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Overcoming barriers and seizing opportunities in the innovative adoption of next-generation digital technologies

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ABSTRACT

In a world increasingly driven by digital transformation, emerging technologies such as blockchain, artificial intelligence, and the metaverse hold great promise for economic and social progress. However, their widespread adoption is influenced by various factors that can either hinder or facilitate this process. This study aims to investigate the key factors affecting the adoption of next-generation digital technologies and determine whether these factors act as barriers or opportunities. By integrating diffusion of innovations (DOI) theory and institutional theory, we develop a new analytical framework to examine these influences. Utilising a two-factor fixed effects model, we analyse panel data from 116 countries from 2019 to 2022. Our analysis identifies key barriers, such as privacy concerns, illiteracy, and limited economic accessibility, and highlights opportunities provided by supportive regulatory environments and proactive government initiatives. The findings provide a nuanced understanding of the conditions necessary for the successful adoption of digital technologies, offering actionable insights for policymakers and stakeholders aiming to foster a conducive environment for technological advancement.

Introduction

Positioned as a significant milestone within the realm of digital transformation, Industry 4.0 underscores the substantial influence exerted by digital technology on the operational frameworks of conventional industries (Sung, 2018; Castelo-Branco et al., 2023). From automation and the Internet of Things (IoT)[1] to the integration and application of cloud computing and other technologies, Industry 4.0 realises intelligent, flexible and efficient production (Majid et al., 2022; Chi et al., 2023). Specifically, in light of the ongoing ascension of next-generation digital technologies, including blockchain (Aoun et al., 2021; Li et al., 2021b), artificial intelligence (AI) (Lyu & Liu, 2021; Nafizah et al., 2024), and the metaverse (Wang et al., 2023), societies and organisations are confronted with increasingly extensive and pervasive transformations (Skare et al., 2023; Cheng et al., 2024).

Blockchain is gradually changing the traditional way of managing and transacting data (Yang, 2019). The decentralised nature of blockchain and the temper-proof ledger make information transactions more secure and transparent, helping to break down information silos and improve the efficiency of data sharing (Gao et al., 2020), which is significant in the fields of finance, logistics, and healthcare. For example, in supply chain management, the use of blockchain technology can track the flow of goods and prevent counterfeit and shoddy products (Kshetri, 2018). In the financial field, blockchain technology can establish a more secure payment system and reduce transaction costs (Sonmez et al., 2022). Moreover, blockchain technology is also driving changes in the way societies and organisations collaborate and govern. The emergence of smart contracts has made the execution of agreements more efficient while also helping reduce the cost of trust (Hewa et al., 2021). In addition, blockchain technology provides the basis for the rise of decentralised autonomous organisations (DAOs), changing the traditional organisational structure and operation mode (Shahaab et al., 2021).

Beyond the changes triggered by blockchain technology, AI,

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[1] The Internet of Things (IoT) refers to the connection of any object to a network through information sensing devices, according to an agreed protocol, and the exchange of information and communication of objects through the medium of information dissemination to realise the functions of intelligent identification, positioning, tracking and supervision.

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distinguished by its powerful data processing and sophisticated decision-making proficiencies, has emerged as one of the key engines driving the digital revolution. McKinsey & Company (2018) noted that the present trajectory of AI technology uptake alone has the potential to engender an economic impact of approximately $13 trillion on a global scale by the year 2030. Through machine learning and data analysis, AI can quickly extract useful information from massive amounts of data to help companies make more informed decisions (Metcalf et al., 2019). In the medical field, AI performs well in enhancing diagnostic processes (Soto et al., 2021; Schwamm and Silva, 2023), facilitating drug discovery (You et al., 2022), and increasing health care benchmarks (Fakotakis et al., 2023). In finance, AI has been applied in risk evaluation (Kong et al., 2024), transaction scrutiny, and other areas to increase the efficacy and resilience of finance ecosystems (Guidici et al., 2024). When integrated with sensors, geo-location systems, robotics, and other technologies, AI can be applied in diverse domains, including speech recognition (Duan et al., 2021), customer service (Prentic & Nguyen, 2020), computer vision (Kim et al., 2023), supply chains (Widder & Nafus, 2023), weather forecasting (Ebert-Uphoff & Hilburn, 2023), and anomaly detection (Jiang et al., 2023a). Leveraging techniques such as deep learning and neural networks, generative AI has the capacity to emulate human creativity (Dwivedi et al., 2022, 2023). It can create textual, visual, auditory, and various content mediums that exhibit significant promise across diverse sectors, including education, healthcare, entertainment and beyond (Aldausari et al., 2023; Preiksaitis & Rose, 2023).

As technologies such as blockchain, AI and other cutting-edge innovations continue to advance and be applied, the concept of the metaverse has emerged. It is a convergence of many existing technologies, including 5th generation mobile communication technology (5G) ,[2] cloud computing, AI, virtual reality, blockchain, digital currency, the IoT, and human–computer interactions (Lim et al., 2023). This convergence has gradually caught the attention of the community and led to an interest in the emerging metaverse (Xu et al., 2023b). The metaverse creates a virtual digital world for people, allowing them to engage in all kinds of communication (Oh et al., 2023), creation and interaction through their virtual identities (Aung et al., 2024). The metaverse further changes the way people live and interact socially, expanding the boundaries of the digital space and bringing new experiences and possibilities to education, entertainment, socialisation and other fields (Zhang et al., 2022; Tlili et al., 2023).

With digitalisation, conventional industries and businesses are undergoing a redefinition process, leading to significant transformations in the overall social framework (Blanka et al., 2022). The implementation of digital technology has introduced more streamlined production methodologies and enhanced avenues for information retrieval (Yi et al., 2023). However, such technological advances have created a series of challenges. First, as technology becomes more deeply integrated into all aspects of life, security risks, such as data breaches, privacy violations and cyberattacks, become increasingly acute (Wang et al., 2019). Second, these technologies place greater demands on the ability and literacy of users, requiring not only technical operational skills but also an in-depth understanding of areas such as data analysis and cybersecurity (Reddy et al., 2022). In addition, high technology adoption (Sharma et al., 2023) and maintenance costs may become difficult thresholds for small businesses or low-income groups to cross, exacerbating the problem of the digital divide (Reddick et al., 2020). The construction of a regulatory environment and the exemplary role of the government are not only means to address the problems that arise in the process of technology adoption but also key opportunities to promote the widespread use of technology and the transformation of society. By actively building a regulatory environment that protects user interests and data security while encouraging technological innovation and application, it can provide a clear direction and reliable guarantee for technological development (Zhang et al., 2023). Through government demonstration applications, public confidence and acceptance of new technologies can be enhanced while providing enterprises with opportunities for cooperation and pilot projects (Hwang et al., 2022).

Consequently, focusing on the adoption of digital technologies entails not only capitalising on opportunities but also remaining vigilant against challenges. However, most of the existing studies have focused on the impediments to the use of digital technologies by individuals or firms (Chang et al., 2020; Valencia-Arias et al., 2023; Al-Adwan et al., 2023; Ahmad Almagrashi et al., 2023; Antsipava et al., 2024), and there is a lack of global empirical research on the simultaneous consideration of opportunities and challenges. Additionally, in the existing studies on technology or innovation diffusion and adoption, there are several common theoretical foundations, such as the technology acceptance model (TAM) (Davis et al., 1989), the theory of planned behaviour (TPB) (Ajzen, 2020), the unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003), diffusion of innovations (DOI) theory (Rogers, 1995) and institutional theory (DiMaggio & Powell, 1983). However, most of the studies based on these theories are related to individual choices (Chang et al., 2020; Lim & Zhang, 2022; Al-Adwan et al., 2023; Chen, 2023; Scur et al., 2023). Institutional theory usually focuses on a stable institutional environment and fails to adequately account for the rapid changes and uncertainties that can occur in the process of technology adoption. Therefore, to study more systematically the factors affecting the adoption of next-generation digital technologies at the national level, we integrate DOI theory and institutional theory to construct a research framework. We summarise three dimensions (i.e., basic conditions, risks and supportive environments) and further explore the impact of five specific factors (i.e., illiteracy, unaffordability, privacy and security risks, regulatory environment and governmental leadership). On the basis of these factors, we discuss the barriers and opportunities that may hinder or facilitate the adoption of the next generation of digital technologies. This study thus provides a reference for countries to better seize opportunities and overcome the barriers to the adoption of digital technologies. We compile relevant country-level indicators from 2019 to 2022 for 116 countries and build panel regression models. Through a battery of statistical tests, we employ a two-factor fixed effects model to explore the influence of each factor on the adoption of digital technologies.

Specifically, the main contributions of this paper are summarised as follows: (1) This study provides a comprehensive analysis of the opportunities and barriers to adopting next-generation digital technologies from a macro perspective. By examining a diverse set of 116 countries, we highlight the global trends and challenges in digital technology adoption, offering valuable insights into how different national contexts influence this process. (2) We innovatively combine concepts from DOI theory and institutional theory to identify three key dimensions that affect digital technology adoption at the national level. This integration not only provides a novel theoretical framework for understanding technology adoption in a macro context but also bridges gaps between these two theories, contributing to the broader literature on technology diffusion and institutional impacts. (3) This study employs a robust two-factor fixed effects model to empirically assess the impact of identified opportunities and barriers on digital technology adoption across 116 countries. This methodological approach allows for the control of unobserved heterogeneity and provides more accurate estimates of the factors influencing adoption rates, thereby enhancing the reliability and validity of the findings. (4) On the basis of the empirical results, we provide actionable policy recommendations aimed at overcoming barriers and leveraging opportunities for the adoption of next-generation digital technologies. These recommendations are designed to guide

[2] The 5th generation mobile communication technology (5G) is a new generation of broadband mobile communication technology characterised by high speed, low latency and large connectivity, and 5G communication facilities are the network infrastructure for realising the interconnection of people, machines and things.

policymakers and stakeholders in formulating strategies that promote digital inclusion and foster technological advancement at the national level.

The remainder of the paper is organised as follows: Section 2 reviews the existing literature on barriers to and opportunities for the adoption of digital technologies and proposes several hypotheses. Section 3 reviews the relevant theories and constructs the theoretical framework of this paper. In Section 4, the specification of the empirical model, the definitions of the variables and the statistical characteristics are described in detail. Section 5 analyses the regression results and performs robustness tests and heterogeneity analysis. On the basis of the empirical results, we provide further interpretations and implications in Section 6. Finally, Section 7 summarises the work of this paper and provides some policy recommendations.

Literature review

Barriers to and opportunities for the adoption of next-generation digital technologies are crucial factors that shape the digital transformation landscape (Kutnjak & Pihir, 2019).

Challenges in adopting digital technologies

Digital technologies have made significant strides in improving productivity and driving social change. However, their effective adoption is impeded by some barriers, such as privacy and security risks, limited digital literacy skills and insufficient affordability.

Privacy and security risks

Social media provides an open platform for online users, enabling them to develop networks. The latest Datareportal (2023) survey showed that there are currently 5.16 billion Internet users and 4.76 billion social media users worldwide, representing 59.4% of the world's total population. The growing accessibility of personal data and widespread information dissemination pose escalating threats to individual privacy (Stewart, 2023). On social media platforms, users inadvertently share a vast amount of personal information, including identity particulars, location data, and daily activities, which may increase their vulnerability to unauthorised exposure or mishandling (Such & Criado, 2018). Moreover, the advancement of novel digital technologies has made data management, storage, sharing and utilisation more complex.

On a theoretical level, privacy protection and data security are key determinants of digital technology adoption. According to privacy computing theory, users' concerns about privacy protection when digital technologies are used directly affect their technology adoption behaviours (Zhang et al., 2024). Especially in the case of technology applications involving sensitive personal data, privacy and security risk concerns tend to be the main barriers to users' reluctance to adopt (Xu et al., 2023a). For example, Islam et al. (2021) noted that IoT technology has expanded the collection of personal data through household and wearable devices, heightening the risks to privacy if robust safeguards are not in place. Cui et al. (2022) noted that technology enables both private companies and public agencies to utilise data from personal wearables to control their activities on an unprecedented scale. However, owing to the inherent openness of wearable devices, they are limited by the network, terminal resources and technology, which hinders the design of security and privacy protection programs for wearable devices and networks (Alsubaei et al., 2018). Moreover, users' concerns about data leaks and misuse reduce their acceptance of new technologies. Although the decentralised nature of blockchain technology is seen as an advantage in enhancing data security, practical applications still face privacy protection challenges, which limit its widespread adoption in areas such as finance and healthcare (Soltanisehat et al., 2023). Chen et al. (2023) reported that almost all blockchain-based data sharing models suffer from the difficulty of protecting the privacy and integrity of uses' data, as well as their data ownership. Gao et al. (2020) noted that the open network and publicly stored data of blockchain pose serious risks of data theft and user privacy leakage, which has become a core issue that restricts blockchain technology from becoming practical. AI systems usually require large amounts of data for training and learning, and there is a potential for data privacy to be abused or illegally accessed (Ellahham et al., 2020). Chen et al. (2023) noted that privacy-related anxieties can significantly impede the acceptance and utilisation of digital health innovations.

Digital technology adoption also faces multiple challenges, such as data integrity, authentication and intellectual property (Todorov & Lutfiu, 2023). Data integrity concerns how to ensure that data are not tampered with or corrupted during transmission. Authentication confirms the identity of the user to prevent impressions and fraud (Awuson-David et al., 2019). In particular, with the advent of generative AI, ethical considerations around generating content, potential bias, and intellectual property will be new anxieties (Khatun et al., 2023). Therefore, ensuring information security is essential for safeguarding uses' rights and interests, protecting data security, and increasing digital technology adoption. To this end, we propose the following hypothesis:

H1: Privacy security risks have a negative impact on the adoption of digital technologies.

Digital illiteracy

States and societies are becoming increasingly knowledge- and information technology-intensive. Information technology-based learning will become a key factor affecting the digital divide between people, thereby affecting the well-being of countries and societies at large (Wei et al., 2011). Fossen & Sorgner (2022) noted that learning ability and digital literacy are important abilities for individuals to adapt to a digital society. Digital literacy is a basic ability necessary for individuals to participate in social, economic and cultural activities in the context of the information explosion of the twenty-first century (Dorozhkin & Chemoskutova, 2020; Jang et al., 2021). It involves not only basic computer operating skills but also more complex competencies, such as the identification, evaluation, utilisation and creation of information (Reddy et al., 2022). According to Wang & Luan (2022), the lack of digital literacy has become a key factor limiting the widespread adoption of digital technologies, especially in terms of education, employment and social participation, with obvious negative consequences. Individuals who lack digital literacy often have difficulty judging the authenticity and reliability of information when confronted with vast amounts of information (Svyrydenko & Terepyshchyi, 2020). Jiang et al. (2023b) noted that the level of information searching skills of Internet users directly affects the quality of the information they obtain. Digital technology adoption is not just about purchasing or being exposed to new technologies but also about being able to use them effectively. According to the (TAM) and the extended TAM, a user's perceived ease of use and usefulness of a new technology directly affects their willingness to adopt it (Davis, 1989; Venkatesh & Davis, 2000). The presence of digital illiteracy reduces users' ability to understand and operate new technologies, leading to lower perceived ease of use and thus inhibiting adoption (Hamad et al., 2021). For example, in the application of complex technologies such as AI and blockchain, digitally illiterate users often struggle to understand the basic concepts and operational processes of the technology, which makes their acceptance of these technologies significantly lower.

Some empirical studies have also revealed that in developing countries, despite the increasing penetration of smartphones and the internet, many people still face significant barriers to using digital technologies due to their lack of basic digital skills (Zheng et al., 2020). ScheeL et al. (2022) noted that individuals with learning deficits have difficulty updating their knowledge base in a timely manner, leading to a lag in the technologies and methods they use. Nikou et al. (2022) also reported that individuals with an insufficient learning ability may not be able to fully grasp and utilise the full capabilities of these technologies, even if they adopt them. A typical example is that with the increasing popularity of remote work, for employees who are unable to quickly learn and adapt to telecommuting software, their productivity and ability to collaborate as a team may plummet, which in turn affects the efficiency of the organisation as a whole (Kohn et al., 2023). In some rural areas of Africa and South Asia, high rates of digital illiteracy have led to relatively low adoption of new technologies such as mobile payments and e-commerce. Similarly, among older populations, high rates of digital illiteracy limit the diffusion of health management applications and online services (Mbunge et al., 2024). In these contexts, digital illiteracy not only affects individual technology adoption decisions but can also lead to wider social exclusion and economic inequality, hindering the digital transformation of society as a whole. To this end, we propose the following hypothesis:

H2: Digital illiteracy has a negative impact on the adoption of digital technologies.

Limited affordability

Affordable access to broadband services enables individuals to enjoy the benefits of digital connectivity and allows businesses to thrive in the digital economy (Policy Brief, 2022). In 2022, the International Telecommunication Union (ITU) estimated that although the majority of the world's population (95%) is covered by mobile broadband networks, every third person on the planet is offline (ITU, 2022). In many developing countries, the cost of mobile data can exceed the normal reach of individuals (Statista, 2022). A World Bank study in 11 emerging countries revealed that 48 percent of respondents have difficulty servicing their mobile data usage and that 42 percent limit the amount of data they use (World Bank, 2021). Habib et al. (2023) noted that high data prices relative to income levels are a major barrier to accessing digital services and information. According to rational choice theory (RCT), individuals weigh the potential benefits and costs of technology when making technology adoption decisions (Becker, 1993). For users with a limited ability to pay, high initial costs and ongoing maintenance costs can significantly reduce their willingness to adopt new technologies. In addition, the TAM has shown that users' perceived usefulness and perceived ease of use directly influence their technology adoption decisions (Davis, 1989). When the ability to pay is limited, users' perceived ease of use and availability of a new technology decreases, thus reducing the likelihood of adoption.

Several existing empirical studies have also discussed the impact of a limited ability to pay on technology adoption. According to Ayanso & Lertwachara (2015), a lack of access to affordable mobile data has reduced the use of digital technologies such as mobile apps, online services and e-commerce platforms. This, in turn, limits the opportunities for education, healthcare and economic empowerment that they can enhance. Reddick et al. (2020) noted that without affordable access to mobile data, individuals, organisations and society as a whole will be unable to realise the full potential of digital tools for personal and professional development, and organisational improvement and social progress will be difficult to achieve. Sandhu (2022) noted that in big data analytics and cloud computing applications, which require the storage and processing of large amounts of data, the inability of individuals or enterprises to afford expensive cloud services limits their ability to participate in relevant fields. Owing to low economic levels and limited social resources, many people find it difficult to afford the high cost of communications, equipment and digital services, especially in some developing countries or regions (World Bank, 2021). This has limited the diffusion of digital technologies, leading to the exacerbation of the digital divide. In addition, tax policies also have a direct effect on affordability. Excessive taxation increases the prices of digital products and services, adding to the burden on customers (Guo et al., 2022). A heavy tax burden on the digital industry discourages research and innovative activities by enterprises, reducing the affordability of digital technologies.

Furthermore, a limited ability to pay not only directly affects the adoption decisions of individuals or households towards the new generation of digital technologies but also may negatively affect technology investments by businesses and government agencies. Among small and medium-sized enterprises (SMEs), limited funds and resources make it difficult for them to afford the high cost of technology required for digital transformation, thus limiting innovation and competitiveness (Babilla, 2023). Similarly, when governments promote digital infrastructure development, they may find it difficult to provide adequate financial support due to financial constraints, leading to a slowdown in the process of technology diffusion (The et al., 2024). To this end, we propose the following hypothesis:

H3: Digital unaffordability has a negative impact on the adoption of digital technologies.

Opportunities facilitated by digital technologies

The new generation of digital technologies is bringing great opportunities to the fields of business, health care and agriculture, as well as to society as a whole. However, to realise the full potential of these technologies, a good regulatory environment and sound governmental leadership are indispensable.

Changes in three representative industries

The rapid development of digital technologies is bringing unprecedented opportunities for various aspects, driving economic growth, social progress and technological innovation.

For businesses, these technologies enable data-driven decision-making, personalised marketing, and improved operational efficiency. Karagozlu et al. (2020) noted that cloud computing provides scalable and cost-effective solutions for organisations to store, process and access data and applications over the internet, enabling them to align resources with changing needs. Hadded & Hamrouni (2022) also noted that cloud-based services facilitate seamless collaboration and communication between remote teams, allowing for increased productivity and workflow efficiency. In customer service, AI-powered chatbots and virtual assistants can improve response times and resolution rates, leading to increased overall customer satisfaction (Hsu & Lin, 2023). By analysing large datasets, AI can also predict customer behaviour and preferences, making it possible for personalised recommendations and targeted marketing campaigns (Chiu & Chuang, 2021). Additionally, the tokenisation of blockchain allows for partial ownership of assets, facilitating crowdfunding and investment opportunities. Mahjoub et al. (2022) asserted that this democratisation of capital markets opens new avenues for funding and investment, especially for startups and SMEs seeking alternative finance solutions. Moreover, according to Firmansyah & Umar (2023), the metaverse can provide immersive and interactive virtual environments for business activities where users can socialise, collaborate and transact with each other.

In healthcare, using historical data and machine learning algorithms, healthcare providers can predict disease progression, identify at-risk populations, and implement preventive interventions (Abraham et al., 2022). Cloud-based electronic health record (EHR) systems enable healthcare providers to access patient information remotely, improving the coordination and continuity of care between different healthcare organisations (Joshi et al., 2018). Cloud-enabled telemedicine allows remote consultations, remote monitoring, and telehealth intervention, especially in underserved and rural areas, where patients can access healthcare services at home (Li et al., 2021a). The metaverse can facilitate virtual consultation, medical simulation and training environments for healthcare professionals. Virtual reality (VR) and augmented reality (AR) technologies achieve immersive and interactive experiences, allowing healthcare providers to conduct virtual consultations and examinations, remotely monitor patients' vital signs, and perform virtual surgeries in a simulated environment (Kanschik et al., 2023; Twamley et al., 2024).

In the agricultural sector, digital technologies facilitate precision agriculture, crop monitoring and supply chain optimisation (Kim & Heo, 2024). Technologies such as global positioning systems (GPSs), IoT sensors and drones are being used to optimise agricultural practices and resource management. Machine learning algorithms can process data from a variety of sources, including weather forecasts, soil surveys and historical crop yields (Ragunath et al., 2022). Supply chain optimisation technology improves transparency, traceability and efficiency across the agricultural supply chain (Kamble et al., 2020). Blockchain technology provides end-to-end traceability of produce from farm to fork by recording every transaction and movement on an immutable ledger (Torky & Hassanein, 2020). Consumers can verify the authenticity and origin of produce, which in turn ensures food safety and quality.

Regulatory environment

Next-generation digital technologies present significant opportunities and transformations for a number of representative industries, but the key to realising the full potential of these technologies is to facilitate their widespread adoption. A good regulatory environment can provide a clear legal framework and data protection standards to reduce risks and uncertainties in the application of technology (Zhang et al., 2023). This includes not only direct regulation of technology adoption, such as regulations to ensure data security and protect consumer privacy but also policies that provide support for technological innovation. Good regulation not only boosts the confidence of market participants in new technologies but also provides an equal playing field for all businesses by ensuring fair competition (Yakubi, 2022).

For example, clear privacy protection regulations and data security standards can enhance business and consumer trust in technologies such as digital payments, e-commerce and big data analytics. In the United States and Europe, strict data protection laws (e.g., GDPR) not only safeguard consumers' privacy but also motivate businesses to pay more attention to data security and compliance, which promotes the innovative application of technology and healthy development of the market (Woerle & Gstrein, 2024). Therefore, a good regulatory environment provides a solid foundation for the commercial application of digital technologies and encourages more enterprises to invest in the development and application of new technologies, thereby promoting economic growth and innovation.

Clear regulations and standards can help healthcare organisations and technology providers standardise their operations and facilitate the diffusion of digital health technologies such as electronic medical records, telemedicine, and AI diagnostic systems. In the UK, the government has established standardised requirements for EHRs through the Health and Social Care Act, which has promoted the nationwide diffusion of EHRs and improved the efficiency and quality of healthcare services (Bach-Mortensen et al., 2024). This favourable regulatory environment has reduced compliance costs for healthcare organisations and increased technology acceptance and adoption.

Reasonable environmental regulations and data protection policies provide legal safeguards for farmers and agribusinesses to use drones, sensor networks, and blockchain technologies for precision management and supply chain optimisation. For example, in the European Union, regulations related to agricultural data sharing and management have facilitated transnational agricultural cooperation and data sharing and provided support for agri-tech enterprises to develop markets (Ibrahim & Truby, 2023). Therefore, a good regulatory environment not only promotes the application of new-generation digital technologies in agriculture but also promotes the development of sustainable agriculture. Thus, we propose the following hypothesis:

H4: A good regulatory environment has a positive impact on digital technology adoption.

Governmental leadership

In addition to the impact of the regulatory environment on the adoption of next-generation digital technologies, governmental leadership plays an important role. Sound governmental leadership can promote the popularisation and deepening of new technologies through strategic planning, policy support and financial incentives.

For example, by providing financial support, tax incentives and technical training, the government can help SMEs overcome cost barriers to technological transformation and enhance the digitalisation of their enterprises. In Singapore, the government has provided a series of financial incentives and policy support through the Smart Nation Program to encourage enterprises to adopt AI and big data technologies for business model innovation and efficiency improvement (Woods et al., 2024). This strong government guidance not only promotes the popularisation of technology but also enhances the overall competitiveness of the country.

By establishing demonstration programs, providing financial support, and setting industry standards, governments can effectively lower the barriers to the adoption of new technologies by healthcare organisations. In the United States, the government has promoted the adoption of electronic health records through the Health Information Technology for Economic and Clinical Health (HITECH) Act, which has improved the efficiency of healthcare services and patient health outcomes (Bohn & Schiereck, 2023). This policy guidance and support has accelerated the process of digital transformation in healthcare and created favourable conditions for the spread of new technologies.

Through subsidies and project funding, governments can encourage farmers and agribusinesses to adopt advanced technologies such as drone monitoring, smart irrigation, and agricultural product traceability systems. In Israel, the government has promoted the widespread adoption of precision agriculture technologies by supporting agri-tech startups and research institutes, significantly improving agricultural productivity and water management efficiency (Shani, 2024). This strong policy guidance not only promotes the modernisation of agriculture but also the development of the rural economy.

On the basis of the above discussion, we believe that sound governmental leadership has effectively lowered the threshold for the adoption of next-generation digital technologies through policy support, financial assistance and demonstration projects and has promoted the widespread application of these technologies in various fields. Thus, we propose the following hypothesis:

H5: Sound governmental leadership has a positive impact on the adoption of digital technologies.

Theoretical gaps

To delve into the factors affecting technology adoption, as mentioned earlier, this section analyses and discusses these factors from a theoretical level. First, we introduce two existing theories.

Diffusion of innovations (DOI) theory

Diffusion of innovations (DOI) theory is an important theory in sociology that involves four key elements, i.e., innovation, communication channels, time, and social systems (Rogers, 1995). Innovation has five characteristics that have a direct effect on the willingness and speed with which an individual or organisation adopts a new technology. A comparative advantage is the improvement that an innovation may bring to an individual or business. Compatibility is the level of affinity of the innovation with existing values and needs. Complexity is the level of difficulty in understanding or using the innovation. Trialability describes how easily an innovation can be tested. Observability is the degree to which the innovation is visible to others (Martins et al., 2016). Communication channels serve as a medium for innovation diffusion, either directly between individuals or through the media. The time factor relates to the adoption process of the innovation, the length of time it takes the innovator to make a decision, and the rate at which it spreads through the social system (Rogers, 1995). The content of social systems, such as social norms, cultural values, social networks, and the influence of leadership, can also have an impact on the diffusion and adoption of technology.

DOI theory is widely used in digital technology research to explain the adoption of technologies such as IoT, AI, blockchain, and the metaverse. For example, Saylam & Ozdemir (2022) integrated the TAM and DOI theory to analyse the military's acceptance of the IoT, revealing that risk factors do not seem to have a significant effect on IoT acceptance and that there seems to be a positive correlation between risk and trust, contrary to the expected negative correlation. Al-Dhaen et al. (2023) utilised DOI theory to consider the risks and complexities involved in using AI and reported that despite the contradictions of AI, sustained willingness-to-use behaviour can be predicted during the diffusion of IoT technologies. Xu et al. (2023) extended DOI theory to consider technological threats and examined the adoption of AI in the workplace from a dynamic, differential effects perspective, finding an association between the threat of AI (i.e., concerns about job security) and employees' increasingly negative attitudes towards adopting AI over time. Kumar et al. (2024) used DOI theory to study the adoption intention behaviour of enterprise metadata, and the results revealed that the dimensions of DOI theory are closely related to the use intention of enterprise metadata.

On the basis of the above discussion, we find that DOI theory provides an important perspective for understanding technology adoption in individuals and organisations, but its role in explaining technology adoption at the national level has not been sufficiently discussed in the existing literature.

Institutional theory

Institutional theory is an important theoretical framework in organisation studies that is used to explain how organisations operate and develop in an institutional environment. The theory focuses on how formal laws and regulations, informal social norms, and cultural perceptions influence organisational behaviour and decision-making (DiMaggio & Powell, 1983). Scott (1987) further extended institutional theory by proposing three pillars of the institutional environment: the normative pillar, the cognitive pillar, and the regulatory pillar. The role of the normative pillar in technology adoption is reflected in social norms and industry standards. For example, Zhang et al. (2024a) explored the role of individual cultural values in the adoption of socially sustainable supply chain management (SSCM) by Chinese suppliers facing normative institutional pressures on guanxi, emphasising the dominant role of guanxi in improving SSCM practices due to its normative institutional power. The cognitive pillar reflects how cultural perceptions and collective beliefs influence the technology adoption process. The regulatory pillar is concerned primarily with the mandatory requirements of laws, regulations, and policies for technology adoption. Zhao et al. (2023) utilised institutional theory, social network theory and survey data from 689 female micro e-commerce entrepreneurs in China to explore the impact of the institutional environment on entrepreneurial performance, and the results revealed that the institutional environment (including both regulatory and cognitive dimensions) has a significant positive impact on entrepreneurial performance.

Institutional theory has also been used in a wide range of different fields and contexts. Zhang et al. (2023) studied a sample of 236 traditional manufacturing firms on the basis of institutional theory and showed that the institutional environment affects the association between digital technology adoption and business model innovation and that policy support strengthens the impact of digital technology adoption on strategic flexibility. Bennich (2024) conducted a study on digitisation in the water industry[3] and reported that water companies face institutional pressures to digitise, which in turn affects how they respond to digitisation. In addition, institutional theory is applied when discussing the development of specific emerging digital technologies. Nahar (2024) simulated system dynamics modelling with institutional theory to make predictions about innovation in AI from 2022 to 2030. Allen et al. (2020) noted that a policy environment conducive to the adoption and use of blockchain technology can trigger entrepreneurial experimentation in institutional forms. Drawing on institutional theory, Lin et al. (2023) explored how various institutional forces influence stakeholder adoption of blockchain and metaverse technologies.

Institutional theory explains the impact of the external institutional environment on technology adoption, which provides important insights into the factors that influence technology adoption. However, it does not contain elements that go beyond institutional pressures (Martins et al., 2016).

Limitations of existing theories

On the basis of the above discussion, we find that there are several limitations to the existing single theories. DOI theory focuses on how technology diffuses at the individual or organisational level, emphasising the influence of the characteristics of technology adopters and social networks on technology diffusion. However, it has several limitations in analysing technology adoption at the macro level. It usually ignores the institutional environment, policy factors, and country-level influences that play crucial roles in the global technology adoption process. Institutional theory, which emphasises that organisational behaviour is influenced by the external environment, regulations, and social norms, is useful in understanding technology adoption at the organisational and industry levels. However, the theory often lacks a focus on the process of technological innovation, especially given the dynamic nature of technology diffusion and the early stages of innovation. It usually focuses on stable institutional environments and fails to adequately consider the rapid changes and uncertainties that can occur in the process of technology adoption.

Owing to the limitations of the above theories, fully explaining the global adoption process of next-generation digital technologies by using DOI theory or institutional theory alone is difficult. At the macro level, the adoption of digital technologies is not only influenced by the characteristics of the technology itself and social networks but also closely related to the policies, legal environment, economic conditions and cultural background of each country. Therefore, relying on a single theory alone is not sufficient to provide a complete explanatory framework.

Therefore, this paper combines DOI theory and institutional theory, which synthesise the effects of basic conditions, risks, and supportive environments on the adoption of digital technologies.

Theoretical framework

This section describes the integration of DOI theory and institutional theory to present an integrated framework for a more comprehensive and systematic analysis of the factors that influence technology adoption at the national level. This framework contains three main dimensions: basic conditions, risks, and supportive environments. Specific factors related to the five hypotheses are then incorporated into this baseline framework to reveal how they work together to influence technology adoption at the national level.

[3] "Digitisation in the water industry" refers to the integration of digital tools and technologies—such as advanced data analytics, sensors, and automated systems—into water management processes.

Theory integration

In accordance with the characteristics of DOI theory, this paper summarises the following aspects that influence the adoption of emerging digital technologies at the national level. (1) We use public literacy and affordability to indirectly reflect the complexity and compatibility of the new generation of digital technologies and consider these two factors related to the public to be fundamental conditions that influence the adoption of emerging digital technologies in the country as a whole. (2) Effective communication channels are an important aspect in driving digital technology adoption at the national level. Government departments, the media, educational institutions, and social groups can serve as mediums for information dissemination, and the spread of the internet and mobile communications provides channels for the diffusion of new technologies. (3) Technology adoption is a process that evolves over time. From early exploration to full implementation, the process involves multiple stages of strategy development, technology testing, policy adjustment and public education. (4) Social system characteristics at the national level, such as the policy environment, level of economic development, cultural values, education levels, laws and regulations, all have an impact on the adoption of digital technologies.

We apply institutional theory to explore the factors influencing digital technology adoption at the national level, focusing primarily on the institutional environment, including policies, laws, and education. Governments can promote the development and adoption of digital technologies by formulating favourable policies and regulations. Laws and regulations (e.g., data protection laws and electronic transaction laws) provide a legal framework and a foundation of trust for the adoption of digital technologies. The level of the education system and human capital underpin the adoption and development of digital technologies in a country. A high-quality education system can produce the necessary technical and managerial talent to support the development of the digital economy. Institutional changes at the national level, including changes in political, economic and social systems, provide the impetus and conditions for the innovation and adoption of digital technologies.

Theoretical framework

On the basis of the discussions in Sections 2.3 and 3.1, we believe that DOI focuses on the intrinsic characteristics of technology and the level of technological knowledge of individuals, whereas institutional theory emphasises the influence of social and institutional environments on the behaviours of individuals and organisations. This paper summarises the intrinsic capabilities and external conditions of individuals and organisations as the *basic conditions* for digital technology adoption. DOI theory emphasises the role of knowledge sharing and social imitation in technology diffusion, and institutional theory focuses on the guiding role of the government, policy incentives, and the establishment of regulations and standards to support technology adoption. Thus, we conclude that *supportive environments* are key factors in facilitating technology adoption. Moreover, *risks* in technology adoption cannot be ignored. Therefore, we summarise the following three dimensions that influence the national adoption of emerging technologies, namely, the basic conditions underlying technology acceptance and use, supportive environments and risks for technology adoption. The benchmark theoretical framework is shown in Fig. 1.

From the perspective of considering barriers and opportunities and incorporating the five hypotheses presented in Section 2, the theoretical research framework of this paper is shown in Fig. 2. Digital literacy and affordability form the basic conditions for technology adoption, and they determine the ability of individuals or organisations to use new technologies. Privacy and security are risk factors that affect users' trust in technology and their willingness to adopt it. These three aspects are the barriers that may be encountered in the process of technology adoption. The regulatory environment and governmental leadership form the external environments that facilitate technology adoption, which together contribute to the social acceptance and widespread use of technology.

Methodology

This section explains our research methodology in terms of variable selection, data and modelling.

Variable selection

This subsection provides a basic description of the 11 datasets that make up the set of dependent, explanatory and control variables. In addition, the data extraction and preprocessing processes required for the empirical analysis are discussed.

First, we identify the dependent variable for this paper.

Dependent variable

Digital technology adoption (*DTA*): Hooks et al. (2022) explored factors that influence the technology adoption rate using information about network readiness as the quantified index. Referring to this, we use the network readiness index (NRI) as the measure of *DTA*. The NRI is based on four fundamental dimensions—technology, people, governance, and impact—and covers issues ranging from futuristic technologies such as AI and the IoT to the role of digital transformation in achieving the sustainable development goals (SDGs), providing a holistic picture of a country or region's ability to use digital technologies (World Economic Organization, 2022). The data are derived from the annual Network Readiness Index Report published by the World Economic Organization.[4] It is scored on a scale of 0 to 100, which denotes the digital technology adoption rate from lowest to highest.

Explanatory variables

On the basis of the five hypotheses presented in the previous section, we identify the five core explanatory variables for this paper.

Privacy and security risks (*PSR*): We choose the global cybersecurity index (GCI) as the measure of the *PSR*. The GCI is a measure of countries' level of commitment to cybersecurity, initiated and maintained by the ITU,[5] which assesses the cybersecurity status of countries on the basis of five key areas: legal measures, technological measures, organisational measures, capacity building and cooperation. The data come from the GCI report published by the ITU and range from 0 to 100, with higher scores indicating better cybersecurity in that country. In this work, we take the opposite value to indicate the level of security risks; the smaller the value is, the lower the level of risks.

Illiteracy (*ILT*): This paper uses the literacy rate to express the situation of illiteracy from the opposite side. The literacy rate indicator is an important tool for measuring a country's level of education and national capacity. This indicator is usually defined as the proportion of the population aged 15 and over who can read and write. We collect the data from the Global System for Mobile Communications Association (GSMA) .[6] This platform normalises literacy data published by UNESCO[7] to obtain each country's score under the literacy indicator. The data are subsequently measured on a scale from 0 to 100, with 0 indicating the lowest level of literacy and 100 indicating the highest level of literacy. We take the opposite of this value to indicate the level of illiteracy; the smaller the value is, the lower the level of illiteracy.

Unaffordability (*UAF*): We use the opposite of mobile data affordability (MDA) to reflect the degree of unaffordability. The MDA focuses

[4] https://networkreadinessindex.org/

[5] https://www.itu.int/en/ITU-D/Cybersecurity/Pages/global-cybersecurity-index.aspx

[6] https://www.mobileconnectivityindex.com/

[7] https://uis.unesco.org/en/topic/literacy

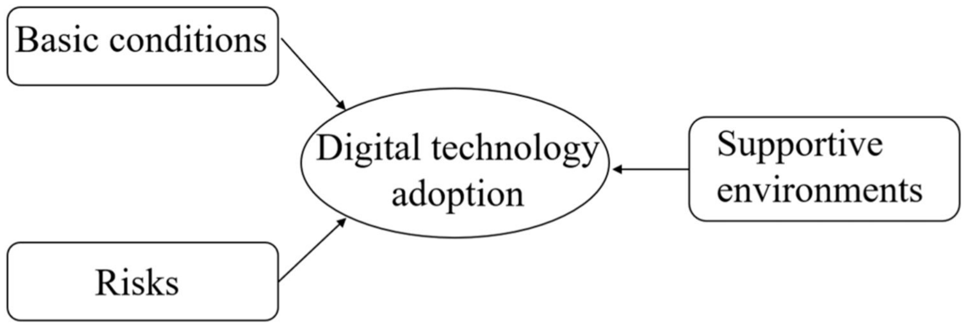

Fig. 1. The benchmark theoretical framework.

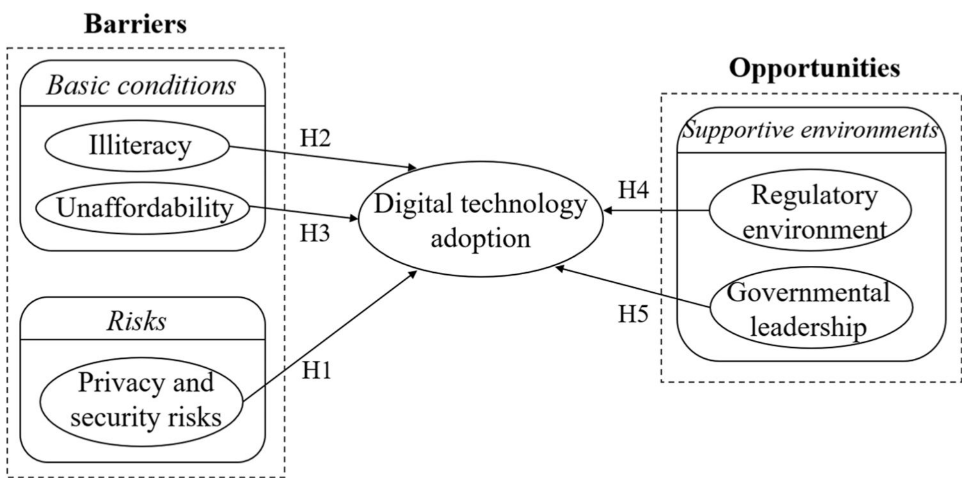

Fig. 2. Research theoretical framework.

on the affordability of individuals or households to pay for mobile data services. It relates to four different types of affordability. The data are derived from the MDA subindex within the affordability pillar of the mobile connectivity index (MCI) published by the GSMA. The GSMA collates the data originating from Tarifica[8] and averages these four affordability scores to obtain a final MDA score (0–100). Larger values indicate greater affordability. Since we take the opposite value to indicate the level of unaffordability, the smaller the value is, the lower the level of unaffordability.

Regulatory environment (*RE*): We use the information and communications technology (ICT) regulatory environment indicator as a measure of the regulatory environment in digital society. This indicator is based on the ICT regulatory tracker composite index, which provides a measure of the existence and features of ICT legal and regulatory frameworks.[9] A healthy ICT regulatory environment encourages technological innovation and market competition and helps drive the development and adoption of emerging technologies, as it ensures an open and fair market (Zhang et al., 2023). A mature and adaptable ICT regulatory environment provides a stable foundation for the long-term development of the digital economy, supporting the growth of emerging business models ranging from e-commerce to teleworking. According to the annual report of the NRI,[10] scores are standardised on a scale of 0 (worst environment)-100 (greatest environment).

Governmental leadership (*GL*): We use the e-government development index (EGDI) to reflect governmental leadership. The EGDI is based on a comprehensive survey of the online presence of all 193 member states of the United Nations.[11] It is a composite indicator that measures a country's level of e-government development and assesses the development of e-government in countries on the basis of three main dimensions: the online services index (OSI), the telecommunications infrastructure index (TII) and the human capital index (HCI). These indicators reflect a country's degree of digitisation in the delivery of public services and its ability to use ICT to promote accessibility and efficiency in public services. This assessment provides a relative rating of countries' e-government performance rather than an absolute measure. According to the annual report of the NRI,[12] scores are standardised on a scale of 0 (worst developed) to 100 (best developed).

Control variables

After discussing the selection of explanatory variables for this paper, we next present the control variables used in the study. These control variables can help us further eliminate other factors that may affect technology adoption and thus more accurately assess the role of explanatory variables.

The GDP per capita (current USD$) is an important indicator of a country's level of economic development and the state of average wealth of its inhabitants. A higher GDP usually implies a stronger economy and a higher standard of living, factors that respond to influence the adoption of digital technologies. The data are obtained from the World Bank.

Secure internet servers (*SIS*) quantify the number of secure internet servers per million people in a country or region. By normalising the number of secure servers to the size of the population, the metric

[8] https://tarifica.com/
[9] https://app.gen5.digital/tracker/metrics
[10] https://networkreadinessindex.org/
[11] https://publicadministration.un.org/egovkb/en-us/About/Overview/-E-Government-Development-Index
[12] https://networkreadinessindex.org/

provides a way to compare the level of investment and sophistication in cybersecurity infrastructure in different countries or regions, regardless of their population size. The data are obtained from the World Bank.

The extent to which companies invest in emerging technologies (*CIET*) can be used as a measure of technology innovation. Data are obtained from NRI annual reports. The report normalises the data in the World Economic Forum's Executive Opinion Survey (EOS) ,[13] with values ranging from 0 (lowest extent) to 100 (highest extent).

The school life expectancy (*SLE*) indicator reflects the number of years a child is expected to spend in the education system, ranging from the most basic level of education to the highest. The data are derived from the *SLE* subindicator in the MCI database published by the GSMA, which originated from UNESCO.[14] The GSMA normalises the original data with values ranging from 0 (shortest average years of schooling) to 100 (longest average years of schooling).

The infrastructure development index (*IDI*) published by GSMA[15] refers to the level of development of mobile network infrastructure, which includes the coverage of networks from the most basic 2G networks to the more advanced 4G and 5G networks, as well as network performance and the use of the radio spectrum. GSMA aggregates these three dimensions to produce the IDI score. The IDI is scored between 0 and 100, and a higher score is associated with greater infrastructure development.

To better understand the role and characteristics of these variables in the study, we move on to more specific descriptions and statistical analyses of the variables in the next subsection.

Variable descriptions

To understand the barriers and opportunities that the vast majority of countries globally generally face in the adoption of next-generation digital technologies, we use international data for 116 countries (see Table 1). Since NRI data were not available for the years 2018 and 2017,[16] we collecte and analyse data for the years 2019–2022. Countries are filtered on the basis of economies that appear in the 2019–2022 Network Readiness Index reports and have fewer missing values for the relevant variables.

Fig. 3 shows the NRI heatmap of the 116 sample countries for the four years from 2019 to 2022. The colour from light to dark indicates that the NRI value is small to large, representing the country's adoption of digital technologies from bad to good. We can intuitively see from the darkness of the colour of the country panels in the figure that the NRIs of the vast majority of European countries, Australia, and Canada have always been at a high level, and the NRIs of the countries in the African region have always been on the low side. Compared with the beginning of the statistical year 2019, China's NRI value has improved in the latter three years. Fig. 4 shows the literacy rates of different countries by year. The shade of the colour indicates the level of literacy, with darker red indicating a lower literacy rate and darker blue indicating a higher literacy rate. The graph allows for a visual comparison of how literacy rates have changed from year to year for each country, which is also equivalent to showing the illiteracy rate for this paper, which uses the opposite value of the indicator of the literacy rate to refer to the illiteracy rate.

According to the hypotheses in Section 2 and the theoretical structure in Section 3, we categorise the five core explanatory variables into the opportunities and barriers faced by each country in adopting digital technologies to explore their impact on the explanatory variable *DTA*. Table 2 shows the main results of the descriptive statistical analysis of each variable and the categories corresponding to each of them. We find that there are slight missing data for the *GDP* and *CIET* indicators. The values of *GDP* and *SIS* are too large and have large standard deviations.

To make the dataset as complete as possible and to support more accurate and reliable analysis, we use interpolation in STATA to fill in some of the missing data. The variance is stabilised by taking the logarithm of *GDP* and *SIS*. The pre-processed data are shown in Table 3.

After clarifying the definition of each variable and its statistical characteristics, to further analyse the relationships among these variables, we detail the model used in this study and its specific construction process.

Model specification

On the basis of the theoretical framework of Section 3, we aim to empirically analyse how various factors, representing both barriers and opportunities, influence the adoption of next-generation digital technologies across different contexts. According to Section 3.1, time remains a key factor when we apply the theory of DOI to discuss digital technology adoption at the national level. The state of emerging technology adoption changes over time, as do national policies and institutions. The adoption of digital technology varies from country to country because of different economic levels, regional differences and other factors. Therefore, this paper considers the use of panel data to discuss the factors affecting the adoption of digital technology. The panel data methodology combines longitudinal and cross-sectional data. It is suitable for estimating the adoption behaviour of digital technologies across countries because it can offer estimations when no observable heterogeneities emerge for each country or across time (Bliese et al., 2020). Therefore, we construct an empirical model based on national-level panel data to investigate the determinants of digital technology adoption. The model is as follows:

$$DTA_{it} = \alpha + \beta_1 \times PSR_{it} + \beta_2 \times ILT_{it} + \beta_3 \times UAF_{it} + \beta_4 \times RE_{it} + \beta_5 \times GL_{it} + \sum \beta_j \times X_{j,i,t} + \mu_i + \tau_t + \varepsilon_{it}$$

where the subscript *i* denotes a different country and *t* denotes a year.

DTA_{it} indicates the adoption of next-generation digital technologies. PSR_{it} denotes the privacy and security risks. ILT_{it} denotes national illiteracy. UAF_{it} reflects the national unaffordability in relation to digital technology. RE_{it} denotes the conditions of the regulatory environment. GL_{it} denotes governmental leadership. $X_{j,i,t}(j = 6, 7, 8, 9, 10)$ are other control variables.

Empirical analysis

On the basis of the data included in Table 3, this paper analyses the correlation results of each variable, as shown in Table 4. We also carry out a variance inflation factor test on the correlation variables, and the results (in Table 6) show that the variance inflation factor (VIF) of the variables is less than 10 (in Table 5), so there is no multicollinearity problem. On this basis, we conduct further regression analysis.

Hypothesis test

Before the benchmark regression, this paper conducted the Hausman test (Hausman, 1978) for the estimation of the random effects and fixed effects of the model, and the results are shown in Table 6. The p value of the test is less than 0.01, which significantly rejects the original hypothesis and indicates that the fixed effects model is applicable to the estimation in this paper.

In addition, to determine whether to choose a one-factor fixed effects model or a two-factor fixed effects model, this paper adds time as a dummy variable into the model, and the regression results are shown in Table 7. Model 1 fixes for individual effects, and the F test statistic corresponds to a p value of less than 0.01, suggesting that there are

[13] https://www.weforum.org/publications/
[14] http://data.uis.unesco.org/
[15] https://www.mobileconnectivityindex.com/index.html
[16] https://networkreadinessindex.org/

Table 1
List of countries in the sample.

Country					
Albania	Algeria	Argentina	Armenia	Australia	Austria
Azerbaijan	Bahrain	Bangladesh	Belgium	Bosnia and Herzegovina	
Botswana	Brazil	Bulgaria	Cambodia	Cameroon	Canada
Chile	China	Colombia	Costa Rica	Croatia	Cyprus
Czechia	Denmark	Dominican Republic	Ecuador	Egypt	El Salvador
Estonia	Eswatini	Ethiopia	Finland	France	Georgia
Germany	Ghana	Greece	Guatemala	Honduras	Hungary
Iceland	India	Indonesia	Iran	Ireland	Israel
Italy	Jamaica	Japan	Jordan	Kazakhstan	Kenya
South Korea	Kuwait	Kyrgyzstan	Laos	Latvia	Lebanon
Lithuania	Luxembourg	Madagascar	Malawi	Malaysia	Mali
Malta	Mauritius	Mexico	Moldova	Mongolia	Morocco
Mozambique	Namibia	Nepal	Netherlands	New Zealand	Nigeria
North Macedonia	Norway	Oman	Pakistan	Panama	Paraguay
Peru	Philippines	Poland	Portugal	Qatar	Romania
Russian Federation	Rwanda	Saudi Arabia	Senegal	Serbia	Singapore
Slovakia	Slovenia	South Africa	Spain	Sri Lanka	Sweden
Switzerland	Tajikistan	Tanzania	Thailand	Tunisia	Turkey
Uganda	Ukraine	United Arab Emirates	United Kingdom	United States of America	
Uruguay	Vietnam	Zambia	Zimbabwe		

Source: Authors' summary

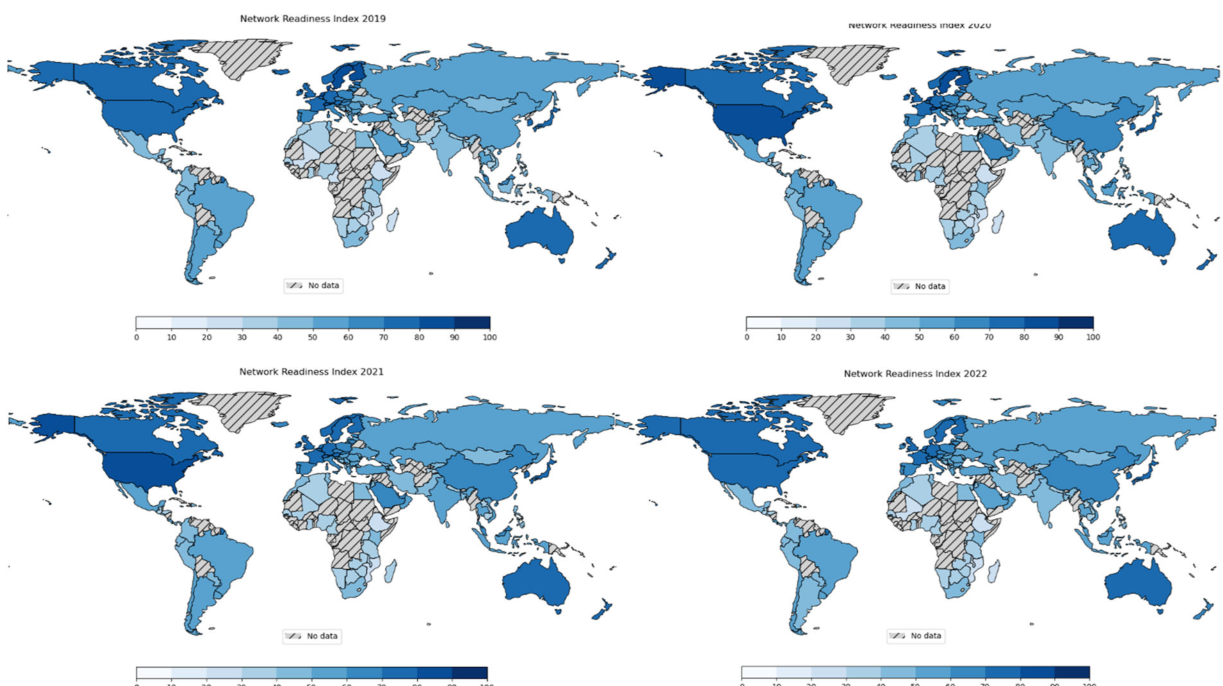

Fig. 3. Network Readiness Index Heat Map for 116 countries, 2019–2022.

differences in the use of digital technologies across countries, so individual-specific unobservable heterogeneity needs to be controlled for. Model 2 fixes both individual and time effects and observes through hypothesis testing that the coefficients on all time dummy variables are simultaneously zero and that the time effect statistically significantly affects the dependent variable *DTA*.

Therefore, we take the regression results of Model 2 as the baseline regression results. The results show the statistically significant impacts of illiteracy, privacy security, and unaffordability as barriers to technology adoption. The regulatory environment has a positive and statistically significant effect on digital technology adoption. However, governmental leadership has a positive but not statistically significant effect on digital technology adoption.

Fig. 5 visualises the impact of each core explanatory variable on the dependent variable.

Analysing the year variable, we find that there are significant positive coefficients for 2020 and 2021 relative to the benchmark year 2019, indicating a significant increase in the adoption rate in these years compared with the benchmark year. This may be related to the growth in digital technology adoption rates within these years, such as telework and the rise of online education. Conversely, the negative coefficient for 2022 indicates a decline in the digital technology adoption rate relative to that in 2019, which could be due to market saturation, technology fatigue, or other economic and social factors.

Robustness test

Remove extreme values

To reduce the interference of the extreme values of the sample data on the regression results, this paper is based on the value of the NRI,

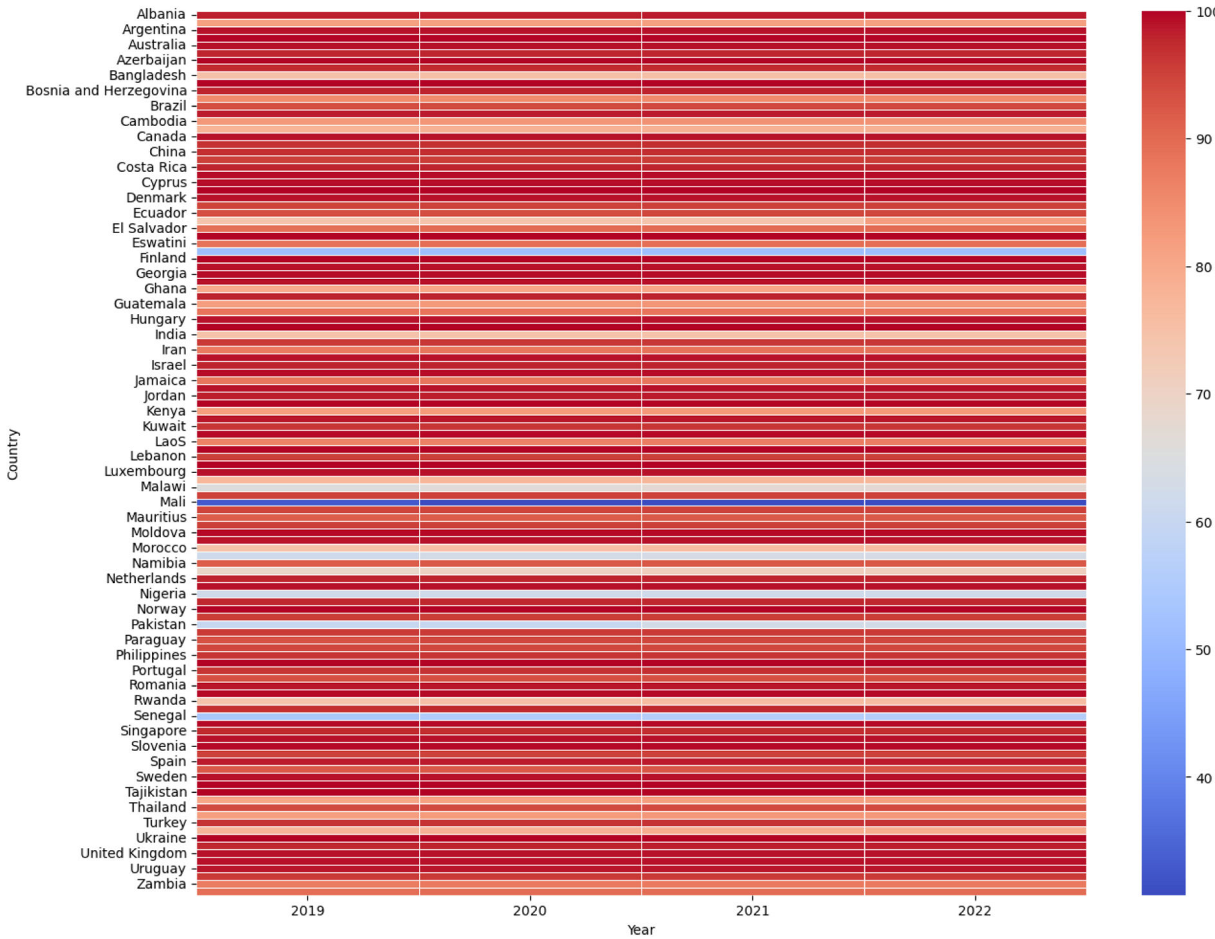

Fig. 4. Literacy Rate by Country and Year (Only a selection of countries is shown here.).

Table 2
Descriptions of original variables.

Variables	Category	N	Mean	Sd	Min	Max
DTA	Dependent variable	464	52.62	14.66	23.49	82.75
PSR	Barrier	464	-71.21	27.10	-100	-2.20
ILT	Barrier	464	-91.83	11.94	-100	-30.76
UAF	Barrier	464	-58.63	21.85	-100	-0.72
RE	Opportunity	464	78.96	17.42	0	100
GL	Opportunity	464	69.74	18.69	18.04	100
GDP	Control variable	463	19,890	24,135	456.6	133,712
SIS	Control variable	464	18,741	38,454	1.450	277,331
CIET	Control variable	459	46.88	20.56	0	100
IDI	Control variable	464	68.15	12.15	38.44	97.94
SLE	Control variable	464	62.00	18.72	13.26	100

Source: Authors' analysis with STATA 16
Note: The abbreviations of the variables correspond to those in Section 4.1. Variables are variables in the model and indicators are used to quantify the variables. N denotes the number of variables, and mean, Sd, min, max denote the mean, standard deviation, minimum, and maximum of a set of data, respectively.

Table 3
Descriptions of pre-processed variables.

Variables	N	Mean	Sd	Min	Max
DAT	464	52.62	14.66	23.49	82.75
PSR	464	-71.21	27.10	-100	-2.20
ILT	464	-91.83	11.94	-100	-30.76
UAF	464	-58.63	21.85	-100	-0.72
RE	464	78.96	17.42	0	100
GL	464	69.74	18.69	18.04	100
GDP	464	9.110	1.360	6.120	11.80
SIS	464	7.410	2.740	0.370	12.53
CIET	461	46.83	20.53	0	100
IDI	464	68.15	12.15	38.44	97.94
SLE	464	62.00	18.72	13.26	100

Source: Authors' analysis with STATA 16
Note: N denotes the number of variables, and mean, Sd, min, max denote the mean, standard deviation, minimum, and maximum of a set of data, respectively.

removing the top 12 countries and the bottom 12 countries in the NRI rankings in 2022 to conduct a robustness test on the sample data. Table 8 shows that some of the coefficients in the regression results after removing the 24 observed countries have changed slightly, but generally, the results remain consistent, indicating that the model is robust. For example, the coefficient on *ILT* increases from -0.603 to -0.539 but is still significant; the coefficients on *PSR* and *UAF* remain significant and negatively correlated. This robustness test suggests that the main factors affecting the NRI retain their direction of influence and most of their strength of influence, even after removing countries with potentially extreme effects. The impact of the year variable has changed but still shows a similar pattern to that of the benchmark regression.

This robustness test confirms the reliability of our model by demonstrating that the key findings are not unduly influenced by countries with extreme NRI values. The consistency in direction and significance of the main variables, even after excluding outliers, reinforces the validity of our conclusions regarding the factors affecting next-generation digital technology adoption. This analysis provides a strong foundation for our policy recommendations and theoretical contributions, ensuring that they are based on robust and stable

Table 4
Results of correlation analysis of variables.

Variable	*DTA*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
DTA	1										
(1) *ILT*	-0.635***	1									
(2) *PSR*	-0.728***	0.445***	1								
(3) *UAF*	-0.825***	0.568***	0.743***	1							
(4) *GL*	0.822***	-0.588***	-0.741***	-0.754***	1						
(5) *RE*	0.497***	-0.253***	-0.500***	-0.448***	0.498***	1					
(6) *IDI*	0.880***	-0.612***	-0.691***	-0.773***	0.760***	0.482***	1				
(7) *GDP*	0.913***	-0.682***	-0.622***	-0.813***	0.749***	0.468***	0.860***	1			
(8) *SIS*	0.889***	-0.700***	-0.632***	-0.804***	0.760***	0.511***	0.798***	0.848***	1		
(9) *CIET*	0.747***	-0.309***	-0.522***	-0.578***	0.527***	0.242***	0.625***	0.633***	0.555***	1	
(10) *SLE*	0.793***	-0.692***	-0.577***	-0.730***	0.724***	0.458***	0.758***	0.809***	0.799***	0.412***	1

Source: Authors' analysis with STATA 16
Note:
*** $p < 0.01$
** $p < 0.05$
*$p < 0.1$,

Table 5
VIF of variables.

Variable	*GDP*	*SIS*	*IDI*	*UAF*	*SLE*	*GL*	*PSR*	*ILT*	*CIET*	*RE*
VIF	7.16	5.57	4.95	4.57	3.99	3.65	3.09	2.48	2.10	1.62

Source: Authors' analysis with STATA 16

Table 6
Hausman specification test.

	Coef.
Chi-square test value	407.61
p-value	0.0000

Source: Authors' calculation with STATA 16

empirical evidence.

Reducing the variables

In addition to the primary robustness test, we conducted another set of analyses to further verify the stability of our results. By reducing the core explanatory variables in the model, we separately examine the impact of barriers and opportunities on the new generation of digital technologies. Model 4 in Table 9 represents the impact of the three explanatory variables representing barriers on the regression results after removing the two core explanatory variables representing opportunities. Model 5 represents the effect of the two explanatory variables for opportunity on the regression results.

The results show that the coefficients and significance of each explanatory variable are almost consistent with those of benchmark Model 2, further validating the conclusions of this paper. That is, illiteracy, privacy and security risks, and unaffordability can hinder the use of digital technologies, whereas the regulatory environment and government demonstrations can promote the use of next-generation digital

Table 7
Fixed effects model selection.

Variables	Model 1	Model 2
ILT	-0.462** (-2.30)	-0.603*** (-3.40)
PSR	-0.112*** (-3.84)	-0.063** (-2.07)
UAF	0.002 (0.11)	-0.052*** (-2.59)
GL	0.034 (1.46)	0.028 (1.36)
RE	0.037 (1.43)	0.047** (2.09)
Control variables	Controlled	Controlled
2019.year		0.000 (.)
2020.year		1.443*** (4.43)
2021.year		0.714** (2.19)
2022.year		-1.154*** (-3.14)
Constant	33.891(1.65)	-3.507 (-0.17)
N	461	461
Adjusted r^2	-0.004	0.230

Note: t statistics in parentheses.
*$p<0.1$
** $p<0.05$
*** $p<0.01$
Source: Authors' calculation with STATA 16

technology to some extent.

The separate examinations in Models 4 and 5 confirm that the core conclusions of our study hold true across different model specifications. This suggests that the identified factors—both barriers and opportunities—are fundamentally influential in shaping the adoption of next-generation digital technologies and that their impacts are not merely

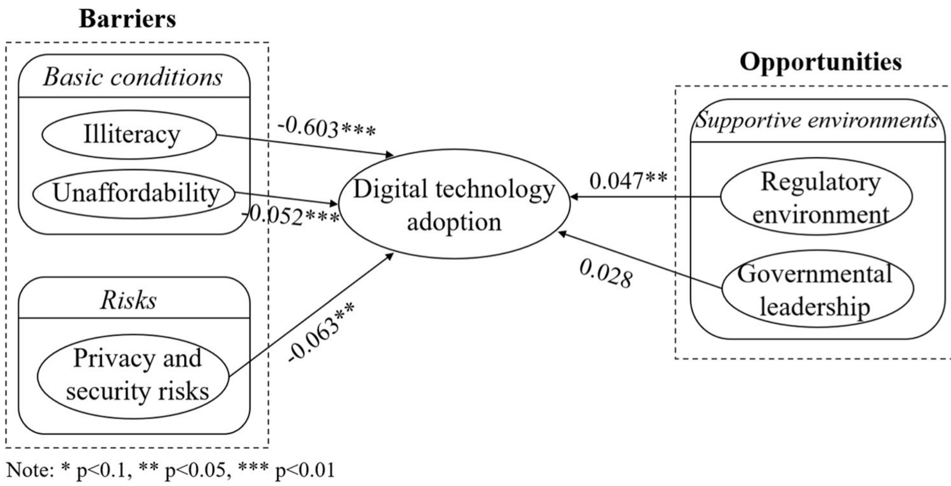

Fig. 5. Regression results embodied in the theoretical model.

Table 8
Robustness test: Remove extreme values.

Variable	Model 3
ILT	-0.539*** (-2.96)
PSR	-0.067** (-2.18)
UAF	-0.038* (-1.81)
GL	0.019 (0.90)
RE	0.051** (2.24)
Control variables	Controlled
2019.year	0.000 (.)
2020.year	1.697*** (4.93)
2021.year	0.952*** (2.77)
2022.year	-0.984*** (-2.60)
Constant	7.395 (0.35)
N	365
Adjusted r^2	0.227

Note: t statistics in parentheses.
* p<0.1
** p<0.05
*** p<0.01
Source: Authors' calculation with STATA 16

Table 9
Robustness test: Reduce explanatory variables.

Variables	Model 2	Model 4	Model 5
ILT	-0.603*** (-3.40)	-0.663*** (-3.60)	
PSR	-0.063** (-2.07)	-0.063** (-1.99)	
UAF	-0.052*** (-2.59)	-0.041** (-1.99)	
GL	0.028 (1.36)		0.020 (0.95)
RE	0.047** (2.09)		0.050** (2.16)
Control variables	Controlled	Controlled	Controlled
2019.year	0.000 (.)	0.000(.)	0.000(.)
2020.year	1.443*** (4.43)	1.037***(3.16)	1.888***(6.50)
2021.year	0.714** (2.19)	0.594*(1.75)	1.383***(4.97)
2022.year	-1.154*** (-3.14)	-1.662***(-4.52)	-0.312(-1.01)
Constant	-3.507 (-0.17)	-6.774(-0.33)	48.617***(3.76)
N	461	461	461
Adjusted r^2	0.230	0.166	0.184

Note: t statistics in parentheses.
* p<0.1
** p<0.05
*** p<0.01
Source: Authors' calculation with STATA 16

artefacts of model specification.

Heterogeneity analysis

To examine the differences in the impact of barriers and opportunities on next-generation digital technology adoption between countries at different economic levels and with reference to the World Bank's criteria for categorising countries into income levels, this paper categorises the 116 countries in the sample into 47 high-income (GNI per capita greater than $13,205) countries, 31 middle-income (GNI per capita ranging between $4256 and $13,205) countries, and 38 low-income (GNI per capita lower than US$4256) countries. Columns (1) to (3) in Table 10 report the estimates of factors affecting the use of digital technologies in high-, middle- and low-income countries, respectively. The results show that illiteracy has a significant negative effect on high-income countries but not on countries with medium and low levels of income. Privacy and security risks have a significant negative impact on low-income countries. Unaffordability has a significant negative impact at all income levels but is most significant in countries with low income levels. Governmental leadership has a significant positive effect on low-income countries. The regulatory environment has a significant positive effect on medium-income countries.

These results suggest that increasing literacy rates, affordability, privacy and security have different levels of impact and urgency on

Table 10
Analysis of heterogeneity in levels of economic development.

Variable	(1) High	(2) Middle	(3) Low
ILT	-4.896*** (-3.73)	-0.906 (-1.27)	0.146 (0.94)
PSR	0.019 (0.38)	-0.053 (-1.12)	-0.132*** (-3.44)
UAF	-0.000 (-0.01)	-0.039 (-1.41)	-0.076** (-2.20)
GL	0.032 (1.12)	0.046 (1.23)	0.040* (1.67)
RE	-0.060 (-1.52)	0.096** (2.42)	0.045* (1.86)
Control variables	Controlled	Controlled	Controlled
2019.year	0.000 (.)	0.000 (.)	0.000(.)
2020.year	0.551 (1.35)	1.419** (2.61)	2.319*** (4.88)
2021.year	-0.822* (-1.84)	1.491** (2.57)	2.841*** (6.16)
2022.year	-3.420*** (-6.38)	-0.836 (-1.27)	0.966* (1.94)
Constant	-391.836*** (-3.02)	-49.977 (-0.64)	23.812 (1.52)
N	185	124	152
Adjusted r^2	0.673	0.253	0.557

Note: t statistics in parentheses.
* p<0.1
** p<0.05
*** p<0.01
Source: Authors' calculation with STATA 16

economic development in countries with different income levels. Policymakers should focus on different areas of development to maximise economic growth in these different groups of countries. High-income countries may need to focus on overcoming illiteracy; middle-income countries should focus on upgrading the regulatory environment; and middle-income countries may need to work on upgrading cybersecurity and the regulatory environment across the board.

Discussion

Interpretation of findings

The theoretical framework in Fig. 2 links barriers (privacy and security risks, illiteracy, and unaffordability) and opportunities (governmental leadership and the regulatory environment) to digital technology adoption. Combined with the results of the regression analysis in Section 5, we can draw several key conclusions.

Regarding the impact of barriers, we find that higher levels of illiteracy and unaffordability lead to a lower rate of digital technology adoption. These findings suggest that literacy and affordability are basic conditions for the adoption of digital technology. Improving literacy and economic access to digital technologies is critical for establishing a strong base for widespread technology use. Therefore, policy interventions that focus on enhancing digital literacy education and the economic accessibility of digital technologies are essential strategies to facilitate adoption. Higher levels of privacy and security risks lead to a lower adoption rate of digital technologies, indicating that concerns about privacy and security are significant deterrents to the uptake of new technologies. This highlights the need for robust privacy and security measures to build public trust in digital environments. Governments and organisations should prioritise the development of comprehensive data protection laws and cybersecurity protocols to address these concerns and encourage broader acceptance and use of digital technologies.

Regarding the impact of opportunities, we find that a supportive regulatory environment has a positive influence on digital technology adoption, although the effect of governmental leadership is not statistically significant. This finding emphasises the importance of creating a conducive regulatory framework that supports innovation and market entry while safeguarding user interests. Regulatory measures should evolve alongside technological advancements to ensure that they remain relevant and effective in fostering technology adoption.

Theoretical implications

These findings not only reveal the key factors facing the adoption of the new generation of digital technologies but also suggest new ways of thinking about existing theories of technology adoption. On the basis of the theoretical model, we investigate the impact of five specific factors (i.e., illiteracy, unaffordability, privacy and security, the regulatory environment and governmental leadership) under the three dimensions (i.e., basic conditions, risks and supportive environments) on the adoption of next-generation digital technologies. The research has certain theoretical significance:

(1) The integration of DOI theory and institutional theory extends the perspective of traditional innovation diffusion theory, which usually focuses on technological characteristics and internal decision-making processes, includes the influence of external environmental factors, and provides a reference for future research to analyse the influencing factors of digital technology adoption via multiple frameworks.
(2) On the basis of DOI theory and institutional theory, this paper explores five potential variables affecting the application of digital technology from the perspectives of opportunities and barriers, which are informative for further clarifying the expansion process of digital technology.
(3) The validity of the theoretical model is verified through empirical analysis, and factors with significant influence are identified. This provides an important foundation for subsequent research and encourages researchers to further explore the similarities and differences in digital technology adoption among different countries and regions, as well as to analyse in depth the conditions and mechanisms of governmental exemplary effects.

Practical implications

Based on the above analysis of theoretical insights, further exploration of the implications of these findings in practical applications is equally important. This paper highlights the importance of strengthening the regulatory environment to facilitate the adoption of digital technologies. For policymakers, this means that it is important to start building policy frameworks that are more open and flexible and encourage innovation. Moreover, it is important to increase the digital literacy of the population through education, to increase public acceptance of new technologies, and to make technologies more affordable through measures such as financial subsidies or tax incentives. In addition, although the role of governmental exemplars is not statistically significant, the role of governmental demonstrations in the adoption of new technologies should not be ignored, and the effective use of governmental demonstration effects to promote technology adoption should continue to be explored.

For businesses, understanding the barriers to and facilitators of technology adoption can help them better plan their technology investments and marketing strategies. Businesses should emphasise investments in privacy and data security to reduce consumer concerns and enhance the attractiveness of their products and services. At the same time, firms also need to pay close attention to policy changes and seize opportunities presented by a positive regulatory environment, as well as use government policies and programs as levers to drive technology adoption.

Conclusion and policy recommendations

This paper provides a comprehensive analysis of the adoption of next-generation digital technologies through macrolevel analysis, theoretical modelling, and empirical data. Our study integrates DOI theory with institutional theory to explore key dimensions affecting technology adoption at the national level, i.e., basic conditions, risks, and supportive environments. On the basis of these three dimensions, we further discuss five factors that can be viewed as barriers or opportunities to impede or facilitate technology adoption. By analysing data from 116 countries via a two-factor fixed effects model, we identify several crucial findings. That is, illiteracy, privacy and security risks, and lack of affordability are proven to be significant deterrents to the adoption of digital technologies. A supportive regulatory environment is a major positive factor in promoting digital technology adoption. Effective regulations encourage the integration and expansion of digital technologies. While governmental leadership has a positive influence, its effect is less significant than that of other factors. To overcome foundational barriers, it is essential to focus on improving digital literacy, enhancing economic accessibility, and strengthening privacy and cybersecurity measures. Creating a favourable regulatory environment and enhancing government leadership are crucial for fostering a supportive ecosystem for digital technology adoption.

On the basis of our study, the following policy recommendations are proposed:

(1) Governments can promote basic knowledge and skills training in digital technology through the education system and appropriately increase public investment in upgrading digital literacy

skills. This includes the provision of free or low-cost computer courses and online learning resources, as well as the introduction of information technology curricula in schools.

(2) To promote the economic accessibility of digital technologies, governments can encourage enterprises to develop and sell reasonably priced digital equipment through tax reductions, subsidies or cooperative projects. The provision of rental services for computers and other digital equipment through the sharing economy model could enable more people to access essential technological resources at a lower cost.
(3) It is necessary to develop and implement comprehensive data protection legislation to standardise the collection, processing and storage of personal information. Raising public awareness of cybersecurity is also important and can be accomplished through media and public education campaigns.
(4) Governments need to create a regulatory environment that supports innovation and the adoption of digital technologies, which may involve streamlining the approval process, lowering barriers to entry and encouraging competition. At the same time, it is important to ensure that regulatory measures keep pace with the development of technology and do not become a hindrance.
(5) Governments can demonstrate through their own digital transformation how to make effective use of digital technologies, including digitalised public services and e-government, to increase public confidence in and acceptance of new technologies. In addition, governments can encourage private sector participation and innovation by initiating public−private partnership projects.

In building on our findings, in future studies, we will consider the complex relationships among the factors that influence the adoption of next-generation digital technologies, such as the interplay between different barriers to technology adoption in various contexts and their cumulative effects. Further attention should also be given to more nuanced intercountry differences, such as comparative studies across different countries, to understand the influence of local factors on technology adoption.

Ethical approval

All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Marinko Skare**:** Conceptualization; Data curation, Supervision; Visualization; Validation, Writing - review & editing, Resources, Investigation.

Jinglin Xiao: Data curation, Formal analysis, Supervision; Visualization; Validation, Writing - original draft.

Zeshui Xu: Data curation, Methodology, Validation, Reviewing, Writing - original draft, Writing - review & editing.

Anran Xiao: Data curation, Methodology, Validation, Reviewing, Writing - original draft, Writing - review & editing.

Xinxin Wang**:** Data curation, Methodology, Software, Visualization, Writing - original draft, Writing - review & editing.

CRediT authorship contribution statement

Jinglin Xiao: Writing – original draft, Visualization, Validation, Supervision, Formal analysis, Data curation. **Zeshui Xu:** Writing – review & editing, Writing – original draft, Validation, Methodology, Data curation. **Anran Xiao:** Writing – review & editing, Writing – original draft, Validation, Methodology, Data curation. **Xinxin Wang:** Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Data curation. **Marinko Skare:** Writing – review & editing, Validation, Supervision, Resources, Investigation, Conceptualization.

Declaration of competing interest

Jinglin Xiao declares she has no conflict of interest.
Zeshui Xu declares he has no conflict of interest.
Anran Xiao declares she has no conflict of interest.
Xinxin Wang declares she has no conflict of interest.
Marinko Skare declares he has no conflict of interest.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jik.2024.100622.

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