The effects of AI technology, externally oriented corporate culture and environment on blockchain technology adoption

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Abstract

Purpose – Our study investigates the economic importance and statistical significance of artificial intelligence (AI) technology, externally oriented corporate culture and the business environment on the adoption of blockchain technology (BT) based on the technology, organisation and environment (TOE) model.

Design/methodology/approach – In line with the TOE framework, we collect secondary data for a sample of 27,400 firm-year observations of Chinese A-share listed firms for the period 2013–2021. Blockchain data are obtained through a manual search of annual reports for the keyword blockchain technology; relevant content is assessed to confirm companies' BT adoption status. We use the Python-based Web Crawler to collect AI patent and corporate culture data from the management discussion and analysis section of the annual reports and the China National Knowledge Infrastructure.

Findings – We find that AI technology and externally oriented corporate cultures, such as those focused on competition and creation, positively affect BT adoption. Environmental factors such as market competition, government support and the level of digital financial development across provinces also positively affect BT adoption. Further testing showed that BT adoption reduces the level of earnings management practice.

Originality/value – Our study extends the TOE theory by providing comprehensive evidence of the internal and external factors affecting BT adoption. We also provide the first empirical evidence that creation- and competition-oriented corporate cultures positively influence BT adoption. Our additional testing of economic significance clarifies the economic importance of factors influencing BT adoption.

Keywords Blockchain technology, Artificial intelligence, Corporate culture, Technology-organisation-environment framework, China

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1. Introduction

Blockchain technology (BT) is the most important and revolutionary recent innovation (Dai & Vasarhelyi, 2017); it provides an alternative approach to traditional recording methods notable for its efficiency, speed and data integrity, and it has therefore attracted significant

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investment from venture capitalists (Yermack, 2017). Distributed ledger technology has the potential to be used in a variety of industries (Bonsón & Bednárová, 2019). Indeed, Jayasuriya and Sims (2023) believe that BT is a significant disruptive force in many industries related to accounting and management, while Angelis and Ribeiro da Silva (2019) point out that BT adoption has not been limited to the financial industry, because the new technology is a distributed system that allows all transactions to be recorded and shared among all participants.

BT is also an international phenomenon that affects global markets (Han, Lu, & Wu, 2024). It enables the development of effective trust mechanisms and transformation of social business, while inspiring a new wave of technological innovation that may ultimately enhance social, economic and environmental outcomes (Wang, Su, & Li, 2020). However, the uncertainty of the commercial value of BT adoption has prevented some industries and companies from embracing it (Di Vaio & Varriale, 2020), although the adoption of innovative tools such as Bitcoin and blockchain provides an avenue for future research (Han *et al.*, 2024). The factors that motivate management to adopt BT when they face a new technology and lack an understanding of IT thus bear investigation (Guo, Walton, Wheeler, & Zhang, 2021).

China has stressed the importance of BT for industrial transformation and technological innovation (Cai, Sun, Zheng, Xiao, & Qiu, 2021), and the Chinese government has provided strong policy support for BT, while aiming to lead in the blockchain industry (Wang *et al.*, 2020). China's supreme leader has outlined clear instructions for advancing BT industry development, which may have significant strategic and practical implications. With governmental support, many Chinese companies in the Internet and information sectors have started to explore the blockchain industry (Hou, Wang, & Luo, 2020). To date, several Chinese companies have sought to integrate BT into key industry sectors, such as cloud computing, the Internet of Things (IoT), artificial intelligence (AI) technology and 5G to create new forms of infrastructure (Cai *et al.*, 2021). The first standard specification for financial blockchain issued by the People's Bank of China marks a deeper application of blockchain in the finance industry. This is important, as firms are generally willing to adopt emerging technologies when they provide benefits to survive in a competitive market (Gökalp, Gökalp, & Çoban, 2022). This provides motivation to investigate the elements that influence BT adoption in the massive wave of blockchain innovation.

Tornatzky and Fleischer's (1990) technology, organisation and environment TOE framework is a widely used to examine the determinants of technology innovation and investment. Gökalp *et al.* (2022) argue that the technology acceptance theory (TAM) (Davis, 1989) and unified theory of acceptance and use of technology (UTAUT) (Venkatesh, Morris, Davis, & Davis, 2003) models primarily concentrate on exploring factors that affect the acceptance of new technologies from an individual viewpoint. In contrast, the TOE framework examines the technology adoption at the organisational level. The tripartite structure is based on the idea that the relationship between technology and organisation can provide valuable insights into how technology can be integrated into the existing ecosystem of companies (Liang, Kohli, Huang, & Li, 2021). Companies adopt BT if the emerging technology is compatible with their existing IT systems, so it is crucial, according to Liang *et al.* (2021), to validate the impact of TOE factors on BT adoption in a strategic decision-making context.

Prior studies have examined the factors driving BT adoption, with surveys being the most widely used method to collect data, followed by qualitative methods such as interviews and case studies. For example, Liang *et al.* (2021) investigated the drivers of BT adoption from a fit-viability perspective by surveying 242 managers; they found that the functional and symbolic benefits of BT (e.g. brand image, organisational innovation and company reputation) positively affected managers' adoption decisions. Gökalp *et al.* (2022) examined the 14 key determinants of BT adoption in the supply chain management context using 30 responses from face-to-face interviews. They found that the environmental factors faced by companies (e.g. policy support and industry competition) are the most important for managers when investing in BT compared to technological (e.g. firm innovation capability and the relative advantage of technology) and organisational factors (e.g. firm size, firm cash flow and the characteristics of the enterprise's executives). However, Clohessy and Acton (2019) show that organisational factors also play a significant role in determining whether an organisation adopts an IT innovation. They use a case study grounded on the TOE framework and find that BT adoption is driven by organisational factors such as upper management support, financial resources, human resources and enterprise infrastructure. Hashimy, Jain, and Grifell-Tatjé (2022) used an online survey method based on the TOE framework and TAM to study BT adoption; their results indicate that competitive pressure, competence (e.g. employee skills and knowledge), upper management support and relative advantages are positively correlated with the motivation of managers to use BT. At the same time, technical complexity may prevent BT implementation.

Few studies have used large secondary data to examine the drivers of BT adoption. Exceptions include, for example, Guo *et al.* (2021), who collected empirical data from 142 companies adopting BT and found that companies with greater technological innovation are more likely to adopt BT in their development. In addition, few prior studies have used the TOE model to examine the potential impacts of BT adoption from all three TOE perspectives. Existing studies lack insight into how technology integration and corporate culture impact BT adoption decisions; for example, Gökalp *et al.* (2022) focus on the complexity and scalability of the technology itself and the IT and financial resources of organisations. In the TOE model, technical capability, externally oriented corporate cultures and the environment companies face are the most relevant factors in adopting a new technology such as BT. We therefore examine the potential impact of AI technology on BT adoption, because BT can eliminate AI-related concerns about data security by enabling secure storage and sharing (Mistry, Tanwar, Tyagi, & Kumar, 2020). Externally oriented corporate cultures emphasise an innovative and competitive orientation (Fiordelisi & Ricci, 2014; Barth & Mansouri, 2021), while environmental factors include government policies, market competition and local economic development levels. Existing studies on the determinants of BT adoption have not, however, considered such factors. How management adopts BT within its innovative capacity, corporate culture and external environments is therefore an important issue that should be investigated. We therefore examine the role of AI technology, externally oriented corporate cultures – including those oriented towards competition and creation – and the external environment (e.g. government subsidies, industry competition and financial inclusion) on BT adoption.

We use archival data to examine whether all three factors in the TOE framework affect the managerial decision to adopt BT based on a sample of 27,400 firm-year observations from 2013 to 2021. The regression results provide evidence that companies with AI technology patents are more likely to use BT, and organisations with competition- and creation-oriented cultures are incentivised to use BT. Some environmental factors are also positively associated with BT adoption, including competitive pressures on enterprises, policy support and being in a region with high financial development. After conducting several robustness tests (e.g. eliminating the impact of strategic disclosures, substituting blockchain-related variables and excluding COVID-19), the main regression results remain robust. Heterogeneity tests further validate the results across firms with different ownership properties, technological backgrounds and industries. Finally, further tests indicate that BT adoption can reduce earnings management practices.

We also created theoretical economic models to investigate the economic importance of the impact of the explanatory variables on BT adoption. Prior research has investigated the key drivers of BT adoption, and while the results of these studies show statistical significance, they fail to assess the economic importance of the explanatory variables effectively. Linear regression also cannot measure the percentage at which each explanatory variable contributes to the dependent variable – it can only show the correlation between these factors and BT adoption. We therefore introduce theoretical models to investigate the economic importance of the impact of the explanatory variables on BT adoption based on Holgersson, Norman, and Tavassoli (2014). We provide evidence that the key factor affecting BT adoption, from an economic perspective, is a competition-oriented culture.

Our study makes several contributions to the current literature on BT adoption. First, we extend TOE theory by adding new variables – that i.e., AI technology and corporate culture – to the framework in the context of BT adoption. Considering the integration and interaction of emerging technology, the rise of AI has the potential to accelerate companies' technological innovation. However, prior studies have not provided evidence about the effect of AI on BT adoption, so our study extends the literature on BT adoption. Existing technology acceptance models (e.g. TAM and UTAUT) also tend to focus on individual acceptance of technology use. Our study focuses on corporate culture, which has not been examined in the literature regarding BT adoption, although prior studies have examined the impact of corporate culture on management decisions for business operations (Farh, Hackett, & Liang, 2007), technological innovation (Damanpour, 1991), information systems adoption (Abdul Rashid, Sambasivan, & Abdul Rahman, 2004; Chai & Pavlou, 2004; Twati & Gammack, 2006) and innovation ability (Kitchell, 1995). Our study thus fills the gap in current research and clarifies corporations' acceptance of adopting BT technology from an organisational culture perspective.

We also provide new evidence for the importance of the external competitive environment, government policies and financial inclusion as determinants of BT adoption, as these have not been considered in prior studies. For example, Guo *et al.* (2021) focus only on the associations between technological innovation and costs, risks and regulations in studying the determinants of early adoption of blockchain according to Rogers' (2003) diffusion of innovation theory. Our study focuses on TOE theory. Furthermore, Lardo, Corsi, Varma, and Mancini (2022) point out that although BT has a demonstrated relevance and potential for application in accounting, it remains less explored at a corporate level. Our results thus add new knowledge in that context.

Our additional test of economic significance also clarifies the economic importance of factors influencing BT adoption. This method contrasts with the statistical significance tests used in previous studies (Angelis & Ribeiro da Silva, 2019; Clohessy & Acton, 2019; Gökalp *et al.*, 2022; Hashimy *et al.*, 2022), which allows for a comprehensive understanding of the degree to which factors affect BT adoption. Our study thus offers important insights into the key drivers of BT adoption and modelling that can be used to explore the economic importance of the influencing factors. Our study therefore provides business executives with evidence of TOE factors that support an organisation's tendency to use BT and insights into adjusting organisational, cultural and innovative strategies within firms.

2. Theoretical framework and hypothesis development

2.1 Theory and related literature

Tornatzky and Fleischer (1990) developed the TOE framework to consider three categories of factors that affect IT innovation, and the framework considers internal and external factors at the firm level to predict the likelihood of technology adoption (Hashimy *et al.*, 2022). It also examines factors affecting managerial decisions to adopt technological innovation (Liang *et al.*, 2021). Here, technological factors refer to relative advantages, complexity, compatibility, interoperability, standardisation, security and scalability (Rogers & Shoemaker, 1971; Gökalp *et al.*, 2022). Organisational factors include organisational readiness, upper management support, innovativeness, organisation size, culture and IT resources (Damanpour, 1991; Gökalp *et al.*, 2022). The environmental context includes factors such as industry competition, government support and consumer readiness (Ramdani, Chevers, & Williams, 2013; Liang *et al.*, 2021).

TOE is a comprehensive and widespread theoretical model for capturing IT adoption in an organisation (Zhu, 2004). By incorporating three categories of factors, TOE provides a significant advantage over other models in terms of studying the adoption and value creation of technological innovations (Zhu & Kraemer, 2005; Ramdani, Kawalek, Lorenzo, Dwivedi, & Papazafeiropoulo, 2009; Hossain & Quaddus, 2011). Previous research into technology adoption has predominantly concentrated on individual categories from the TOE framework (Clohessy & Acton, 2019; Gökalp *et al.*, 2022; Hashimy *et al.*, 2022), which thus provides a foundational model for evaluating the integration of various forms of technological innovations. Therefore, our study employs this framework to examine a firm's decision-making process regarding implementing BT innovation by considering three different dimensions.

2.2 Hypothesis development

2.2.1 AI and BT adoption. BT is a peer-to-peer network technology composed of interconnected blocks and chains, where each block records transactions that are linked to other blocks through chains (Sinha, 2020). It is the technology behind the cryptocurrency Bitcoin, developed by Nakamoto in 2008 (Schmitz & Leoni, 2019). In recent years, organisations have adopted AI technology in their businesses (Mariani, Machado, Magrelli, & Dwivedi, 2023) for tasks including innovation analytics (Kakatkar, Bilgram, & Fuller, 2020), digital experimentation and digital innovation (Mariani & Nambisan, 2021), and AI and big data integration within business processes (Wamba & Mishra, 2017). BT is currently undergoing a transformation from a secure cryptocurrency transaction system to part of an emerging technology ecosystem, including AI, IoT, robotics and crowdsourcing technologies (Dai & Vasarhelyi, 2017). In particular, AI technology is effective in enhancing a firm's innovation in BT. For example, Mariani *et al.* (2023) found that companies can foster innovative development through the use of AI, and AI can also enhance collaboration and information sharing to improve operational efficiency (Briscoe & Rogan, 2016).

By analysing information and allocating resources more accurately, companies can invest more resources in technology innovation. AI can also assist in effectively managing and analysing data to reduce research and development costs and risks (Rose, Hölzle, & Björk, 2020). This is of interest, as patents are an essential intellectual property that indicates a business's innovation activity and performance, which is closely tied to technological innovation (Alencar, Porter, & Antunes, 2007). Implementing AI systems may allow firms to detect emerging technologies and develop innovative products (Mariani *et al.*, 2023). AI technology can automatically analyse and identify patterns in massive datasets using deep learning methodologies (Makridakis, Polemitis, Giaglis, & Louca, 2018); however, the major obstacle to AI adoption is the centralised management and storage of data, which may result in data tampering, manipulation, or privacy issues (Salah, Rehman, Nizamuddin, & Al-Fuqaha, 2019). Blockchain is the secure decentralised ledger that underpins cryptocurrencies, and this could bridge the gap in AI's data security. Integrating AI and BT could thus provide a secure, trusted platform to process large volumes of data for computing, deep learning and decision-making (Ekramifard, Amintoosi, Seno, Dehghantanha, & Parizi, 2020). In accounting, BT can prevent AI algorithms from generating misleading conclusions due to system failures or tampering with data sources by verifying the identity of the data generator (Kumar, Lim, Sivarajah, & Kaur, 2023). The presence of AI may therefore lead to more companies embracing BT, thus leading to a positive correlation between AI use and BT adoption. Therefore, we propose the following hypothesis:

H1. AI is positively associated with BT adoption.

2.2.2 Externally oriented cultures and BT adoption. Organisational factors encompass firms' characteristics and available resources, which play a significant role in using BT (Lu, Lin, & Tzeng, 2013). Based on Quinn and Rohrbaugh's (1983) competing values framework, corporate culture can be categorised into two types: internally and externally oriented. Internally oriented cultures can focus on collaboration or control, while externally oriented cultures tend to focus on competition or creation. In a collaboration-oriented culture, organisations encourage employees to develop positive interpersonal and cooperative relationships to foster positive attitudes towards their work and to improve production processes (Fiordelisi & Ricci, 2014), and there are generally higher levels of trust between employees and management (Bhandari, Mammadov, Thevenot, & Vakilzadeh, 2022). In contrast, control-oriented cultures emphasise hierarchical management structures and efficient use of managerial resources. From a theoretical point of view, internally oriented cultures (i.e. collaboration- and control-oriented cultures) are less relevant to technology adoption. Our study therefore focuses on externally oriented cultures (i.e. competition- and creation-oriented cultures).

A competition-oriented culture prioritises external benefits and aims to enhance competitiveness through organisational efficiency and customer focus (Fiordelisi & Ricci, 2014), while a creation-oriented culture encourages employee innovation and expansion (Bhandari *et al.*, 2022). Companies with a competition-oriented culture adopt aggressive business strategies to enhance market competitiveness (Cameron, Quinn, DeGraff, & Thakor, 2006), which incentivises organisations to invest in research and development (R&D) in new technology, such as new BT business models (Cai *et al.*, 2021). Barth and Mansouri (2021) show that a competition-oriented culture can enhance organisational effectiveness by ensuring that the organisation competes aggressively and responds quickly to challenges. BT can thus be considered a differentiator in the market within competition-oriented cultures, demonstrating the company's innovative and technological capabilities, thereby increasing the company's overall competitiveness.

Fiordelisi and Ricci (2014) show that a creation-oriented culture allows an organisation to create future market opportunities by focusing on innovation in its products and services. This type of organisational culture allows companies to invest in and research new products, develop revolutionary processes and redefine distribution and logistics. Kimani *et al.* (2020) posit that, as one of the most significant innovations in the financial industry, BT can be applied in many fields, such as finance, international trade, taxation, supply chain management and business operations. BT is also revolutionising the digital world, with business processes becoming more secure, resilient and efficient (Sciarelli, Prisco, Gheith, & Muto, 2022). Within creation-oriented cultures, management is likely to appreciate these advantages of BT and be motivated to adopt it. Therefore, we propose the following hypothesis:

H2. Externally oriented corporate cultures (i.e. those oriented towards competition and creation) are positively associated with BT adoption.

2.2.3 Environmental factors and BT adoption. The environment-related factors in the TOE framework comprise external competition pressure and government policy and regulations (Liang *et al.*, 2021; Gökalp *et al.*, 2022). These are critical factors for studying technology innovation (Gökalp *et al.*, 2022). In this study, we consider industry competition, government subsidies and the level of digital financial development in the regions, as these factors are relevant to the adoption of technology.

Iacovou, Izak, and Albert (1995) define competitive pressure as the extent to which an organisation competes with its industry peers for resources such as customers and market share. Porter and Millar (1985) suggest that businesses adopt information systems to transform their competitive environment, including the competition rules, market structure and ability to compete with peers. Ramdani *et al.* (2009) found that industry competition significantly affects technology adoption, and management is therefore motivated to investigate BT to enhance the firm's industry and competitive position under competition pressure (Prewett, Prescott, & Phillips, 2020). The benefits of using BT also motivate management to consider its use to enhance the firm's competitive position. For example, Hashimy *et al.* (2022) point out that BT adoption can give companies an advantage in a competitive market by enabling new products with new services and features. BT can improve accuracy, traceability and transparency by saving the costs and effort involved in keeping records and processing transactions (Karajovic, Kim, & Laskowski, 2019). It also increases trading efficiency and effectiveness, as well as the sharing of information and data communication between all participants in the business ecosystem (Wang & Kogan, 2018). Such benefits can lead management to view BT as an effective solution to help companies take advantage of a competitive market (Pun, Swaminathan, & Hou, 2021). Companies in a competitive environment are thus expected to value BT applications more than those in a less competitive environment.

Governments provide policies to support new technologies by regulating and supervising their implementation (Gökalp *et al.*, 2022). For example, government policies such as tax credits and subsidies are designed to support firms' R&D investment, which can reduce innovation costs and stimulate further R&D (Xu, Wang, & Liu, 2021). Based on a study of a market in a manufacturing industry, Pun *et al.* (2021) suggest that government subsidies can encourage manufacturers to adopt BT to benefit customers and society by lowering retail prices as part of subsidies passed on to them. Ahmed *et al.* (2024) indicate that the government influences technology innovation and investment. In China, for example, the Chinese Government has introduced several policies, laws and regulations since 2013 to support investment in the blockchain sector and foster the sustainable development of BT (Wang *et al.*, 2020). Favourable policies have contributed to blockchain development and led some companies to introduce blockchain projects. Government support thus plays a significant role in BT development and adoption (Xu *et al.*, 2021).

Financial inclusion refers to the creation of a financial system where all layers and groups of society have access to services effectively and comprehensively. It allows underdeveloped areas and people with lower incomes access to more convenient and affordable financial services (Varghese & Viswanathan, 2018). Individuals and businesses should have access to the financial products and services relevant to their needs. The digital transformation of traditional financial institutions has been caused by the growth of the digital economy, and this has resulted in increased activities for financial inclusion (He & Liu, 2024). Mhlanga (2023) points out that governments should prioritise BT investments to improve citizens' access to financial services. An example of this is the Chinese Government's 2014 introduction of policies to support rural-inclusive finance and promote rural financial reform and innovation (He & Liu, 2024). The potential benefits of BT in financial transactions, savings, the provision of credit and insurance verification can promote digital financial inclusion (Mhlanga, 2023), so the development of financial inclusion reflects the strength of the local financial infrastructure, which positively affects investment in and development of BT. Companies may also need to adopt BT to align new business models with financial inclusion strategies. Our study therefore proposes the third hypothesis as follows:

H3. External environmental factors (i.e. competitive pressures, government support and financial inclusion) are positively associated with BT adoption.

3. Research design

3.1 Data and sample selection

Our study uses a large sample of 32,914 firm-year observations spanning nine years (2013–2021) and covering both Shenzhen and Shanghai Stock Exchange–listed companies. After excluding financial institutions (741 firm-year observations) and missing data (4,773 firm-year observations), the final sample comprises 27,400 firm-year observations. The sample period started in 2013 because that is when the Chinese Government began issuing policies to promote the sustainable development of BT (Wang *et al.*, 2020). Our study extracts primary data from the Chinese Stock Market and Accounting Research (CSMAR) database, which contains annual reports for measuring BT and corporate culture and financial data for control variables. Continuous variables are winsorised at the 1st and 99th percentiles.

3.2 Research model and measures of variables

3.2.1 Research model. Based on Tornatzky and Fleischer's (1990) TOE framework and Bhandari *et al.*'s (2022) research model, our study employs a regression model to examine the potential determinants influencing BT adoption.

$$\begin{aligned} \mathrm{BT}_{i,t} = a_0 + a_1\, AI_{i,t} = a_2 Compete_{i,t} &+ a_3 Compete_{i,t} + a_4 HHI_{i,t} + a_5 Subsidy_{i,t} \\ &+ a_6 DFI_{i,t} + a_7 Size_{i,t} + a_8 ROA_{i,t} + a_9 Cash_{i,t} + a_{10} Growth_{i,t} \\ &+ a_{11} Lev_{i,t} + a_{12} MTB_{i,t} + a_{13} Nestloss_{i,t} + a_{14}\ Top1_{i,t} \\ &+ a_{15} Agescale_{i,t} + a_{16} SOE_{i,t} + a_{17} HTT_{i,t} + a_{18} Big_{i,t} \\ &+ \sum Year + \sum Industry + \in_{i,t} \end{aligned} \tag{1}$$

The dependent variable for Model (1) is the adoption of BT (*BT_Adoption*). The independent variables are artificial intelligent (*AI*), competition-oriented culture (*Compete*), creation-oriented culture (*Create*), industry competition (*HHI*), government support (*Subsidy*) and financial inclusion (*DFI*); firm and year are denoted by *i* and *t*, respectively. The measurement of each variable in Model (1) is described below.

3.2.2 BT measures. To understand the blockchain activities in listed companies, we manually collect BT-related information from the annual reports of listed Chinese firms. Based on the measurement used by Huang, Wang, and Yen (2024), a firm's BT activities are coded as implemented if the firm has disclosed BT projects and investments in its annual reports. To collect this information, we first obtain a list of 273 listed companies from the blockchain sector of China's capital market. Second, we search for the keyword *blockchain technology* in annual reports and read the relevant content to confirm whether the companies have adopted BT. The manual collection process yielded 257 firms with blockchain projects and investments in their business. Thus, *BT_Adoption* equals one if the firm discloses a blockchain-related project or investments, and zero otherwise.

3.2.3 Externally oriented corporate culture measures. Previous studies have mentioned several measurements and definitions of corporate culture (Cameron *et al.*, 2006; Hartnell, Ou, & Kinicki, 2011; Fiordelisi & Ricci, 2014). Our study uses the frameworks provided by Cameron *et al.* (2006) in collaboration with Fiordelisi and Ricci (2014) to identify the list of words associated with an externally oriented corporate culture. To extract and calculate corporate culture variables, we first obtain the vocabulary lists (see Appendix II) from Fiordelisi and Ricci (2014). Second, we cross-referenced the vocabulary lists (English version) and created a Chinese list based on the *Oxford Advanced Learner's English–Chinese Dictionary* (9th edition) (Hornby, 2018). Third, we use Python Crawler software to extract corporate culture-related keywords from the management discussion and analysis (MD&A) section of the annual reports of listed companies based on the Chinese version of the vocabulary lists. Finally, the extracted keywords are counted to compute the independent variables. The independent variables for competition- (*Compete*) and creation-oriented (*Create*) corporate culture are defined by the proportion of corporate culture–related keywords to the total number of words in the annual reports; the results are multiplied by 100 for the empirical analysis.

3.2.4 Other independent and control variables. We use the Python-based Web Crawler method to obtain the number of AI patents from 2013 to 2021 from the China National Knowledge Infrastructure [1]. *AI* is a dummy variable that equals one if the company has AI-related patents in the current year. Our study includes industry competition (*HHI*), government support (*Subsidy*) and financial inclusion (*DFI*). *HHI* is the Herfindahl–Hirschman index, which reflects the level of market competition. A larger index value indicates a stronger monopoly in the market, which leads to a less competitive environment. *Subsidy* indicates government support for business innovation, measured using the natural logarithm of government subsidies. *DFI* represents the level of digital financial development in the regions. We use the *Peking University Digital Financial Inclusion Index of China* [2] as a proxy for financial inclusion.

Model (1) also includes some control variables. We control for firm size (*Size*), calculated as the natural logarithm of total assets. The profitability of listed firms is also considered in the regression, including *ROA*, *Cash*, *Growth*, *Lev*, *MTB* and *Netloss*. *ROA* is the annual return on assets at the end of the financial year. *Cash* represents the corporate financing constraint by calculating cash flow from operating activities divided by the total assets. *Growth* measures the growth rate of a firm's sales revenue. *Lev* is the company's leverage ratio. *MTB* is defined as the ratio of market value to the netbook value of firms. *Netloss* is a dummy variable that equals one if the company faces a net loss and zero otherwise.

We also consider firms' equity concentration (*Top1*), age (*Agescale*), nature of ownership (*SOE*) and industry characteristics (*HTT*). *Top1* indicates the percentage of shares held by the largest shareholder. *Agescale* represents the age of the enterprise in years. *SOE* equals one when the firm is owned by the state and zero otherwise. *HTT* equals one if the firm belongs to the high-technology industry [3]. *Big4* is set to one if the company hires a Big Four accounting firm. Data for all control variables are available on the CSMAR database. The definitions for all variables in Model (1) can be found in Appendix III.

4. Empirical results

4.1 Descriptive statistics

Table 1 shows the descriptive statistics for all variables in our study. The dependent variable, *BT_Adoption*, ranges from 0 to 1.000, with a mean value of 0.033, which indicates that 3.3% of listed firms have used BT. *Compete* and *Create*, the independent variables, have mean values of 0.931 and 0.299. Considering that the variables are multiplied by 100 to make it easier to observe the empirical results, this indicates that the average proportion of words related to competition- and creation-oriented culture found in the MD&A section of annual reports is 0.931% and 0.299%, respectively. The mean values for AI, market competition (*HHI*), government support (*Subsidy*) and financial inclusion (*DFI*) are 0.009, 0.140, 15.179 and 0.326, respectively.

For the variables related to firms' financial characteristics, the mean value for firm size and market-to-book value (*MTB*) are 22.198 and 2.131, respectively. On average, the return on assets, cash flow as a percentage of total assets (*Cash*), sales revenue growth rate (*Growth*) and asset–liability ratio (*Lev*) are 3.2%, 4.6%, 17.7% and 42.5%, respectively. In addition, a

Table 1. Sample descriptive statistics

Variables	*N*	Mean	SD	Min	P25	Median	P75	Max
BT_Adoption	27,400	0.033	0.178	0.000	0.000	0.000	0.000	1.000
AI	27,400	0.009	0.095	0.000	0.000	0.000	0.000	1.000
Compete	27,400	0.931	0.108	0.650	0.861	0.931	1.002	1.200
Create	27,400	0.299	0.051	0.177	0.267	0.297	0.328	0.472
HHI	27,400	0.140	0.149	0.026	0.057	0.090	0.155	0.891
Subsidy	27,400	15.179	4.072	0.000	14.827	16.099	17.170	20.240
DFI	27,400	0.326	0.082	0.142	0.265	0.337	0.397	0.459
Size	27,400	22.198	1.307	19.240	21.275	22.025	22.940	26.181
ROA	27,400	0.032	0.077	−0.398	0.013	0.037	0.068	0.212
Cash	27,400	0.046	0.070	−0.182	0.008	0.046	0.086	0.251
Growth	27,400	0.177	0.452	−0.628	−0.026	0.107	0.271	2.923
Lev	27,400	0.425	0.211	0.057	0.255	0.412	0.576	0.952
MTB	27,400	2.131	1.483	0.849	1.262	1.659	2.398	9.893
Netloss	27,400	0.121	0.326	0.000	0.000	0.000	0.000	1.000
Top1	27,400	0.359	0.149	0.000	0.246	0.343	0.459	0.748
Agescale	27,400	3.016	1.411	1.000	2.000	3.000	4.000	5.000
SOE	27,400	0.320	0.467	0.000	0.000	0.000	1.000	1.000
HTT	27,400	0.259	0.438	0.000	0.000	0.000	1.000	1.000
Big4	27,400	0.056	0.230	0.000	0.000	0.000	0.000	1.000

Netloss of 0.121 indicates that 12.1% of the sample faces a net loss on average. For the variables related to firms' governance characteristics, the average shareholding of the largest shareholders (*Top1*) is 35.9%. On average, state-owned enterprises (*SOE*) account for 32.0% of the sample, 5.6% hire Big Four accounting firms (*Big4*) and 25.9% are high-tech enterprises (*HTT*). Firm age (*Agescale*) is segmented by quartiles from 1 to 5, representing the five stages of business development, with the results yielding a mean value of 3.016.

4.2 Pearson correlation

Table 2 presents the Pearson correlations among the dependent, independent and control variables. Column (1) of Table 2 shows that *BT_Adoption* positively correlates with *AI*, *Compete*, *Create*, *Subsidy and DFI* at a 1% significance level. A negative correlation between *BT_Adoption* and *HHI* can also be observed at a 1% significance level. The results of the correlation analysis indicate that all variables in the model are significantly correlated, and there is no evidence of multicollinearity.

4.3 Regression results

We conducted regression analysis using Model (1) to investigate the determinants of BT adoption. As shown in Column (1) of Table 3, AI is positively associated with BT adoption (regression coefficient = 0.072, $p < 0.05$), which indicates that AI-based businesses are more likely to embrace BT. The focus of corporate culture on competition (regression coefficient = 0.042, $p < 0.05$) and creation (regression coefficient = 0.068, $p < 0.10$) are positively related to BT adoption. This suggests that companies with a culture of competition and innovation tend to adopt aggressive strategies that drive management to invest in new technology. We also find that *HHI* is negatively associated with *BT_Adoption* (regression coefficient = −0.058, $p < 0.01$), which indicates that BT adoption is likely to be slower and less widespread in industries with strong monopolies. Businesses are thus more likely to adopt blockchain when monopolies decline, allowing the market to become more competitive.

The *Subsidy* coefficient is significantly positively associated with BT adoption (regression coefficient = 0.001, $p < 0.01$), and the results suggest that many companies use blockchain applications when they receive government subsidies. In other words, government policies encourage businesses to explore the blockchain. Finally, the *DFI* coefficient is significantly positive (regression coefficient = 0.040, $p < 0.05$), which suggests that blockchain projects are more likely to be an investment priority for listed companies with higher digital financial inclusion. Financial inclusion entails all citizens having adequate access to high-quality financial services from formal financial institutions (Shen, Hueng, & Hu, 2020), and the degree of financial inclusion thus reflects the level of regional financial development. The results indicate that the level of local financial development positively affects BT adoption. The company-related variables presented mixed results. Larger companies (*Size*) are more likely to use BT, but companies with higher *ROA*, cash flow (*Cash*), growth rate of revenue (*Growth*), state ownership and ownership ratio (*Top1*) are less likely to adopt BT.

Column (1) in Table 3 shows that competition- and creation-oriented cultures, a competitive market (these appear as negative numbers, because we use market monopoly as a proxy variable and lower *HHI* reflects stronger market competitiveness), government support and financial inclusion positively affect BT adoption. We further tested the individual determinants of BT adoption and found the same results (shown in Table 4). Hypothesis one (H1) – that AI is positively associated with BT adoption – is therefore supported. Hypothesis two (H2) – that externally oriented corporate cultures (i.e. oriented towards competition and creation) are positively associated with BT adoption – and hypothesis three (H3) – that external environment factors (i.e. competitive pressure, government support and financial inclusion) are positively associated with BT adoption – are also supported.

Table 2. Pearson correlation matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) BT_ Adoption	1.000								
(2) AI	0.070***	1.000							
(3) Compete	0.069***	−0.007	1.000						
(4) Create	0.065***	0.016***	0.381***	1.000					
(5) HHI	−0.019***	−0.009	−0.017***	−0.059***	1.000				
(6) Subsidy	0.029***	0.041***	−0.096***	−0.099***	−0.014**	1.000			
(7) DFI	0.115***	0.048***	0.045***	0.191***	0.004	−0.008	1.000		
(8) Size	0.016***	0.072***	−0.373***	−0.125***	0.034***	0.248***	0.111***	1.000	
(9) ROA	−0.057***	0.017***	0.136***	0.050***	−0.059***	0.050***	−0.036***	0.026***	1.000
(10) Cash	−0.023***	0.015**	0.006	−0.035***	0.002	0.067***	0.034***	0.080***	0.365***
(11) Growth	−0.023***	−0.004	0.090***	0.030***	−0.004	0.003	0.007	0.029***	0.215***
(12) Lev	−0.012*	0.008	−0.327***	−0.139***	0.049***	0.060***	0.040***	0.469***	−0.380***
(13) MTB	0.008	0.006	0.190***	0.058***	0.009	−0.120***	−0.053***	−0.419***	0.062***
(14) Netloss	0.051***	−0.017***	−0.078***	−0.027***	0.047***	−0.049***	0.063***	−0.068***	−0.689***
(15) Top1	−0.096***	−0.003	−0.059***	−0.014**	0.025***	0.052***	−0.085***	0.132***	0.200***
(16) Agescale	0.031***	0.008	−0.080***	0.051***	0.019***	−0.075***	0.320***	0.167***	−0.086***
(17) SOE	−0.050***	0.009	−0.284***	−0.203***	0.058***	0.040***	−0.012**	0.359***	−0.048***
(18) HTT	0.153***	0.080***	0.148***	0.102***	−0.199***	0.032***	0.020***	−0.159***	0.033***
(19) Big4	0.010	0.058***	−0.174***	−0.057***	0.045***	0.079***	0.043***	0.321***	0.046***

	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
(10) Cash	1.000									
(11) Growth	0.016***	1.000								
(12) Lev	−0.182***	0.009	1.000							
(13) MTB	0.050***	0.048***	−0.206***	1.000						
(14) Netloss	−0.215***	−0.181***	0.236***	0.049***	1.000					
(15) Top1	0.133***	−0.002	−0.051***	−0.117***	−0.154***	1.000				
(16) Agescale	−0.016***	−0.033***	0.172***	−0.037***	0.070***	−0.112***	1.000			
(17) SOE	−0.002	−0.071***	0.252***	−0.142***	−0.008	0.119***	0.196***	1.000		
(18) HTT	0.009	0.024***	−0.199***	0.195***	−0.006	−0.095***	−0.083***	−0.118***	1.000	
(19) Big4	0.078***	−0.008	0.085***	−0.074***	−0.043***	0.122***	0.028***	0.131***	−0.042***	1.000

Note(s): *** indicates significance at the 1% level ($p < 0.01$); ** indicates significance at the 5% level ($p < 0.05$); * indicates significance at the 10% level ($p < 0.1$). Standard errors are adjusted for firm-level clustering. Variable definitions are presented in Appendix III

Table 3. Determinants of blockchain technology adoption

Variables	(1) *BT_Adoption*	(2) Variables importance
AI	0.072** (2.23)	0.11%
Compete	0.042** (2.13)	6.43%
Create	0.068* (1.74)	3.35%
HHI	−0.058*** (−3.82)	1.34%
Subsidy	0.001*** (3.27)	2.34%
DFI	0.040** (2.09)	2.18%
Size	0.010*** (4.79)	38.41%
ROA	−0.063** (−2.06)	0.33%
Cash	−0.035* (−1.89)	0.27%
Growth	−0.008*** (−3.51)	0.23%
Lev	−0.013 (−1.06)	0.00%
MTB	0.000 (0.29)	0.00%
Netloss	0.007 (1.21)	0.00%
Top1	−0.070*** (−5.69)	4.15%
Agescale	0.001 (0.32)	0.00%
SOE	−0.011** (−2.45)	0.58%
HTT	0.002 (0.46)	0.00%
Big4	0.006 (0.68)	0.00%
Constant	−0.243*** (−4.69)	40.28%
Year fixed effect	YES	
Industry fixed effect	YES	
N	27,400	
Adj_R^2	0.118	

Note(s): *** indicates significance at the 1% level ($p < 0.01$); ** indicates significance at the 5% level ($p < 0.05$); * indicates significance at the 10% level ($p < 0.1$). Standard errors are adjusted for firm-level clustering. Variable definitions are presented in Appendix III

4.4 Variables importance

Prior studies on the factors affecting BT adoption have used statistical significance to determine whether there is a causal relationship between the dependent and independent variables. Zimmerman (1992), however, suggests analysing the results in terms of economic significance instead of statistical significance. When multiple independent variables are examined simultaneously on the dependent variable, it is challenging to evaluate the extent to which each independent variable contributes to the dependent variable using only econometric

Table 4. Determinants of blockchain technology adoption

Variables	(1) *BT_Adoption*	(2) *BT_Adoption*	(3) *BT_Adoption*	(4) *BT_Adoption*	(5) *BT_Adoption*	(6) *BT_Adoption*
AI	0.074**					
	(2.26)					
Compete		0.051***				
		(2.62)				
Create			0.095**			
			(2.41)			
HHI				−0.058***		
				(−3.77)		
Subsidy					0.001***	
					(3.30)	
DFI						0.039**
						(2.02)
Size	0.010***	0.012***	0.011***	0.011***	0.010***	0.011***
	(4.63)	(5.30)	(4.98)	(4.84)	(4.35)	(4.77)
ROA	−0.052*	−0.058*	−0.054*	−0.055*	−0.052*	−0.053*
	(−1.72)	(−1.90)	(−1.77)	(−1.82)	(−1.72)	(−1.73)
Cash	−0.039**	−0.037**	−0.037**	−0.038**	−0.041**	−0.040**
	(−2.07)	(−1.98)	(−1.98)	(−2.02)	(−2.15)	(−2.11)
Growth	−0.007***	−0.008***	−0.007***	−0.007***	−0.007***	−0.007***
	(−3.26)	(−3.71)	(−3.34)	(−3.31)	(−3.28)	(−3.35)
Lev	−0.018	−0.014	−0.015	−0.018	−0.018	−0.018
	(−1.48)	(−1.14)	(−1.25)	(−1.49)	(−1.47)	(−1.49)
MTB	0.000	0.000	0.000	0.000	0.001	0.000
	(0.13)	(0.20)	(0.24)	(0.36)	(0.38)	(0.23)
Netloss	0.006	0.006	0.006	0.006	0.006	0.006
	(1.18)	(1.15)	(1.13)	(1.10)	(1.15)	(1.09)
Top1	−0.070***	−0.070***	−0.071***	−0.070***	−0.071***	−0.070***
	(−5.70)	(−5.70)	(−5.78)	(−5.70)	(−5.74)	(−5.65)
Agescale	0.000	0.000	0.000	0.000	0.000	−0.000
	(0.17)	(0.21)	(0.20)	(0.24)	(0.27)	(−0.00)
SOE	−0.013***	−0.011**	−0.011**	−0.013***	−0.012***	−0.013***
	(−2.85)	(−2.49)	(−2.57)	(−2.90)	(−2.79)	(−2.88)
HTT	0.007	0.008	0.007	0.005	0.008	0.008
	(1.46)	(1.52)	(1.41)	(0.85)	(1.53)	(1.57)
Big4	0.004	0.007	0.005	0.006	0.005	0.005
	(0.42)	(0.71)	(0.57)	(0.62)	(0.54)	(0.50)
Constant	−0.156***	−0.241***	−0.207***	−0.162***	−0.163***	−0.179***
	(−3.41)	(−4.71)	(−4.26)	(−3.46)	(−3.49)	(−3.77)
Year fixed effect	YES	YES	YES	YES	YES	YES
Industry fixed effect	YES	YES	YES	YES	YES	YES
N	27,400	27,400	27,400	27,400	27,400	27,400
Adj_R^2	0.115	0.114	0.114	0.115	0.114	0.114

Note(s): *** indicates significance at the 1% level ($p < 0.01$); ** indicates significance at the 5% level ($p < 0.05$); * indicates significance at the 10% level ($p < 0.1$). Standard errors are adjusted for firm-level clustering. Variable definitions are presented in Appendix III

significance. The mean decomposition of variables, however, provides a method for assessing variables' economic importance based on Holgersson *et al.* (2014). Sterck (2019) does, however, point out some deficiencies in using mean value decomposition to determine the economic significance of variables. First, once a variable has a regression coefficient in the regression results, it has economic importance, even if the results are not statistically significant – that is, the *p*-value is greater than 0.1. Second, the method of mean value decomposition is not appropriate when the regression coefficients or the mean value of variables are negative, which can lead to offsetting the contributions of the variables. Thus, according to the research of Holgersson *et al.* (2014) and Sterck (2019), we use absolute values to calculate the importance of variables for economic analysis and exclude the variables that are not statistically significant. The models are as follows:

$$\overline{Y} = \widehat{\beta}_0 + \widehat{\beta}_1\overline{X}_1 + \widehat{\beta}_2\overline{X}_2 + \ldots + \widehat{\beta}_n\overline{X}_n, \text{ and} \tag{2}$$

$$1 = \frac{\widehat{\beta}_0}{\overline{Y}} + \frac{\widehat{\beta}_1\overline{X}_1}{\overline{Y}} + \frac{\widehat{\beta}_2\overline{X}_2}{\overline{Y}} + \ldots + \frac{\widehat{\beta}_n\overline{X}_n}{\overline{Y}}, \tag{3}$$

where $\overline{X}$ represents a sample mean of the explanatory variables, $\widehat{\beta}$ is the regression coefficient of each explanatory variable. $\overline{Y}$ is the total contribution percentage of the explanatory variables to the dependent variable. According to the results of Column (2) in Table 3, firm size (*Size*) plays a major role in determining the adoption of enterprise blockchain innovation and contributes 38.41% to the variance (e.g. $\widehat{\beta} = 0.010$, $\overline{X} = 22.198$, $\widehat{\beta} * \overline{\mathrm{X}} = 0.222$, which is 38.41% of total contributions). The economic importance of *AI*, *Compete*, *Create*, *HHI*, *Subsidy* and *DFI* is 0.11%, 6.43%, 3.35%, 1.34%, 2.34% and 2.18%, respectively. The results indicate that competition-oriented culture has the most significant impact on companies' use of blockchain, which is among the major influences considered in our study. A creation-oriented culture also contributes more significantly to companies' decisions to use blockchain than AI patents, market competition, government subsidies and financial inclusion.

5. Robustness tests

5.1 Excluding the effects of strategic disclosure

Firms strategically manipulate the readability of the textual content of financial reports to hide adverse information (Li, 2008; Lo, Ramos, & Rogo, 2017). In this study, we extract blockchain keywords from annual reports. Therefore, we use two methods to eliminate the effects of management's strategic disclosure on the research results. First, we exclude a sample of firms penalised by the China Securities Regulatory Commission (CSRC) during the sample period. The results of Column (1) of Table 5 indicate that *AI* (regression coefficient = 0.077, $p < 0.05$), *Compete* (regression coefficient = 0.032, $p < 0.10$), *Create* (regression coefficient = 0.068, $p < 0.10$), *Subsidy* (regression coefficient = 0.001, $p < 0.01$) and *DFI* (regression coefficient = 0.036, $p < 0.10$) are positively associated with BT adoption. We find that *HHI* (regression coefficient = −0.050, $p < 0.01$) has a negative effect on BT adoption.

Second, we remove the sample of listed companies whose disclosure quality is rated as pass or fail by the Shenzhen and Shanghai Stock Exchanges, thus retaining only firms with excellent and good ratings. The disclosure quality rating list is obtained from CSMAR. The results in Column (2) are consistent with those in Column (1) of Table 5. The five determinants – *AI* (regression coefficient = 0.078, $p < 0.05$), *Compete* (regression coefficient = 0.039, $p < 0.10$), *Create* (regression coefficient = 0.091, $p < 0.10$), *Subsidy* (regression coefficient = 0.001, $p < 0.01$) and *DFI* (regression coefficient = 0.084, $p < 0.01$) – have a positive relationship with BT adoption. However, *HHI* (regression coefficient = −0.055, $p < 0.01$) continues to have a negative relationship with BT adoption. The results are consistent with the main regression after conducting tests to eliminate the effect of strategic corporate disclosure. Thus, the findings remain robust.

5.2 Analyses with alternative measures for BT adoption

We used two alternative measures of BT adoption to test the robustness of the regression results, including *BT_Disclosure_Proportion* and *BT_Disclosure_Only*. We use the MD&A

Table 5. Excluding the effects of strategic disclosure

Variables	(1) *BT_Adoption*	(2) *BT_Adoption*
AI	0.077**	0.078**
	(2.30)	(2.16)
Compete	0.032*	0.039*
	(1.72)	(1.73)
Create	0.068*	0.091*
	(1.83)	(1.85)
HHI	−0.050***	−0.055***
	(−3.26)	(−2.80)
Subsidy	0.001***	0.001***
	(3.40)	(3.03)
DFI	0.036*	0.084***
	(1.90)	(3.10)
Size	0.010***	0.010***
	(4.49)	(3.58)
ROA	−0.073**	−0.134***
	(−2.18)	(−2.78)
Cash	−0.030*	−0.017
	(−1.65)	(−0.69)
Growth	−0.007***	−0.006*
	(−2.94)	(−1.69)
Lev	−0.008	−0.013
	(−0.68)	(−0.77)
MTB	0.001	0.001
	(0.86)	(0.80)
Netloss	0.003	0.001
	(0.57)	(0.07)
Top1	−0.063***	−0.067***
	(−5.27)	(−4.51)
Agescale	0.000	0.000
	(0.25)	(0.14)
SOE	−0.010**	−0.016***
	(−2.14)	(−2.60)
HTT	0.003	0.006
	(0.61)	(0.99)
Big4	0.005	0.012
	(0.59)	(0.91)
Constant	−0.228***	−0.257***
	(−4.51)	(−3.89)
Year fixed effect	YES	YES
Industry fixed effect	YES	YES
N	24,694	18,190
Adj_R^2	0.114	0.125

Note(s): *** indicates significance at the 1% level ($p < 0.01$); ** indicates significance at the 5% level ($p < 0.05$); * indicates significance at the 10% level ($p < 0.1$). Standard errors are adjusted for firm-level clustering. Variable definitions are presented in Appendix III

section for textual analysis for the following reasons. In 2012, the Chinese regulator revised the No. 2 Guideline on the content and format of information disclosure, which resulted in a more standardised and rationalised content of the MD&A section in the annual reports of listed companies. Using disclosure information to measure technology adoption has also been applied in prior studies. Some studies have also adopted a text analytics method to extract keywords from the MD&A section to measure corporate digital transformation (Dou, Guo, Chang, & Wang, 2023; Wu & Lu, 2023; Zhang & Wang, 2024) or extract blockchain-related keywords from MD&A and construct them as dependent variables using a machine-learning approach.

We obtain blockchain-related information by first using the *Chinese Blockchain Technology and Application Development White Paper* [4] to collect blockchain-related keywords. We then create a dictionary library using this word list. We transform the MD&A section of the annual reports of the listed companies into vocabulary lists using Python (Barth & Mansouri, 2021). Finally, following Zhao, Sun, Zhao, and Xing (2022) and Bhandari *et al.* (2022), we determine the frequency of blockchain-related keywords mentioned in the MD&A section using the Jieba database and the Python-based Web Crawler method based on the dictionary library. Thus, the dependent variable *BT_Disclosure_proportion* is the ratio of the number of blockchain-related words to the total length of the MD&A text. Appendix I contains a definition list that includes all blockchain-related keywords used in our study. We also further refine the blockchain keywords in the dictionary, which means that we only use the keyword *blockchain technology* and remove other blockchain-related keywords; *BT_Disclosure_Only* is the natural logarithm of the number of blockchain words disclosed in the MD&A section of annual reports.

Table 6 shows the positive correlations between *AI* [Column (1) = 0.066, $p < 0.01$; Column (2) = 0.095, $p < 0.05$], *Compete* [Column (1) = 0.089, Column (2) = 0.080, $p < 0.01$], *Create* [Column (1) = 0.078, Column (2) = 0.125, $p < 0.05$], *Subsidy* [Column (1) = 0.001, $p < 0.01$; Column (2) = 0.001, $p < 0.05$], *DFI* [Column (1) = 0.049, $p < 0.10$; Column (2) = 0.063, $p < 0.05$] and BT adoption. There is also still a negative correlation between *HHI* [Column (1) = −0.045, Column (2) = −0.081, $p < 0.01$] and BT adoption. The findings reported in Table 4 thus provide additional strong evidence to support H1, H2 and H3.

5.3 Excluding COVID-19-affected observations

Many companies in different fields were affected by the COVID-19 pandemic and experienced a decline in share prices, revenues and profit (Bapuji *et al.*, 2020). To eliminate the effect of COVID-19, we re-ran the regression model after removing the samples after 2020 (the samples from 2013–2019 were retained). The results shown in Table 7 align with the main regression results, confirming the robustness of the findings in our study (*AI* = 0.072, *Compete* = 0.042, *Create* = 0.067, $p < 0.05$; *HHI* = −0.055, *Subsidy* = 0.001, *DFI* = 0.039, $p < 0.01$).

6. Heterogeneity test

Given the substantial variations among firms in terms of ownership, technological capabilities and industry attributes, this section explores the differences in decision-making factors regarding BT adoption between SOEs versus non-SOEs, high-technology versus non-high-technology firms, and manufacturing versus non-manufacturing industries. The results shown in Columns (1) and (2) of Table 8 indicate that all factors, including *AI*, *Compete*, *Create*, *HHI* and *Subsidy*, significantly affect BT adoption in the non-SOE group. However, only *AI*, *HHI* and *DFI* significantly correlated with BT adoption in the SOE group (*AI* = 0.133, *HHI* = −0.066, $p < 0.01$; *DFI* = 0.044, $p < 0.05$). A possible explanation for this is that non-SOEs have less policy support and face greater market competition. They are thus more sensitive to government support (*Subsidy*), which leads to the statistical significance. Additionally, SOEs are situated in monopolistic industries, which leads to lower motivation to innovate (*Create*) and compete (*Compete*). SOEs' blockchain platforms do, however, have greater credibility in using local financial resources to connect with small- and medium-sized enterprises. Thus, *DFI* has a significant impact on BT adoption in the SOE group.

A comparison of high-technology and non-high-technology companies is shown in Columns (3) and (4) of Table 8. The results show that *AI* (regression coefficient = 0.052, $p < 0.01$), *Compete* (regression coefficient = 0.142, $p < 0.01$), *Create* (regression coefficient = 0.244, $p < 0.01$), *HHI* (regression coefficient = −0.209, $p < 0.01$) and *Subsidy* (regression coefficient = 0.003, $p < 0.01$) significantly affect BT adoption in the

Table 6. Results using alternative measures of blockchain technology

Variables	(1) *BT_Disclosure_Proportion*	(2) *BT_Disclosure_Only*
AI	0.066***	0.095**
	(3.49)	(2.14)
Compete	0.089***	0.080***
	(4.54)	(3.26)
Create	0.078**	0.125**
	(2.17)	(2.41)
HHI	−0.045***	−0.081***
	(−3.67)	(−4.30)
Subsidy	0.001***	0.001**
	(4.41)	(2.25)
DFI	0.049*	0.063**
	(1.95)	(2.50)
Size	0.013***	0.011***
	(6.46)	(3.67)
ROA	−0.048**	−0.069
	(−2.04)	(−1.62)
Cash	−0.144***	−0.102***
	(−8.12)	(−3.72)
Growth	−0.005**	−0.014***
	(−2.35)	(−4.15)
Lev	0.008	−0.025
	(0.74)	(−1.46)
MTB	0.002*	−0.001
	(1.82)	(−0.30)
Netloss	−0.015***	−0.006
	(−3.01)	(−0.75)
Top1	0.004	−0.029*
	(0.32)	(−1.81)
Agescale	−0.002	−0.001
	(−1.63)	(−0.27)
SOE	−0.011***	−0.001
	(−2.83)	(−0.24)
HTT	0.014***	0.011*
	(2.86)	(1.66)
Big4	−0.018***	−0.017*
	(−2.97)	(−1.88)
Constant	−0.325***	−0.305***
	(−6.38)	(−4.40)
Year fixed effect	YES	YES
Industry fixed effect	YES	YES
N	27,400	20,668
Adj_R²	0.118	0.133

Note(s): *** indicates significance at the 1% level ($p < 0.01$); ** indicates significance at the 5% level ($p < 0.05$); * indicates significance at the 10% level ($p < 0.1$). Standard errors are adjusted for firm-level clustering. Variable definitions are presented in Appendix III

high-technology group. However, *DFI* had no significant correlation with BT adoption in this group. The results indicate that high-technology companies have established internal innovation mechanisms and process robust technical expertise. The benefits provided by technology also strengthen companies with strong financing capabilities, so *DFI* plays no significant role in BT adoption.

We then divide the sample into manufacturing and non-manufacturing industry groups. The results in Columns (5) and (6) of Table 8 show that *AI* (regression coefficient = 0.109,

Table 7. Results of eliminating the impacts of COVID-19

Variables	(1) *BT_Adoption*
AI	0.072**
	(2.13)
Compete	0.042**
	(2.45)
Create	0.067**
	(2.09)
HHI	−0.055***
	(−4.80)
Subsidy	0.001***
	(3.53)
DFI	0.039***
	(2.86)
Size	0.008***
	(4.36)
ROA	−0.037
	(−1.29)
Cash	−0.032*
	(−1.80)
Growth	−0.004**
	(−2.11)
Lev	−0.014
	(−1.35)
MTB	0.001
	(0.66)
Netloss	0.000
	(0.08)
Top1	−0.049***
	(−4.91)
Agescale	−0.001
	(−0.89)
SOE	−0.010***
	(−2.93)
HTT	−0.000
	(−0.00)
Big4	0.005
	(0.67)
Constant	−0.203***
	(−4.56)
Year fixed effect	YES
Industry fixed effect	YES
N	19,472
Adj_R^2	0.093

Note(s): *** indicates significance at the 1% level ($p < 0.01$); ** indicates significance at the 5% level ($p < 0.05$); * indicates significance at the 10% level ($p < 0.1$). Standard errors are adjusted for firm-level clustering. Variable definitions are presented in Appendix III

$p < 0.01$), *Compete* (regression coefficient = 0.031, $p < 0.01$), *Create* (regression coefficient = 0.042, $p < 0.10$) and *Subsidy* (regression coefficient = 0.001, $p < 0.05$) have significant results in manufacturing industries. In contrast, *Compete* (regression coefficient = 0.068, $p < 0.05$), *Create* (regression coefficient = 0.114, $p < 0.10$), *HHI* (regression coefficient = −0.073, $p < 0.01$), *DFI* (regression coefficient = 0.121, $p < 0.01$) and *Subsidy* (regression coefficient = 0.002, $p < 0.05$) have a significant impact on BT adoption in non-manufacturing industries. The reason for this result is that non-manufacturing industries

Table 8. Heterogeneity test

Variables	(1) *SOE = 1*	(2) *SOE = 0*	(3) *HTT = 1*	(4) *HTT = 0*	(5) Industry = 1	(6) Industry = 0
AI	0.133***	0.042***	0.052***	0.051***	0.109***	0.001
	(9.39)	(2.87)	(2.58)	(3.90)	(10.74)	(0.05)
Compete	0.021	0.054***	0.142***	0.007	0.031***	0.068**
	(1.29)	(3.62)	(4.25)	(0.68)	(2.96)	(2.38)
Create	0.045	0.082**	0.224***	−0.019	0.042*	0.114*
	(1.32)	(2.49)	(2.92)	(−0.87)	(1.79)	(1.94)
HHI	−0.066***	−0.050***	−0.209***	0.011	−0.009	−0.073***
	(−6.15)	(−4.11)	(−8.80)	(1.50)	(−0.81)	(−4.94)
Subsidy	0.000	0.001***	0.003***	0.000*	0.001**	0.002**
	(1.13)	(3.13)	(3.39)	(1.78)	(2.45)	(2.24)
DFI	0.044**	0.040	0.090	0.001	0.007	0.121***
	(2.12)	(1.47)	(1.54)	(0.07)	(0.41)	(2.72)
Size	0.002	0.015***	0.021***	0.008***	0.006***	0.020***
	(1.47)	(9.43)	(5.95)	(7.87)	(5.74)	(6.92)
ROA	0.003	−0.068***	0.031	−0.083***	−0.067***	−0.021
	(0.09)	(−2.66)	(0.56)	(−4.49)	(−3.48)	(−0.44)
Cash	−0.007	−0.053**	−0.123**	−0.006	−0.019	−0.067*
	(−0.31)	(−2.57)	(−2.55)	(−0.40)	(−1.30)	(−1.67)
Growth	−0.004	−0.009***	−0.024***	−0.002	−0.003	−0.014***
	(−1.17)	(−3.00)	(−3.49)	(−0.86)	(−1.38)	(−2.62)
Lev	0.021**	−0.030***	0.003	−0.017***	−0.010	−0.015
	(2.20)	(−3.51)	(0.16)	(−2.97)	(−1.64)	(−0.96)
MTB	0.001	0.000	−0.000	0.002*	0.000	0.004*
	(0.70)	(0.30)	(−0.07)	(1.96)	(0.37)	(1.78)
Netloss	−0.004	0.012**	0.024*	0.002	0.009**	0.002
	(−0.73)	(2.01)	(1.79)	(0.51)	(2.31)	(0.19)
Top1	−0.042***	−0.079***	−0.117***	−0.050***	−0.036***	−0.148***
	(−4.16)	(−8.15)	(−5.41)	(−8.08)	(−5.49)	(−7.98)
Agescale	−0.005***	0.003***	0.006***	−0.002**	0.000	0.001
	(−4.27)	(2.63)	(2.84)	(−2.09)	(0.24)	(0.25)
SOE			−0.006	−0.011***	−0.007***	−0.015**
			(−0.74)	(−5.14)	(−3.23)	(−2.29)
HTT	0.004	0.002			0.006***	0.142***
	(0.93)	(0.45)			(2.75)	(9.88)
Big4	0.001	0.018**	0.042***	−0.004	−0.009**	0.025**
	(0.10)	(2.41)	(2.70)	(−1.10)	(−2.00)	(2.28)
Constant	−0.015	−0.399***	−0.509***	−0.141***	−0.167***	−0.515***
	(−0.38)	(−9.66)	(−5.97)	(−5.46)	(−6.03)	(−7.08)
Year fixed effect	YES	YES	YES	YES	YES	YES
Industry fixed effect	YES	YES	YES	YES	YES	YES
N	8,774	18,626	7,105	20,295	19,195	8,205
Adj_R^2	0.098	0.126	0.174	0.033	0.023	0.169
Chow test	6.07 (0.000)		15.65 (0.000)		5.55 (0.000)	

Note(s): *** indicates significance at the 1% level ($p < 0.01$); ** indicates significance at the 5% level ($p < 0.05$); * indicates significance at the 10% level ($p < 0.1$). Standard errors are adjusted for firm-level clustering. Variable definitions are presented in Appendix III

are generally service-oriented industries, which focus on their business model and customer satisfaction. Thus, non-manufacturing industries do not have the same level of demand for AI technology. Alternatively, the manufacturing sector relies on AI technology as it undergoes transformations and upgrades. Non-manufacturing industries may also rely on blockchain-based credit platforms to access financing sources (*DFI*).

7. Additional testing

Our study seeks to provide an in-depth understanding of the external factors influencing executive decisions on whether to use BT. Markarian and Santalo (2014) find that earnings manipulation occurs in competitive markets due to high levels of competition, while earnings management practices are reduced in a transparent information environment. However, uncertainty remains about whether BT can be used as a control to constrain earnings management practices. Prior studies have indicated that effective corporate governance mechanisms significantly affect earnings management practices (Klein, 2002; Xie, Davidson, & DaDalt, 2003). Yermack (2017) points out, however, that blockchain creates a new method for storing financial records, inviting far-reaching changes in corporate governance, and Garanina, Ranta, and Dumay (2022) show that one of the most crucial aspects of BT is the inability to modify transactions, thus ensuring that all records in the chain are accurate. Enterprises can therefore handle complex data and information to improve effective operational processes with the help of the BT consensus mechanism (Wamba, Kamdjoug, Bawack, & Keogh, 2020). BT also improves information transparency due to verifiable characteristics, thus increasing shareholder trust by reducing managers' opportunity to manipulate profits (Yermack, 2017). The opportunity for accrual earnings management and financial reporting fraud can be reduced if a company stores financial records on a public blockchain. Wang and Kogan (2018) found that a blockchain-based transaction processing system can track transactions in real time, thus preventing managers from manipulating earnings or committing fraud. BT may therefore decrease the likelihood of earnings management. We use Models 4, 5 and 6 to examine the relationship between BT adoption and earnings management.

$$\frac{TA_{j,t}}{A_{j,t-1}} = a_1\frac{1}{A_{j,t-1}} + a_2\frac{\Delta REV_{j,t}}{A_{j,t-1}} + a_3\frac{PPE_{j,t}}{A_{j,t-1}} + \varepsilon_{j.t} \tag{4}$$

According to the modified Jones model (Jones, 1991; Dechow, Sloan, & Sweeney, 1995), $TA_{j,t} = (\Delta \mathrm{CA}_{j,t} - \Delta \mathrm{CASH}_{j,t}) - (\Delta \mathrm{CL}_{j,t} - \Delta \mathrm{CLD}_{j,t}) - \mathrm{DEP}_{j,t}$, where $\Delta \mathrm{CA}_{j,t}$, $\Delta \mathrm{CASH}_{j,t}$, $\Delta \mathrm{CL}_{j,t}$, $\Delta \mathrm{CLD}_{j,t}$ are the changes in current assets, cash and cash equivalents, current liabilities and debt included in current liabilities, respectively. $\mathrm{DEP}_{j,t}$ indicates depreciation and amortisation expenses. The variables in Model (4) include total assets for the previous year ($A_{j,t-1}$), change in revenue ($\Delta REV_{j,t}$), and property, plant and equipment ($PPE_{j,t}$).

$$DAC = \frac{TA_{j,t}}{A_{j,t-1}} - a_1\frac{1}{A_{j,t-1}} - a_2\left(\frac{\Delta REV_{j,t}}{A_{j,t-1}} - \frac{\Delta REC_{j,t}}{A_{j,t-1}}\right) - a_3\frac{PPE_{j,t}}{A_{j,t-1}} \tag{5}$$

Discretionary accruals (*DAC*) are measured when the coefficients a_1, a_2 and a_3 in Model (4) are applied to Model (5). $\Delta REC_{j,t}$ is defined as the changes in net receivables. We use the absolute value of DAC (*absDAC*) as the proxy for earnings management. A larger *absDAC* represents a higher degree of earnings management. The following model was adopted to examine the relationship between BT adoption and firms' earnings management.

$$\begin{aligned} absDAC_{i,t} = {} & a_0 + a_1\, BT_{i,t} + a_1 Size_{i,t} + a_2 ROA_{i,t} + a_3 Cash_{i,t} + a_4 Lev_{i,t} + a_5 MTB_{i,t} \\ & + a_6 Nestloss_{i,t} + a_7\, Top1_{i,t} + a_8 SOE_{i,t} + a_9 Subsidiary_{i,t} \\ & + a_{10} Auditorchange_{i,t} + a_{11} Audtenure_{i,t} + a_{12} Restate_{i,t} \\ & + a_{13} Big4_{i,t} \sum Year + \sum Industry + \in_{i,t} \end{aligned} \tag{6}$$

The dependent variable is *absDAC*, measured by Model (6). We use *BT_Adoption*, *BT_Disclosure_Proportion* and *BT_Disclosure_Only* as the proxy for BT adoption. Control variables such as *Size*, *ROA*, *Cash*, *Lev*, *MTB*, *Netloss*, *Top1* and *SOE* are the same as those in Model (1). We also control for the number of subsidiaries of listed companies (*Subsidiary*), whether or not the firm changes its auditors (*AuditorChange*), how long the auditor has audited the company (*Audtenure*), whether or not the financial report has been restated (*Restate*) and whether the firm has hired one of the Big Four accounting firms (*Big4*).

The results shown in Table 9 provide evidence that BT adoption has the potential to reduce earnings management practices (regression coefficient for *BT_Disclosure_Adoption* = −0.021, $p < 0.01$; *BT_Disclosure_Proportion* = −0.010, $p < 0.05$; *BT_Disclosure_Only* = −0.012, $p < 0.01$). Prior research has presented evidence that supplier

Table 9. Blockchain technology and earnings management

Variables	(1) *absDAC*	(2) *absDAC*	(3) *absDAC*
BT_Adoption	−0.021***		
	(−5.46)		
BT_Disclosure_Proportion		−0.010**	
		(−2.42)	
BT_Disclosure_Only			−0.012***
			(−5.45)
Size	−0.002**	−0.002**	−0.001
	(−2.09)	(−2.14)	(−1.06)
ROA	−0.012	−0.011	−0.004
	(−0.72)	(−0.68)	(−0.23)
Cash	0.046***	0.045***	0.033**
	(3.48)	(3.40)	(2.22)
Lev	0.027***	0.028***	0.032***
	(5.23)	(5.35)	(5.53)
MTB	−0.021***	−0.021***	−0.020***
	(−6.90)	(−6.84)	(−5.54)
Netloss	0.021***	0.021***	0.021***
	(7.63)	(7.54)	(6.88)
Top1	0.020***	0.021***	0.028***
	(3.67)	(3.87)	(4.24)
SOE	−0.014***	−0.014***	−0.014***
	(−8.21)	(−8.21)	(−6.95)
Subsidiary	−0.002***	−0.002***	−0.003***
	(−6.37)	(−6.48)	(−6.08)
AuditorChange	0.004***	0.004***	0.003**
	(2.91)	(2.95)	(2.42)
Audtenure	−0.001***	−0.001***	−0.001***
	(−6.43)	(−6.39)	(−5.62)
Restate	0.006***	0.005***	0.006***
	(3.65)	(3.58)	(3.22)
Big4	−0.003	−0.004	−0.004
	(−1.03)	(−1.11)	(−0.98)
Constant	0.158***	0.159***	0.134***
	(7.51)	(7.56)	(5.35)
Year fixed effect	YES	YES	YES
Industry fixed effect	YES	YES	YES
N	25,339	25,339	19,739
Adj_R^2	0.050	0.049	0.051

Note(s): *** indicates significance at the 1% level ($p < 0.01$); ** indicates significance at the 5% level ($p < 0.05$); * indicates significance at the 10% level ($p < 0.1$). Standard errors are adjusted for firm-level clustering. Variable definitions are presented in Appendix III firms' earnings management increases following the use of BT by their customers (Autore, Chen, Clarke, & Lin, 2024), and that finding differs from the results of our study. Several reasons could explain why the findings of our study differ from those of Autore *et al.* (2024). First, the scope and objective of the research are different. Autore *et al.* (2024) focus on the supply chain setting and investigate how the customers' BT adoption affects suppliers' firm earnings management. Our research includes broader fields and industries (e.g. financial, e-commerce and government affairs systems), and we focus on the companies' adoption of BT and its consequences for earnings management. Second, the setting of the study is different. They use a global sample from the Factiva database and focus on customers' BT adoption. We use a sample of listed Chinese companies and focus on their adoption of BT. Thus, the scope and objective of the study, institutional background and cultural differences may have led to the inconsistent results. Third, Autore *et al.* (2024) used a relatively small sample that covered 45 blockchain adopters. Our study included 257 firms in a more mature phase of technology adoption. The expansion of the sample size and the maturation of the technology may also have led to different results. Autore *et al.* (2024) also point out that their results do not support "the prediction that blockchain adoptions will reduce managers' ability to manipulate reported earnings due to enhanced data integrity" (p. 3). This discrepancy indicates that further research is needed to explore the issue of whether BT adoption increases or decreases firms' earnings management.

8. Conclusions

Our study investigates whether TOE factors are in fact crucial for companies' adoption of BT. More specifically, we explore how AI technology, competition-oriented cultures and creation-oriented cultures, government policy support, market competition and financial inclusion affect BT adoption. We find that AI technology helps businesses adopt BT, and companies are more likely to use BT when their cultures are dominated by competition and innovation. Companies also tend to be more willing to implement BT in an environment with strong policy support, a highly competitive market and developed financial services. The regression results are robust after performing several robustness tests, such as eliminating the effect of strategic disclosure, replacing the dependent variable and considering the effects of COVID-19. Heterogeneity test shows variability across sample groups. Finally, further examination indicates that BT adoption plays a role in preventing managers from engaging in earnings management.

Our study has some practical significance for enterprises, policymakers and governments. Businesses should focus on integrating AI technology and BT, while enhancing collaborative innovation among technologies. It should also prioritise investment in AI technology and broaden its use in innovative processes. We also found that organisations could improve competitive and innovative corporate cultures, which would strengthen motivation for new technological advances.

Policymakers could develop strategies to support innovation in enterprises and facilitate the rapid deployment of BT applications. The creation of a fair and equitable market would help to reduce or eliminate monopolistic behaviour, thus supporting enterprises in enhancing their ability to innovate technologically. Ultimately, the government should promote financial inclusion, which would support the development of China's financial service industry and create opportunities for fintech innovation.

Our study has several limitations. First, using the Python Crawler method to capture blockchain-related keywords from annual reports may not fully capture the extent of BT adoption. Future research could focus on interviewing blockchain users to obtain real data about their use. Second, the measurement of corporate culture was also derived from annual reports, and this language may not accurately represent the firm's underlying culture. Third, our sample is limited to firms listed on Chinese stock exchanges, so future research could expand the scope of the sample by utilising sources from other countries. Fourth, our study examines the economic importance and statistical significance of six factors on BT adoption; however, it is impossible to determine whether there are interactions between these factors or to confirm the level of statistical significance that each factor contributes.

Notes

1. China National Knowledge Infrastructure is China's academic platform providing information and academic resources.
2. The *Peking University Digital Financial Inclusion Index of China* is published by the Peking University Digital Finance Research Centre. It is used to measure the overall level of digital finance development in terms of the breadth of its coverage, the depth of its use and the degree of digitisation of financial inclusion. The financial inclusion report can be found at https://idf.pku.edu.cn/docs/20210421101507614920.pdf. The most recent version contains information up to 2021.
3. According to the Industry Classification Guidelines issued by the CSRC in 2012, the following industries are considered high-tech enterprises in China: biotechnology (C27); railroad, ship, aerospace and other transportation equipment manufacturing (C37); computer, telecommunications and other electronic equipment manufacturing (C39); information transmission, software and information technology services (I); and scientific research and technology services (M).
4. Ministry of Industry and Information Technology. (2016). *Chinese Blockchain Technology and Application Development White Paper.* This is the first official guidance document issued by the Ministry of Industry and Information Technology. It summarises the trend of blockchain development and analyses the future application of blockchain in China.

Supplementary material

The supplementary material for this article can be found online.

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