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Towards Adoption of Generative AI in Organizational Settings

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ABSTRACT

As an emerging technology, Generative Artificial Intelligence (AI) holds immense potential for application across various levels of business and management. However, current studies have not yet investigated the elements that impact the acceptance and implementation of generative AI tools, such as ChatGPT, within organizational settings. To fully leverage its benefits, organizations must embrace and integrate Generative AI at a comprehensive and profound level, making it a valuable area of study. This study aims to put forth and examine the influencing factors impacting the adoption of generative AI technology by utilizing the Technology-Organization-Environment framework in conjunction with the institutional theory and the diffusion of innovation theory. Data from 108 organizations in India is collected and analyzed, leading to valuable insights and implications that contribute to a deeper understanding of the key determinants of generative AI adoption. The study digs out valuable knowledge for organizations looking to embrace this technology.

KEYWORDS

Generative AI; innovation diffusion; TOE framework

Introduction

In the current business landscape, organizations are confronted with dynamic competitive and technological conditions that are reshaping their approach to strategy. The rapid pace of competition requires executives to strategize and execute simultaneously, integrate internet technologies into their strategy processes, and prioritize impactful activities that drive business outcomes. Some executives no longer consider traditional components of business strategy, such as industry analysis and the pursuit of unique resources and capabilities, as relevant. Instead, they perceive strategy as an ongoing process that encompasses decision-making and action-taking, while emphasizing the importance of organizational culture, seen as shared meaning and disciplined performance management. These executives challenge conventional boundaries by embracing open organizations, user communities, and social media. By adopting a trial-and-error approach, they are establishing new strategy principles based on data, communication technology, and the continuous measurement and control of key activities that determine business success. The emergence of deep learning models using transformer architecture and pre-training techniques has potential to explore generative artificial intelligence (AI) assisted decision-making system that can be employed for strategic decision-making in a fast-paced business environment.

Generative AI tools, e.g., ChatGPT, GPT-4, Bart, GitHub, etc., refer to a class of machine learning algorithms that can generate new data from scratch, such as images, text, audio, or videos that are similar to existing data. These algorithms employ models that undergo training on extensive datasets, which enables them to generate fresh data that adheres to the patterns and structure found within the original dataset. Unlike other AI techniques, such as machine learning or deep learning, which are designed to classify, recognize, or predict specific patterns or behaviors from existing data, generative AI models learn to generate new data by analyzing patterns and relationships within a given dataset.¹

Generative AI models, commonly relying on neural networks, employ methods like variational autoencoders, generative adversarial networks, or autoregressive models to generate fresh data that shares similarities in style, content, or context with the training data. These models are often used in creative industries, such as music, art, fashion, or developing new product designs as well as in natural language processing, where they can generate realistic and coherent text-based on a given prompt. While traditional AI models are typically trained using supervised learning where the model is trained on labeled data with a known output, generative AI models are often trained using unsupervised learning

where the model learns to extract meaningful features from the data without explicit guidance.²⁻⁵

With its remarkable ability to comprehend and generate natural language resembling human speech, generative AI holds significant promise in both business and society. It can effectively combine diverse datasets, offer concise summaries of overarching trends, and create compelling descriptions. While it may not be bestowed with the authority to make decisions in the realms of business and society, generative AI has the power to inspire creative thinking among humans. This is primarily because it can generate synthesized summaries from multiple perspectives that businesses may have overlooked in areas such as content creation (e.g., product descriptions, personalized recommendations, marketing messages, and website layouts based on user preferences and behaviors), fraud prevention by analyzing transaction data patterns and issuing alerts when anomalies are detected, facilitating the design and prototyping of new products like furniture or automotive parts by generating numerous variations and selecting the most optimal designs, and much more. The hospitality and tourism, banking, and IT industries are particularly poised to reap significant benefits from implementing generative AI, as it has the potential to greatly enhance critical workflows, optimize user experiences, and improve various business activities, including management and marketing. Overall, the integration of generative AI can lead to substantial advancements in these sectors, bolstering overall business operations.

Undoubtedly, the increasing prominence of generative AI has sparked significant interest in understanding how organizations can leverage information to achieve competitive edge. While the benefits of generative AI have started being documented, it is crucial to investigate how organizations worldwide are implementing and utilizing this technology. Generative AI has emerged as a novel tool for enhancing management efficiency by improving decision-making capabilities along with productivity of organizations in real-time and even preemptively.

The current research in information management has yet to concentrate on the adoption of generative AI, which is just one aspect of the broader adoption process. Merely adopting generative AI does not guarantee its extensive utilization and widespread application. The complete advantages of generative AI cannot be fully experienced without its widespread adoption. Therefore, it is crucial to study its adoption, as highlighted by previous research.^{6,7} Additionally, considering that the economic and regulatory landscapes vary across different geographical regions, it is significant to

explore how contextual factors that influence the assimilation of innovation in such environments.

With the identified theoretical gaps, present research considers an integrative model that combines various determinants impacting the adoption of generative AI in business settings. By incorporating the institutional theory, widely accepted diffusion of innovation theory, and the extensively practiced technology-organization-environment (TOE) framework, the proposed model seeks to offer a holistic comprehension of nine factors (complexity, compatibility, technological resource proficiency, relative advantage, absorptive capacity, organizational size, competition intensity, environmental uncertainty, and regulatory support) influencing the implementation of generative AI within organizations. While there are other factors influencing a company's decision to adopt AI, previous research has consistently demonstrated the significant impact of these factors on a firm's adoption of disruptive technology.⁸⁻¹² **Present study uncovered six important factors having significant influence on the adoption of generative AI in organizations: compatibility, complexity, organizational size, regulatory support, environmental uncertainty, and competition intensity.**

This paper consists of seven sections. Section 2 presents an analysis of the related work. Section 3 delves deeper into the research model, including hypotheses development and its establishment. The research methodology applied in this study is outlined in Section 4. Section 5 covers the data analysis process and presents the results. In Section 6, the outcomes are discussed, including limitations and suggestions for future work. Finally, Section 7 concludes the study.

Related work

Understanding the process of innovation assimilation, which is dynamic and complex, can be enhanced by utilizing multiple stage-based models to support the application of assimilation measures. One well-known three-stage change model⁸ describes the implementation of organizational innovation as consisting of unfreezing and then moving followed by refreezing phases. Another study⁹ categorizes assimilation into three stages described as knowledge-awareness, followed by evaluation-choice, and finally adoption-implementation. In the existing literature, assimilation is acknowledged as a sequential process consisting of six stages from initiation to infusion.¹⁰ Moreover, some other studies suggest stages such as adoption and diffusion, both internal and external,¹¹ adoption to assimilation,¹² etc.

The exploration of diffusion has been conducted by researchers from a multi-stage perspective, with a specific focus on adoption, implementation, and assimilation. These stages of diffusion are further divided into three distinct categories, for example, adoption encompasses initiation, comprehension, early and actual adoption. Implementation comprises adaptation followed by acceptance and then implementation stages. On the other hand, assimilation encompasses normalization, infusion, and complete assimilation stages. Moreover, scholars have investigated the factors that can impact each stage of adoption.¹³

Considering the systematic disposition of stage-based models in representing the innovation adoption, current research suggests employing a cumulative measure to make the adoption of generative AI operational and effective. Drawing on a previous study by Fichman,¹⁴ which examined the measurement of technology based organizational innovation, specific situations were recognized where combined measures resulted in favorable outcomes. In such circumstances, when antecedents exhibit a consistent direction across all adoption stages, aggregation can enhance robustness, generalizability, and predictive validity across stages.¹⁴ To enhance the generalizability and predictive validity of the proposed research model, this study adopts an approach where all predictors are aligned in the same direction across all stages of adoption. This means that behavior is aggregated throughout the entire adoption lifespan within a firm.

The widely practiced TOE framework is utilized to identify the influencing factors that can impact decision-making associated with the innovation adoption in the information systems ecosystem.¹⁵ This framework categorizes these factors into technology, organization, and environment domains. To illustrate the application of the TOE (Technological, Organizational, and Environmental) framework in various research studies, several examples can be highlighted. For instance, Furneaux and Wade¹⁶ conducted a study that utilized the TOE framework to investigate the intention to discontinue information systems. In another research study by Kuan and Chau,¹⁷ the TOE framework was employed to examine the implementation of Electronic Data Interchange (EDI). Similarly, Hong and Zhu¹⁸ employed the TOE framework to explore six variables that distinguish e-commerce adopters and non-adopters. Furthermore, a study conducted by Agrawal¹⁹ focused on the assimilation of big data analytics (BDA) and examined how factors outlined in the TOE framework influenced this adoption process. These studies demonstrate the versatility and use of the TOE framework in exploring technology assimilation and discontinuation across different contexts.

The existing literature has consistently provided empirical evidence supporting the reliability of the TOE (Technological, Organizational, and Environmental) framework. This framework is considered as a robust foundation for analyzing and identifying the relevant determinants in understanding the decision-making process of innovation adoption. Consequently, to explore antecedents within each sub-category, this research uses the TOE framework. The study aims to obtain a comprehensive understanding of the elements that influence the acceptance of innovation by utilizing this framework.

Research model

The classic Diffusion of Innovation (DoI) theory described by Rogers²⁰ outlines five key attributes of innovation within the context of technology. These characteristics encompass relative advantage, which refers to the extent to which an innovation is considered superior to its predecessor or existing alternatives; compatibility, which focuses on how well an innovation aligns with the existing business processes, practices, and values of potential adopters; complexity, which assesses the level of difficulty related with understanding and utilizing the innovation; observability, which pertains to the visibility of the results or outcomes of adopting the innovation to others, and trialability which reflects the ease with which potential adopters can experiment with the innovation before committing to its full implementation. While all five characteristics are relevant, the first three (compatibility, relative advantage, and complexity) are widely found to explain and predict the diffusion of innovations across several studies. As a result, this study recommends incorporating these three factors into the proposed research context.

The organizational context comprises different elements of an organization, such as its size, complexity of managerial structure, level of centralization, degree of formalization, quality of human resources, along with the existence of slack resources.²¹ These factors play a role in explaining why some of the firms are more innovative than others. Significant variations in performance outcomes linked to the diffusion of innovation may be attributed to differences in a firm's resources, including technology infrastructure, managerial knowledge, and past experiences with IT, as supported by research.¹⁵ Furthermore, the effectiveness of firms in extracting value from IT depends on capability to utilize it efficiently.^{22,23} Organizations with convincing managerial capabilities and IT proficiencies are better equipped to efficiently utilize agile technologies like generative AI, giving them an advantage over their competitors. Thus, this research considers organizational size, absorptive

capacity, and technology resource proficiency, which are classified as organizational resources, as factors that influence the study.

The environmental context pertains to the specific business environment in which an organization operates. This encompasses the competitors, industry, and interactions with the government.²⁴ Institutional theory, posits that the institutional environment establishes social expectations and norms that govern the suitable organizational structures and behaviors including operations and practices.²⁵ How a company interprets and responds to such pressures influences its understanding of the broader environment and impacts its attitudes and intentions regarding innovation. Therefore, the current study examines factors within institutional pressures that can influence the adoption processes of generative AI.

Three primary types of institutional pressures²⁵ can be classified as normative pressure, coercive pressure, and mimetic pressure. Normative pressure pertains to the degree perceived by associates of relational channels that have embraced the innovation, as well as the support for information technology from government and industry agencies. According to the proposed research model, the adoption processes of generative AI are influenced by regulatory support, which is seen as a normative pressure. Coercive pressure, on the other hand, refers to the influence exerted by influential firms having dependence of the central firm. Mimetic pressures arise when organizations imitate others because of limited comprehension of organizational technologies, unclear objectives, or unpredictable surroundings.²⁵ Generative AI relies on extensive training of large foundation models using vast quantities of data, much of which is unlabeled or disorganized. These foundation models serve as a foundation for creating more specialized models that can be tailored to specific domains or use cases. To mitigate risks associated with intellectual property (IP) and address concerns related to trust, privacy,

and transparency, organizations should prioritize the development of foundation models trained on their proprietary data and carefully curated external data sources. Investing in such models enables organizations to maintain control over their data while addressing important ethical and legal considerations. Since the standards and market for generative AI are still uncertain, and investments in this technology are irreversible, organizations are inclined to follow the lead of successful adopters. Furthermore, intense competition serves as a motivating factor for organizations to imitate enterprises that have already achieved success in implementing generative AI. Consequently, environmental uncertainty and competition intensity are considered factors that contribute to mimetic pressure in the current research.

Below is a proposed research model aimed at elucidating and forecasting the adoption of generative AI by firms. Expanding on the preceding section, the utilization of the TOE framework aims to pinpoint the elements that impact the acceptance of generative AI. The research model is described below in Figure 1.

Development of hypotheses associated with technological factors

Relative advantage, complexity, and compatibility as influencing factors associated with the technological context are described below.

Relative advantage

Scholars have utilized the relative advantage as one of the technological factors to forecast the adoption including diffusion of innovations. For instance, some studies have investigated the adoption and implementation of Radio Frequency Identification technology (RFID) recognized once as an agile technology.²⁶ The key findings of this

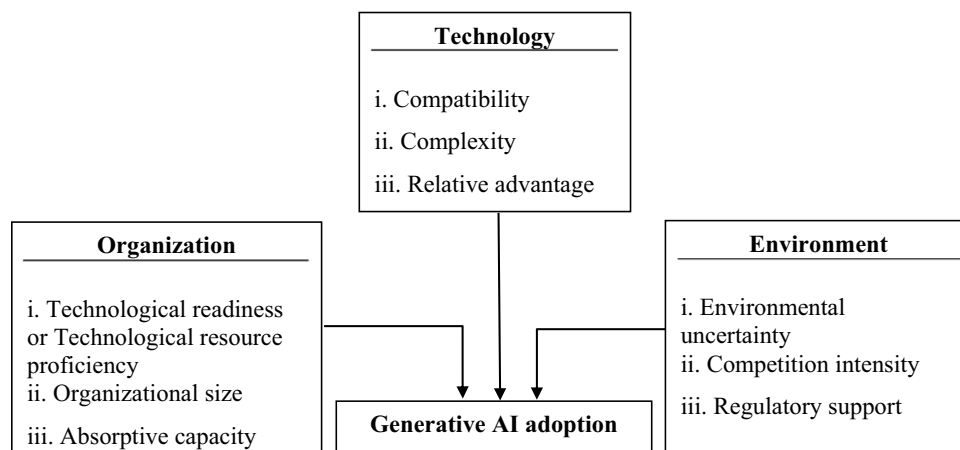


Figure 1. Proposed research model.

study indicated that the adoption of RFID technology was positively influenced by the relative advantage it offered. Zhu et al.¹² conducted a separate study where they examined the factors that impact the subsequent stages of innovation diffusion, focusing on enterprise digital transformation as an illustrative case. Their findings demonstrated that relative advantage has a positive impact on the usage of e-business. Ramdani and Kawalek²⁷ conducted a study to predict the adoption of enterprise systems among small and medium enterprises (SMEs). Their findings suggested that the perceived relative advantage of enterprise systems plays a pivotal role in deciding the likelihood of adoption by SMEs. Kwan and Chau¹⁷ conducted a study where they investigated the adoption of Electronic Data Interchange (EDI) technology and found relative advantage performing a substantial role in influencing the adoption of EDI. Study conducted by Agrawal¹⁹ on big data analytics (BDA) adoption shows relative advantage as a non-significant discriminator. Evaluating the relative advantage of generative AI compared to existing approaches will play a crucial role in their decision-making process. By integrating generative AI with other relevant systems, firms can experience reduced lead times, improved efficiency, and lowered labor costs. Based on these studies, it can be inferred that relative advantage would indeed serve as a significant factor in motivating organizations to embrace generative AI technology. This suggests the following hypothesis.

H1: *Greater the perceived relative advantage of generative AI within firms, higher will be the degree of adoption.*

Complexity

Extant literature refers it as “the degree to which an innovation is perceived as relatively difficult to understand and use.”²⁸ Using this lens, generative AI is generally more complex than traditional AI because it involves creating new data that is statistically similar to the original dataset. This requires a more sophisticated understanding of the underlying patterns and structure of the data. Moreover, the challenges related to generative AI technology include its early stage of development, absence of widely accepted norms, and the complexities involved in incorporating it into established organizational information systems and business operations. Therefore, it is important to examine the intricacy of an innovative technology to ensure that organizations possess sufficient financial and human resources to overcome any challenges that may arise during the implementation phase.

Complexity encompasses two key elements: the obstacles associated with customization and the significant costs involved.²⁶ Customization of generative AI systems is necessary to adapt them to specific working environments. Efforts must be made to enhance coordination between the generative AI backend system and existing IT systems, such as data assimilation and control, in order to achieve better alignment and effectiveness. The second aspect of complexity pertains to the expenses associated with investment and maintenance. The costs involved in operating generative AI, which include skilled personnel and IT infrastructure, can be substantial and difficult to reverse. The absence of standardized generative AI practices further amplifies the costs. Consequently, organizations that perceive significant technological complexity tend to exercise more caution when adopting generative AI and integrating it into their operations. Therefore, the following hypothesis is proposed.

H2: *Greater the perceived complexity of generative AI within firms, lower will be the degree of adoption.*

Compatibility

In the realm of technology, Rogers²⁰ suggests that the perception of how well an innovation aligns with the requirements or established behaviors of potential adopters determines its extent of acceptance. The higher the compatibility, the more likely it is for innovation adoption to occur.¹⁰ Instead of simply replacing existing data-driven technologies in current processes, the implementation of generative AI technologies often involves combining them with process innovations, which can result in improved outcomes. Moreover, resistance to change can emerge as a significant issue when implementing generative AI systems. Hence, compatibility can play a crucial role in determining the adoption of generative AI. The following hypothesis is proposed.

H3: *Greater the perceived Compatibility of generative AI within firms, higher will be the degree of adoption.*

Development of hypotheses associated with organizational factors

Other than the technological aspect, various other aspects within the organizational setting can have an

impact on the processes of adopting generative AI. The current research examines the influence of technological resource proficiency, organizational size, and absorptive capacity in relation to generative AI adoption.

Technological resource proficiency

Being also considered as technological readiness, it encompasses both IT infrastructure along with IT capability.⁷ Grant²⁹ categorized technology related resources into three groups with regards to IT infrastructure, tangible resources which consist of physical components of the technological infrastructure; human IT resources which include managerial IT skills along with technical skillsets; and the third, intangible IT-enabled resources like as customer orientation along with resources in the form of knowledge assets and synergy.

Tangible resources, in line with resource-based theory, play a significant role in enabling firms to quickly assimilate innovations and enhance their products. An integrated technological infrastructure offers a stage that allows for the swift implementation of innovative IT applications, providing a competitive advantage over rivals.²² Hence, tangible resources are important as they can potentially impact the processes of adopting generative AI.

There are two main elements of human resources: managerial skills and technical IT skills. With the integration of generative AI comes significant alterations to business processes along with IT infrastructure, making managerial proficiency critical in managing the tasks associated with process redesign. Meanwhile, analysis to implementation stages of the modified business processes need relevant technical IT skills. Further, customer orientation, knowledge assets, and synergy form the intangible resources component.²² Previous studies have shown that customer orientation is crucial in embracing innovation.

The concept of knowledge asset pertains to the amalgamation of knowledge and skills of employees along with the experiences within an organization's procedures, guidelines, and knowledge storage systems.²² Having robust knowledge assets is crucial for the successful implementation of generative AI. When a company possesses extensive knowledge repositories along with skilled employees, it becomes simpler for them to integrate and adopt new innovations.

The concept of synergy involves the shared use of resources and capabilities among different functional units within an organization.²² An organization capable of effectively sharing knowledge and information across various divisions possesses greater flexibility and responsiveness to deal with various needs in a timely manner. Generative AI technology offers an exceptional

way of sharing such resources and information by enabling real-time information exchange across vital divisions including R&D (Research and Development) unit within a firm. Consequently, the positive relationship between the synergy of intangible resources and the adoption of generative AI is recognized and incorporated into the current research model.

As reviewed above, it can be concluded that physical IT infrastructure, IT resources relating to human beings, along with intangible resources play substantial roles in positively influencing the adoption of generative AI. The IT infrastructure of a firm is a critical business resource that serves as a fundamental basis for sustaining future competitive advantage.²² Thus, the proficiency in technological resources can be considered as a factor that precedes the process of generative AI adoption.

Generative AI is a transformative innovation capable of significantly reshaping the strategic planning and various operational processes of an organization. However, achieving such transformation necessitates extensive IT and managerial capabilities. Further, technologies facilitating significant improvements often impose considerable complementary amends to an organization's structures, policies, and practices.³⁰ As a result, the adoption of generative AI necessitates organizational and more often process adaptations.³¹ Nevertheless, not every firm possesses the necessary managerial skills and expertise in change management to effectively manage such adaptations. The organizational adaptations required for the adoption of generative AI encompass changes in structures and coordination mechanisms, as well as the acquisition of new expertise essential for utilizing the innovation.^{6,31} Therefore, it is crucial to investigate these impacts pertaining to the ability to manage organizational adaptation in order to facilitate the adoption of generative AI.

Various studies have attributed IT failures to management issues, including the absence of synergy amid business and technological skills, inadequate competence regarding technology integration with business strategy, the challenge of acquiring skilled technical personnel, and insufficient training for the utilization of generative AI systems. Such failures highlight that obstacles at the managerial level can hinder the adoption of generative AI, particularly when organizations struggle to implement organizational changes, restructuring of processes, and acquisition of new expertise. This leads to the following hypothesis.

H4: *Greater the technological resource proficiency of firms, higher will be the degree of adoption of generative AI.*

Organizational size

Previous research has discovered that the adoption of innovation is promoted by the size of an organization.^{24,32,33} Larger organizations typically possess more resources to experiment with newly introduced innovations, thus enabling them to better handle the risks and expenses associated with implementing them.³⁴ In order to expedite client projects with secure and contextual generative AI solutions, firms must rely not only on various language tools offered by different providers, but also develop their own proprietary solutions. To foster innovation and maximize value creation, organizations are increasingly leveraging multiple models rather than relying on a single model. However, the costs associated with training and managing these models must be carefully considered. Factors such as cost, effort, data privacy, intellectual property (IP), and security should be considered when making decisions. Moreover, organizations should embrace an open platform approach that allows them to benefit from available models in the open-source community. By adopting this approach, they can access a wider range of models and tap into external expertise. As these models will be deployed across hybrid cloud environments, organizations will require a platform that seamlessly integrates and deploys these models for their specific use cases. This integrated platform will enable organizations to derive value from their models, ensuring efficient utilization and enhancing overall organizational performance. Currently, due to the significant cost associated with generative AI systems, only organizations with substantial financial resources can invest in installing such technology. Therefore, the following hypothesis is suggested.

H5: *Larger the firms, higher will be the degree of generative AI adoption.*

Absorptive capacity

It is the capacity of a firm to realize new exterior information, recognize its value, and effectively apply it for its business purposes. Cohen and Levinthal³⁵ state that the effectiveness of absorptive capacity may be gauged by the acquired knowledge of the firm and the level of effort exerted.

Extant literature views absorptive capacity from the lens of a repository of knowledge, particularly emphasizing the amount of inherited knowledge possessed by the organizations.³⁶ Like path dependency, the ability and motivation of an organization to embrace an innovation is also relevant in the context of absorptive

capacity. The level of related relevant technologies experience within a firm plays a significant role in determining its ability to embrace any innovation. Possessing the necessary technology skillset and wisdom is crucial for the effective acceptance of upcoming technology standards.³⁵ Therefore, firms having experience and knowledge in associated technologies are likely to have acquired technical as well as managerial skills necessary for implementing generative AI technology, in contrast to firms lacking such experiences. Therefore, the hypothesis is proposed as below.

H6: *Greater the absorptive capacity of firms, higher will be the degree of adoption of generative AI.*

Development of hypotheses associated with environmental factors

Section below presents the introduction of environmental factors such as the level of competition, support from regulatory bodies, and the degree of environmental uncertainty that can influence the adoption processes of generative AI.

Environmental uncertainty

According to existing literature, firms that encounter environmental unpredictability are more motivated to embrace inter-organizational innovation (IOS) in order to enhance the exchange of information and decrease uncertainty among their business associates. According to Sharma,³⁷ firms confronted with elevated environmental uncertainty tend to perceive a greater number of opportunities, display proactive behavior, and engage in higher levels of innovation compared to other firms. Moreover, organizations are compelled to embrace new technological revolutions to maintain their competitiveness in the face of environmental and/or market uncertainty.³⁸

Furthermore, the adoption of generative AI technology necessitates significant irreversible investment costs, thereby posing risks to enterprises. Low-profit organizations would face notably higher implementation costs when compared to traditional systems when adopting generative AI technology. Consequently, low-profit organizations are less inclined to take the risk and be at the forefront of adopting generative AI technology.

The absence of government-developed standards for generative AI introduces distinct uncertainty into the market. Moreover, a challenge remains regarding the determination of responsibility for drafting the

standards for generative AI. The lack of clarity regarding the responsible entity for drafting generative AI standards presently hinders the confirmation of standards, thereby impeding the adoption process. Therefore, the following hypothesis is developed.

H7: *Greater the perceived environmental uncertainty, lower will be the degree of adoption of generative AI.*

Competition intensity

The intensity of competition, as stated by Zhu et al.³⁹ implies to the extent to which an organization is influenced by other competitors in the market. According to Porter,⁴⁰ the well-known five-force competitive model highlights the significance of competitive pressure as a crucial external factor that triggers the implementation of inter-organizational innovation among business partners. The involvement of these participants contributes to increased competition within domestic markets, posing challenges to the technological and managerial capabilities of enterprises.¹⁹ In order to overcome these challenges, it becomes imperative for enterprises to adopt new technologies like generative AI to enhance their competitive advantage. Therefore, the intensity of competition is expected to have positive impact on the adoption of generative AI. It leads to the hypothesis given below.

H8: *Greater the competition intensity, higher will be the degree of adoption of generative AI.*

Regulatory support

The presence of regulatory support portrays a vital role in the spread of innovation.^{12,41} Two main approaches can influence innovation diffusion. The first approach involves implementing tax and other measures that either enhance or reduce the incentives for innovation. The second approach focuses on modifying the environment having introduction of innovations.⁴² Another research on the adoption of e-commerce discovers that globally administrations can promote the establishment of e-commerce legislation through the implementation of encouraging regulations and guidelines.¹² Another research study examines the adoption of Internet technologies and reveals that organizations place the utmost importance on the governing environment where they operate.⁴³

Above matters hold global significance. It is evident that governments worldwide are currently formulating

strategies to invest in research and development (R&D) initiatives focused on the Internet and related sectors such as AI, cloud computing, and the development of digital and virtual technologies. Among these advancements, generative AI technology is anticipated to play a pivotal role as the primary catalyst for the Internet along with the digital ecosystem. Establishing a robust governance framework is a critical aspect that guarantees trust, accuracy, and confidence while adhering to regulatory obligations. It is undeniable that generative AI and Large Language Models (LLMs) offer immense potential for organizations to undergo transformative growth. By implementing a governance framework, organizations can effectively manage and mitigate risks associated with the deployment of generative AI. This framework will ensure that ethical considerations are addressed, data privacy is protected, and compliance with relevant regulations is maintained.^{35,37,43} With a well-defined governance framework in place, organizations can confidently embrace the opportunities presented by generative AI, leveraging their capabilities to drive innovation, enhance operations, and achieve sustainable growth. Governmental regulatory support can therefore create a favorable environment that raises awareness among decision-makers regarding this technology, prompting them to consider its adoption within the firm. Therefore, below hypothesis is developed.

H9: *Greater the regulatory support, higher will be the degree of adoption of generative AI.*

Research methodology

Construct measures

The primary measures used in the study were obtained by utilizing preexisting instruments. To accommodate the generative AI context, certain items were adjusted accordingly. The items related to compatibility, relative advantage, and complexity were derived from the extant works.^{11,33} The measures concerning competitive pressure, technology resource proficiency, and partner pressure were derived from the extant studies.^{21,44} The items pertaining to complexity and firm size along with regulatory support were modified from the extant research.³³ Furthermore, items related to the absorptive capacity were borrowed from the study conducted by Soliman and Janz.⁴⁵ The respondents were requested to assess the items on a five-point Likert scale, spanning from 1 (Strongly disagree) to 5 (Strongly agree). This study considered adoption as the dependent variable,

which was a dichotomous measure and it determined whether an organization was an adopter (having initiated the use of generative AI for any business purpose) or a non-adopter of generative AI technology. Measurement items pertaining to the independent variables are shown in Table 1.

Sample profile and instrument validation

For data collection in this study, a survey instrument was used, which included business-related items, as well as items for measuring the predictors and determining whether the surveyed firm had adopted generative AI. The survey was conducted among a randomly chosen sample of 200 firms from the top 300 firms across industries in India. Out of these, a total of 108 (54%) responses were received. Sample profile is presented in Table 2.

To assess the construct validity of the measurements, the extraction technique in principal components factor analysis was used. The extracted factors were then subjected to the varimax orthogonal rotation method. This analysis was performed on all the useful responses received, aiming to examine the underlying structure and relationships among the variables. It was observed

that one item, EnU1 (Generative AI implementation was actively encouraged by our organization's key trading partners), exhibited cross-loadings with multiple factors. As a result, this item was deemed inconsistent and subsequently dropped from the analysis. As outlined in Table 3, the analysis showed a strong correlation between each factor and its corresponding items, as indicated by primary factor loadings surpassing 0.5. Moreover, there were no instances of cross-loadings observed, indicating a robust match between the factors and their associated items. As outlined by Hair et al.,⁴⁶ this finding supports the construct validity of the model. Cronbach's alpha coefficients for the constructs were higher than the predetermined threshold value. This suggests that the items within each construct are highly reliable and consistent in measuring their respective constructs.

Analysis and findings

The composite scores in Table 4 are obtained by taking the mean values of the item scores for each factor.

Despite of multicollinearity sensitive nature of logistic regression, the research model was still tested using this technique. To diagnose it, two-part process was

Table 1. Independent variables and measurement items.

<i>Absorptive capacity</i>	
AbC1.	There is a high probability that my organization will allocate financial resources towards generative AI technologies.
AbC2.	My organization possesses existing knowledge and experience in the realm of related technologies.
AbC3.	Probably my organization is interested in assimilating generative AI technologies to have a competitive edge.
AbC4.	The strategic importance of assimilating generative AI technologies is likely to be considered by my organization.
<i>Organizational size</i>	
OrS1.	The total capital of my organization exceeds the industry average.
OrS2.	The returns of my organization surpass the industry average.
OrS3.	The employee strength at my organization exceeds the industry average.
<i>Technological resource proficiency</i>	
TRP1.	The IT setup of my organization can support applications related to generative AI.
TRP2.	My organization is committed to ensure that staffs are well-versed and knowledgeable about generative AI technologies.
TRP3.	My organization possesses a strong understanding of generative AI technologies.
<i>Regulatory support</i>	
ReS1.	The adoption of generative AI is motivated by initiatives considered by government.
ReS2.	The adoption of generative AI technologies is facilitated by the existence of standards and laws.
ReS3.	The adoption of post-generative AI technology is facilitated by sufficient legal protection.
<i>Competition intensity</i>	
Col1.	My organization faced strong competition in implementing generative AI technology.
Col2.	If my organization had not adopted generative AI technology, we would have been at a competitive disadvantage.
<i>Environmental uncertainty</i>	
EnU1.	Generative AI implementation was encouraged by the primary business allies of my firm.
EnU2.	Generative AI implementation was recommended by the primary business allies of my firm.
EnU3.	Generative AI implementation was requested by the primary business allies of my firm.
<i>Complexity</i>	
CX1.	My firm holds the belief that generative AI technology is challenging to utilize.
CX2.	My firm perceives the adoption of generative AI as an intricate process.
<i>Compatibility</i>	
CP1.	The introduced changes brought by generative AI technology align harmoniously with the existing beliefs and values upheld by my organization.
CP2.	The current infrastructure is compatible with the technology of generative AI.
CP3.	The existing practices in place are in alignment with the changes introduced by generative AI.
CP4.	The prior knowledge of my organization in working with comparable systems make it compatible with the development of a generative AI system.
<i>Relative advantage</i>	
RIA1.	My firm anticipates that generative AI technology will aid in cost reduction.
RIA2.	My firm anticipates that generative AI technology will facilitate swift real-time data handling followed by relevant analysis.
RIA3.	My firm anticipates that generative AI technology will assist in reducing paperwork.

Table 2. Sample profile of firms.

Description	Count	Percentage
Sector/Industry		
IT/ITES	32	29.6
Banking	20	18.5
Consulting	14	13.0
FMCG	12	11.1
Telecom	9	8.3
Financial services	8	7.4
Others	13	12.0
Firm age (in years)		
<10	38	35.2
10–20	34	31.5
20–30	25	23.1
≥30	11	10.2
Employees (Number)		
<500	68	63.0
500–1500	23	21.3
≥1500	17	15.7
Capital (\$ million)		
<1000	59	54.6
1000–3000	38	35.2
≥3000	11	10.2
Generative AI adoption		
Yes	44	40.7
No	64	59.3
Period of generative AI adoption (Year)		
<1	38	86.4
≥1	6	13.6

employed.⁴⁶ As presented in Table 5, no evidence of multicollinearity was found among the independent variables, as indicated by the condition indices. These were less than the threshold level of 30 and the variance proportion was also below 90%.

The proposed model demonstrates a strong fit, as evidenced by the small value of the $-2LL$ ($-2\log$

likelihood) for the goodness of fit. Here the null model acts as a baseline for comparison (as it uses only the mean value of the dependent variable). The $-2LL$ value was 162.17 for the null model, while it was 76.94 for the research model having nine predictors. There was a decrease in the $-2LL$ value, as shown by the chi-square test, for the research model in comparison to the null model, indicating an improvement in model performance. Both Pseudo R^2 measures, Cox and Snell and Nagelkerke were 0.52 and 0.64 respectively and were found satisfactory. Further, the statistical tests also yielded significant results ($p < .001$), indicating the model's reliability and predictive power.

Table 6 demonstrates the reliability of the prediction model. It reveals that the model accurately predicted 84.1% of individuals who adopted generative AI and 90.3% of those who did not adopt generative AI, resulting in an overall accuracy rate of 87.2%. The research model's classification performance is indicated by the accuracy ratios exceeding the 50% threshold. This demonstrates the model's effectiveness in correctly identifying both generative AI adopters and non-adopters.

The Wald statistics was utilized to evaluate the support for the hypotheses by assessing the importance of the regression coefficients associated with the predicted variables.

Table 7 reveals that, at a significance level of 0.05, six factors were identified as significant predictors. These

Table 3. Outcomes of factor analysis and ∞ coefficients.

	AbC	OrS	TRP	ReS	Col	EnU	CX	CP	RIA
AbC1	0.77								
AbC2	0.72								
AbC3	0.78								
AbC4	0.83								
OrS1		0.81							
OrS2		0.79							
OrS3		0.82							
TRP1			0.82						
TRP2			0.78						
TRP3			0.74						
ReS1				0.53					
ReS2				0.76					
ReS3				0.73					
Col1					0.85				
Col2					0.71				
EnU1						0.83			
EnU2						0.69			
CX1							0.89		
CX2							0.84		
CP1								0.65	
CP2								0.78	
CP3								0.82	
CP4								0.85	
RIA1									0.77
RIA2									0.81
RIA3									0.59
∞ coefficient	0.79	0.87	0.84	0.72	0.76	0.73	0.88	0.85	0.72

ReS: Regulatory support; AbC: Absorptive capacity; TRP: Technological resource proficiency; RIA: Relative advantage; OrS: Organizational size; Col: Competition intensity; CX: Complexity; EnU: Environmental uncertainty; CP: Compatibility.

Table 4. List of independent variables and their means.

Independent variables	Generative AI Adopter	Generative AI Non-adopter	All
AbC	3.58	3.52	3.56
OrS	3.78	3.08	3.36
TeRC	3.34	3.16	3.24
ReS	3.21	3.75	3.54
Col	3.06	3.01	3.04
EnU	3.41	3.38	3.40
CX	2.39	3.22	2.86
CP	3.23	3.15	3.19
RIA	3.38	3.46	3.46

Table 5. Multicollinearity outcomes along with condition index.

	Variance proportion									Condition index
	AbC	OrS	TeRC	ReS	Col	EnU	CX	CP	RIA	
AbC	.00	.21	.03	.00	.02	.00	.03	.02	.00	5.40
OrS	.00	.16	.10	.00	.03	.16	.36	.03	.02	11.24
TeRC	.00	.02	.06	.00	.06	.31	.15	.11	.02	12.89
ReS	.01	.01	.12	.03	.71	.02	.07	.04	.03	14.21
Col	.10	.34	.11	.02	.01	.34	.02	.06	.00	14.16
EnU	.07	.04	.28	.01	.06	.02	.27	.02	.39	15.23
CX	.13	.21	.01	.00	.14	.00	.05	.42	.02	16.79
CP	.35	.02	.00	.78	.00	.23	.02	.17	.02	21.52
RIA	.31	.04	.45	.24	.05	.02	.07	.21	.54	23.27

ReS: Regulatory support; AbC: Absorptive capacity; TRP: Technological resource proficiency; RIA: Relative advantage; OrS: Organizational size; Col: Competition intensity; CX: Complexity; EnU: Environmental uncertainty; CP: Compatibility.

Table 6. Findings of the prediction model (with classification matrix).

Actual	Predicted		Correct (%)
	Generative AI Adopters	Generative AI Non-adopters	
Generative AI Adopters	36	9	80.0
Generative AI Non-adopters	8	55	87.3

Table 7. Wald statistics along with β coefficient outcomes given by logistic regression.

Predictor	Wald statistics	β coefficient
AbC	0.31	-.29
OrS	5.98	.59**
TeRC	0.05	.07
ReS	21.72	-3.52**
Col	4.07	.82*
EnU	2.71	.79*
CX	19.39	-2.63***
CP	3.82	1.08*
RIA	0.17	-.21

* $p < .05$, ** $p < .01$, *** $p < .001$, $n = 108$, generative AI adopters = 44.

factors include complexity, competition intensity, compatibility, environmental uncertainty, organizational size, and regulatory support. Among these factors, the regression coefficient signs indicate that the first four factors (compatibility, competition intensity, organizational size, and environmental uncertainty) were positively associated with the likelihood of organizational adoption of generative AI technology. On the other hand, the last two

factors (complexity and regulatory support) showed a negative relationship with the likelihood of adoption. However, the analysis determined that absorptive capacity, relative advantage, and technological resource proficiency were not statistically significant in distinguishing between the groups (generative AI adopters and non-adopters).

Discussion

The presented empirical findings highlight important factors within the TOE framework setting, which is utilized to comprehend the ground-breaking generative AI technology. Furthermore, it indicates that firms adopting generative AI should consider factors pertaining to internal organizational aspects along with the external environment, as well as the inherent characteristics of the technology itself.

Technology context

As mentioned earlier, it was found that complexity had a notably adverse impact on the adoption of generative AI. Implementing generative AI is indeed more challenging due to several factors, including the technology's relative immaturity, the absence of widely accepted standards, and the complexities involved in integrating generative AI with existing information systems and business processes. All these factors collectively serve as barriers to the widespread adoption of generative AI.

On the contrary, compatibility was discovered to have a significantly positive impact on to the decision of organizations to adopt and incorporate generative AI. When organizations have previous experiences with information systems that align with generative AI applications and are compatible with their existing information infrastructure, the introduction of generative AI adoption brings about changes that are consistent with current practices. This alignment leads to a positive impact, making the adoption of generative AI more likely and facilitating its integration in a favorable manner.

In present study, the concept of perceived relative advantage was not found as a significant differentiating factor. This finding aligns with previous research on innovation adoption, as supported by Grover³³ and other studies. A meta-analysis also concluded that the relative advantage of an innovation is not universally significant in determining its adoption.⁴⁷ This suggests that the perceived benefits or advantages of an innovation may not always be the primary driver for its adoption in every case. Although the perceived relative advantage was found to be a non-significant discriminator in this study, it is noteworthy that both generative AI adopters and non-adopters expressed relatively positive views regarding the benefits of adopting generative AI for their competitive advantage. The mean value relating to relative advantage for adopters was 3.38, while for non-adopters it was slightly higher at 3.46. This suggests that both categories of organizations recognize the potential advantages of integrating generative AI into their operations to enhance their competitive position.

Due to its relatively new and nascent stage of development, organizations may currently have limited confidence in the effectiveness and reliability of generative AI systems. The perception of insufficient technical capabilities within organizations can lead them to prioritize maintaining their existing systems instead of adopting new technologies. This aligns with the findings of Chau and Tam,⁴⁸ indicating that when organizations feel they lack the necessary technical capabilities, the relative advantage becomes a non-significant discriminator in the adoption decision. Based on the findings of this study, it appears that organizations give more weight to the potential problems or risks associated with generative AI technology, such as complexity, rather than the potential competitive advantages offered by generative AI systems, such as relative advantage. This suggests that organizations prioritize addressing the challenges and obstacles posed by generative AI before considering its potential benefits when making decisions regarding its adoption.

Organization context

The discovery regarding the size of organizations is logical and has become a crucial factor in determining the adoption of generative AI. Firms that embraced generative AI technology (at least initiated using generative AI for business purposes) were less concerned regarding expenses associated with acquisition, replacement, and ongoing costs. On the other hand, organizations that had not yet adopted this technology expressed greater concerns about these financial aspects. Generative AI adoption also faces obstacles in the form of expenses such as software and hardware costs, consultancy support costs, as well as the challenges related to installation and integration. Therefore, the adoption of generative AI is positively influenced by the size of a firm due to its larger resources, knowledge, and ability to leverage economies of scale.

Unexpectedly, the organizational traits of technological resource proficiency along with absorptive capacity could not have a substantial influence on the generative AI adoption. This outcome could be attributed to the emerging nature of generative AI technologies and the absence of established industry standards. Given this uncertainty and the need for more instances of organizational utilization and validation, firms may opt to adopt a “wait and see” approach, observing the development and trajectory of generative AI technology before making significant commitments. Therefore, during the early stage of generative AI development, the technological resource proficiency and absorptive capacity of firms are not significant factors in distinguishing the adoption of this technology.

Environment context

Contrary to the belief that businesses operating in regulatory-friendly environments are more inclined to adopt emerging generative AI technologies, the discovery of regulatory support unexpectedly hampers the adoption of such technologies, exerting a notably negative impact. Due to their inherent complexity and the need for extensive knowledge and intricate processing, the introduction and management of regulatory support often present greater challenges. As such, regulatory support can potentially foster the adoption of emerging generative AI technologies among organizations that possess higher levels of technological sophistication. Hence, further research is necessary before definitive conclusions can be reached.

Interestingly, it was discovered that environmental uncertainty had a decisive role in facilitating the adoption of generative AI. This could be attributed to the fact

that firms operating in environments characterized by higher levels of uncertainty in their relationships with trading partners tend to perceive more opportunities. As a result, they adopt a proactive approach, engage in greater innovation, and implement strategies to maintain a competitive edge compared to other firms.^{37,38}

The results regarding competition intensity reveal that majority of the firms that adopt generative AI technologies perceive noticeably higher levels of competitive pressure compared to non-adopter firms. Competition intensity, acting as a catalyst within the business environment, has a positive influence on firms, making them more receptive to generative AI technologies. When competitors begin implementing generative AI as a strategic advantage, it heightens the concerns of generative AI adopters regarding competitive differentiation, surpassing the level of concern among non-adopters.

Theoretical contributions

First, the study empirically validates the TOE framework as an appropriate and effective tool for understanding generative AI adoption in organizations, emphasizing its ability to investigate and consider relevant factors influencing innovation-adoption decisions. Six significant determinants of generative AI adoption are identified: compatibility, complexity, organizational size, regulatory support, environmental uncertainty, and competition intensity. This provides valuable insights into the factors that influence the adoption of generative AI and highlights their importance in decision-making processes.

Second, the study reveals that complexity and regulatory support act as barriers to the adoption of generative AI, while the remaining determinants (compatibility, environmental uncertainty, organizational size, and competition intensity) serve as enablers. This information can help organizations anticipate and address challenges and the factors they need to leverage to facilitate successful adoption.

Third, the study finds that absorptive capacity, relative advantage, and technological resource proficiency do not have a substantial impact on the adoption of generative AI. This challenges previous assumptions and highlights the need for organizations to focus on other determinants that have a more significant influence.

Fourth, the study highlights the importance of two previously underexplored determinants, namely environmental uncertainty and regulatory support, in the adoption of generative AI. These factors had received limited attention in previous research on technology

adoption, and their identification as significant determinants in the context of generative AI adoption fills a gap in the literature. This expands the understanding of the complex dynamics involved in the adoption of generative AI technologies.

Implications for practice

By identifying the determinants and their impact on generative AI adoption, the study provides practical implications for decision-makers. Organizations can use this information to assess their readiness for its adoption, identify potential barriers, and develop strategies to address them. They can also leverage the enablers to create a favorable environment for successful adoption.

Practitioners should focus on compatibility, addressing technical limitations, mitigating challenges, harnessing environmental uncertainty, and leveraging competition intensity to effectively adopt and integrate generative AI technologies within their organizations.

The perception of higher competitive pressure among firms that adopt generative AI can act as a catalyst for adoption. When competitors implement generative AI as a strategic advantage, it creates a heightened sense of concern among adopters regarding competitive differentiation. Managers should monitor the competitive landscape, analyze how generative AI can provide a competitive edge and help navigate uncertain relationships with trading partners, and leverage generative AI technologies strategically to respond to market demands.

The finding that regulatory support is a significant determinant of generative AI adoption has implications for policymakers and regulatory bodies. It emphasizes the importance of creating an enabling environment through supportive regulations and policies that foster the adoption of generative AI. Policymakers can use these findings to shape regulations that encourage the responsible and widespread adoption of generative AI technologies while addressing potential concerns.

Limitations and directions for future research

While this study has made valuable contributions, it is important to acknowledge its limitations, which in turn present prospects for future research. One of the limitations of this study is its reliance on data collected solely from Indian firms, which may restrict the generalizability of the findings to other regions or countries. This presents an opportunity for future research to explore the applicability and impact of the determinants of generative AI adoption in diverse geographical contexts.

A limitation of this study is that the sampling frame primarily focused on the top 300 firms in India. It is possible that these firms possess greater resources and capabilities, allowing them to afford investments in generative AI and take on associated risks. Consequently, the adoption rate of generative AI observed in the sample of this study may be more than what is representative of the broader landscape of Indian businesses. This highlights an opportunity for future research to explore the generative AI adoption patterns and challenges among a more diverse range of businesses. Hence, it is important to exercise caution while attempting to generalize the findings. The limitations mentioned earlier, such as the focus on limited number of firms and potential resource disparities, suggest that the findings may not fully represent the broader adoption trends and dynamics across the entire business landscape. To validate or refine the current model, it would be beneficial to collect samples from diverse geographies and/or industries.

To discover the predictors that differentiate between adopters (those who have initiated the use of generative AI for any business purpose) and non-adopters, this research utilized the logistic regression. This method specifically examines the individual relationship between the variables, both independent and the dependent one.⁴⁶ By employing logistic regression, the study aimed to uncover the specific factors that significantly influence the adoption of generative AI within the sample. As a result, the relationships among the independent variables themselves were not explored in detail. The aim was to determine the individual influence and significance of each independent variable in predicting generative AI adoption. However, future research could explore the interrelationships among the independent variables to gain a more comprehensive understanding of their combined effects on generative AI adoption. Future research can adopt a comprehensive approach by simultaneously examining multiple relationships within a predictive model. By doing so, scholars can explore the causality and interrelationships among the predictors.

Conclusion

Despite its potential to offer strategic, operational, and various other benefits, generative AI, an emerging technology, has not yet experienced substantial levels of adoption in organizations across surveyed industries. Due to a lack of recent focused research on generative AI and its organizational adoption determinants, present study aims to bridge this gap by introducing and validating a research model. The study draws upon the institutional theory, diffusion of innovation theory, and the TOE framework to

explore the leading factors affecting the generative AI adoption across industries. Through both academic knowledge and practical insights, this study contributes to the understanding of generative AI adoption by uncovering significant determinants, differentiating enablers and barriers, challenging non-significant determinants, and shedding light on previously underexplored factors. The findings offer valuable insights for organizations looking to adopt generative AI technologies and inform decision-making processes in this domain.

Disclosure statement

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