That is because the data itself is not available. Even if the training data is available, the biases Asian countries are subject to are different from those in western societies. Generally, the biases in AI reflect the social norms and culture of society. For example, the biases in decision-making in the Asian region are not so much about black/white as in Western countries. Therefore, it is better to put the data to the test and examine if certain biases appear clearly, rather than discarding it in the name of biased training data.

Conclusions, Limitations, and Future Research

The paper examined the aspects of AI adoption and implementation in twenty organizations, including six small, one mid-size, and thirteen large organizations. Using a qualitative approach, the study sheds light on what organizations can do to get started on the AI adoption journey, the benefits they can get from implementing AI, the strategies they can adopt to gain business value and have a competitive edge, the typical AI implementations, the AI technologies used for the implementations, the factors that will help them and the factors that they need to overcome to facilitate AI adoption. The literature review also lists influencing factors grouped by the different application areas. The study uses an integrated framework consisting of the TOE framework and the DOI theory.

The results of this study should be interpreted considering its limitations. We studied twenty organizations, of which ten belonged to the IT services sector. This may slightly skew the results toward AI adoption in IT Organizations. Also, there were 13 large organizations, six small organizations, and one mid-size organization. Another limitation of the study was that we used convenience and snowball sampling of the participants, as the experts selected were from our primary and secondary contacts. In the future, the study could be conducted with purposive sampling so that the results can be generalized for the subpopulation based on the criteria. We can also increase the sample size of the study. To get a better understanding of the AI trend in organizations, it will be beneficial to do a longitudinal study. Other variables such as the AI lifecycle, scaling AI, addressing some of the risks and ethical issues of AI, challenges posed by AI in regulation, privacy, and its effect on public policy can be included in future studies.

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Appendix 1 – Interview Questions

The following information was gathered from the respondents in the semi-structured interview.

a. Organization details: Number of employees, annual revenue, industry, the primary line of business
b. Role of the interviewee in the organization
c. AI implementation details such as the business areas where AI is used, AI product/service implemented, number of AI models in production, AI algorithms used, AI platforms used, benefits of implementation, and challenges
d. Factors influencing AI adoption, both facilitators and barriers.
e. Details of AI training programs in the organization
f. The AI implementation trends in the organization and the future of AI in the organization.
g. Details on the AI business models and strategy for AI

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Appendix 2 – Samples of Data Coding

Table A2a – Sample 1

Sample interview text	Rationalized codes	Category/Themes
We have around 20,000 employees around the globe	Number of employees	Demographics
Annual revenue is between 1 and 2 billion USD.	Revenue	
Accounts manager	Role of interviewee	
Computers and electronics company	Sector	
The Organization offers its clients IT Services, product development, and training services.	Services offered	
1000 or more employees	Number of employees	
Our annual revenue is $5.0M	Revenue	
There are only 48 employees in our company	Number of employees	
We provide the infrastructure and devices and enable customers to use Artificial Intelligence and machine learning for automotive and IoT applications. We are the providers of chips and microcontrollers for Autonomous Vehicles.	Services offered	
We have an integrated network service and work in location-based vehicle tracking and payment solutions for truck operators.	Services offered	
Our company employs less than 50 people	Number of employees	
We partner with IBM Watson in some areas, Microsoft Azure in some, and Google Cloud in others	Strategy	Strategy
We have an in-house innovation lab that researches AI and machine learning and works on developing prototypes and implementing AI projects for their clients.	Strategy	
We also conduct workshops for clients to quickly evaluate how AI can be used and the benefits it would bring to the organization through increased productivity, headcount reduction, etc., by identifying the different use cases and creating prototypes. Our focus is on different degrees of process automation for our clients, and we come up with future states and calculate the ROI.	Strategy	
We use Google Cloud AI platform, Microsoft Azure, IBM Watson local python/R Studio	Applications used	Applications used
We use Tensorflow	Applications used	
The organization can be categorized as an Early majority– those who take feedback from early adopters before taking the risk themselves	Stage of AI adoption	Stage of AI adoption
Our organization can be categorized as a Late Majority - willing to take the risk only after it is established in the marketplace.	Stage of AI adoption	

Table A2b – Sample 2		
Sample interview text	Rationalized codes	Category/Themes
Developed an AI-based audio analytics solution for conducting a clinical trial of drugs.	Audio Analytics	AI Implementation
The organization has also deployed customized AI chatbots for its clients.	Chatbots	
The company has also worked with Big Retail clients helping them segment their customer data to find the right product mix.	Customer segmentation	
Deep learning toolkit that provides DL algorithms for vision processors for object detection and classification	Deep learning toolkit	
An AI application has been developed for in-house use which has facial recognition features.	Facial and emotional recognition	
AI chatbot for customer service, which initiates conversation and answers queries on loans, credit, etc., based on the customers' transaction history.	Financial bots	
The company also uses AI in Pharmacovigilance	Pharmacovigilance	
Our algorithms include artificial neural networks, Bayesian networks, convolutional neural networks, deep neural networks, decision trees, k-Nearest neighbors, linear discriminant analysis, linear regression, logistic regression, multi-Layer perceptron, random forest, recurrent neural networks, support vector machines	Algorithms and technologies	Algorithms and technologies
We have used artificial neural networks, deep neural networks, decision trees, linear regression, and logistic regression.	Algorithms and technologies	
The AI product uses deep learning technology trained using millions of CT scans and proprietary AI algorithms	Algorithms and technologies	
We have 100+ AI models in production	Number of AI models	AI models
We have 10 to 50 AI models in production	Number of AI models	

Table A2c – Sample 3		
Sample interview text	Rationalized codes	Category/Themes
The product helps doctors to deliver personalized treatment much faster. The deep learning algorithm improved radiologists' sensitivity by around 20%.	Improved sensitivity	Benefits
An AI application with facial recognition features has been developed for in-house use. This is used by the help desk for authentication and authorization of employees who work remotely and who have, for example, lost their RSA token or have forgotten passwords, etc. This had been especially useful during the time of the Covid-19 crisis when everyone in the organization was working from home. The company also uses AI in Pharmacovigilance to drastically reduce the time to process a case safety report	Reduced time	
The AI integration with the ticketing systems has helped lower operating costs. We also have an AI application for retail fraud detection which has resulted in a 50% reduction in resources	Lowered costs	
Initially, we were in an exploratory phase as far as technology was concerned, experimenting to see which AI tools to invest in. Now, we have narrowed it down and have settled on the tools to use. Since the organization is an IT Services company and not an R&D or products company, we follow the AI trend of what the clients demand. If more and more clients demand AI-enabled IT services and are willing to pay for them, we will step up and develop AI expertise. If AI remains a narrow focus in the client's environment, we will not push for AI.	Trend	Trend and future
The trend that they have seen in the past few years has been that the financial institutes had initially experimented with Robotic Process Automation and are now moving to use AI mostly in their back-office operations and low-impact interactions.	Trend	
Earlier on, we were focused on collecting data. Now we have the data and are trying to find out what to do with it, how to use the data to extract intelligence out of it, how to use data to improve efficiencies and productivity, how to use data to personalize the customer experience, how to have conversations with clients etc.	Trend	
We plan to venture into using the AI radiology solution in other areas as well in the future.	Future	
Initially, we were in an exploratory phase as far as technology was concerned, experimenting to see which AI tools to invest in. Now, we have narrowed it down and have settled on the tools to use. Since the organization is an IT Services company and not an R&D or Products company, we follow the AI trend of what the clients demand. If more and more clients demand AI-enabled IT services and are willing to pay for them, we will step up and develop AI expertise. If AI remains a narrow focus in the client's environment, we will not push for AI.	Trend	

Table A2d – Sample 4

Sample interview text	Rationalized codes	Category/Themes
AI has played an important role in making Call Center Operations more efficient. It has resulted in call resolution improvement with a reduction of over 75% in the resolution time. The AI integration with the ticketing systems has helped lower operating costs. We also have an AI application for retail fraud detection which has resulted in a 50% reduction in resources	Relative Advantage	Facilitators
Collaboration between teams and training helped us understand the benefits of AI, and that helped with diffusion within the organization.	Observability	
Many ML, NLP software, cloud platforms for analytics, and chatbots are available in the market for a free trial	Trialability	
There is the right combination of cloud, and AI/ML as the cloud platforms offer ready-made algorithms. With greater acceptance of the cloud, the use of AI/ML has increased	Compatibility	
Having skilled resources has helped with AI adoption	Other technological factors	
Top management support facilitated the adoption	Leader characteristics	
Organizational culture & priorities were conducive to AI adoption	Organizational characteristics	
AI training, support from the leaders and the top management, business model, and strategy has helped with AI adoption	Other Organizational factors	
Peer competitive pressure has driven us toward AI adoption	Environmental factors	
It is often difficult to get good-quality data for training.	Data challenges	Challenges
There is no robust legal framework in India and no regulatory body to enforce compliance for AI medical devices, so the companies sometimes spend a considerable amount of money trying to get US and European approvals.	Govt. regulations and policies	
We have issues related to financial readiness, unavailability of infrastructure, sometimes there is misalignment between business and technology, and resource constraints	Organizational challenges	
Some challenges we have faced is getting the data for training due to data privacy issues. Hospitals have their own ethics committee which regulate the sharing of data.	Privacy and security laws	
It was trained with months of invoice data, but the accuracy achieved on the new data was not very good.	Other issues	

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