Does AI bring value to firms? Value relevance of AI disclosures

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Summary: This study examines the value relevance of a firm's artificial intelligence (AI) implementation and its awareness of the related risks. We proxy a firm's AI implementation by AI-related disclosures and risk factors in 10-K filings to the U.S. Securities and Exchange Commission. Our results show that AI implementation disclosures in 10-K filings are more value relevant than those without AI disclosures. We also find that the disclosed AI-related risk factors are value relevant, suggesting that investors positively value a firm's AI risk awareness. By further classifying AI risk factors by a topical analysis of the latent Dirichlet allocation, we find that investors value AI-related risk factor disclosures more regarding security and data privacy. Finally, we find that when a firm has better board- or executive-level IT governance, investors place greater value on AI-related risk factor disclosures regarding business operations.

Keywords: artificial intelligence, value relevance, latent Dirichlet allocation, risk factors, IT governance

Bringt KI einen Mehrwert für Unternehmen? Wertrelevanz von KI-Angaben

Zusammenfassung: Diese Studie untersucht die Wertrelevanz der Implementierung von künstlicher Intelligenz (KI) in einem Unternehmen und das Bewusstsein für die damit verbundenen Risiken. Die KI-Implementierung eines Unternehmens wird durch KI-bezogene Angaben und Risikofaktoren in den 10-K-Berichten an die U.S. Securities and Exchange Commission dargestellt. Unsere Ergebnisse zeigen, dass die Angaben zur KI-Implementierung in den 10-K-Filings wertrelevanter sind als jene ohne KI-Angaben. Darüber hinaus stellen wir fest, dass die offengelegten KI-bezogenen Risikofaktoren ebenfalls wertrelevant sind, was darauf hindeutet, dass Investoren das KI-Risikobewusstsein eines Unternehmens positiv bewerten. Durch eine weitere Klassifizierung von KI-Risikofaktoren mittels einer thematischen Analyse der latenten Dirichlet-Zuordnung stellen wir fest, dass Anleger die Offenlegung von KI-bezogenen Risikofaktoren in Bezug auf Sicherheit und Datenschutz höher bewerten. Schließlich stellen wir auch fest, dass Anleger den Angaben zu KI-bezogenen Risikofaktoren in Bezug auf den Geschäftsbetrieb einen größeren Wert beimessen, wenn ein Unternehmen über eine bessere IT-Governance auf Vorstands- oder Geschäftsführungsebene verfügt.

Stichworte: Künstliche Intelligenz, Wertrelevanz, latente Dirichlet-Zuordnung, Risikofaktoren, IT-Governance

1. Introduction

Artificial intelligence (AI) has been developed and evolved continuously, attracting the public's attention for years. McCormick (2021) reports that the AI software market is expected to be more than $60 billion in 2022 as AI software can be used to understand and predict product, market, or customer trends. Kiron and Schrage (2019) suggest that AI can also assist management teams in creating strategies and help them determine the measures of outcomes with priorities. It has also been shown to be applied across industries, including, but not limited to, banking, healthcare, and retail life sciences (Accenture, 2022).

Given the expected benefits of AI, whether AI implementation can bring more value is challenging because it accompanies many new forms of risk that need to be addressed (Taeihagh, 2021). For example, firms must continuously improve algorithms to increase accuracy, and unexpected situations that the algorithms have not processed may cause a large amount of damage. In addition, the compliance risk could increase because of newly applied responsibility and legal liability. Also, the integration of the existing system and newly established AI system could be complicated, so firms will be subject to data-related issues such as correctness, privacy, or governance issues. Thus, whether AI implementation will bring higher firm value is still uncertain (Davenport, 2020).

The present study investigates whether AI implementation can bring positive value to organizations from an investor's perspective. Investors can incorporate all perceived information regarding the benefits and risks of AI implementation to estimate future abnormal profits and reflect them in the current stock price. Thus, we examine the value relevance of AI-related disclosures in firms' 10-K filings to the U.S. Securities and Exchange Commission (SEC). That is, whether a firm discloses AI-related information, which is a proxy for its AI implementation, leads to a higher stock price. Next, we examine whether investors positively value a firm's AI-related risk factors disclosed in Item 1A of 10-K filings because risk disclosures may be viewed as being aware of such risks (Gordon et al., 2010; Berkman et al., 2018). To explore how investors respond to different AI-related risks, we also use latent Dirichlet allocation (LDA) to analyze AI-related risk factors. Finally, given that board-level and executive-level IT governance indicate a firm's competence in AI implementation and the management of corresponding risks (Benaroch & Chernobai, 2017; Haislip et al., 2021), investors may value the AI risk factors differently, which is conditional on a firm's IT governance. Thus, we investigate whether IT governance moderates the different value relevance of AI-related risks.

To perform empirical tests, we use 518 U.S. SEC 10-K filings that include AI-related keywords (i.e., artificial intelligence and its variations) from 1996 to 2018 and 518 firm-year observations without AI disclosures matched by propensity score matching (PSM) as the testing sample. Our regression results based on the value-relevance model of Ohlson (1995) first show that firms with AI disclosures have higher stock prices than those without, suggesting that, on average, investors positively value firms' AI implementation. Second, stock prices are higher for firms disclosing AI-related risk factors in Item 1A, suggesting that investors value firms' risk awareness positively. By classifying the risk factors by LDA, we further find that the value relevance is higher for AI risk factors related to regulation and security. Third, after considering the moderating effect of IT governance, we find that AI risk factors about business operations are value relevant only when the firm has better IT governance. In additional tests, we explore the value relevance of AI disclosures in different topics. We also show that the value relevance of AI disclosures is not different for firms in IT-intensive industries. Finally, the value relevance is higher for subsequent AI disclosures than for first-time disclosures, indicating that investors may view longer development in AI with lower uncertainty. Our empirical results are robust to alternative measures, samples, and model specifications.

Our study has several contributions, as follows: First, we are one of only a few studies to provide empirical evidence of whether AI engagement brings positive value through investors' perspectives. Although AI has been applied in various business functions, many survey results still show management's concern about whether to incorporate AI into their current business (Davenport, 2020; Accenture, 2022) because of the high development cost, maturity of AI, how well it will be incorporated into current systems, and whether the incremental benefits can exceed the costs. These concerns may be difficult to quantify. Because investors consider all available information in the market and estimate potential future cash flows and risks when evaluating a firm's value, our tests directly assess how investors perceive the expected costs and benefits of firms' AI engagements. Second, our study echoes the discussion of AI governance and AI-related risks that need to be addressed. Similar to studies of IT governance, well-established governance is critical for effective AI implementation. Our study provides empirical evidence of how investors view a firm's awareness of AI-related risks and the moderating effect of board- and executive-level IT governance. Third, by adopting LDA, we provide evidence that investors value various AI disclosures differently. This evidence may provide implications and insights for firms on what information about AI firms should communicate with investors because such information is important for investors as they assess the firm value.

The remainder of the paper is organized as follows: In Section 2, we review the relevant business and accounting literature in AI and develop our hypotheses based on the value-relevance literature regarding disclosures in 10-K filings. Our research methodology and findings are reported in Sections 3 and 4. We conclude with a discussion, research limitations, and future research directions in Section 5.

2. Literature review

2.1 Artificial intelligence and related risks

There is a large body of literature on AI from a technical perspective. However, our understanding of how AI affects a business from management and accounting perspectives is very limited (Gray et al., 2014; Sutton et al., 2016; Rikhardsson & Yigitbasioglu, 2018), though with a slightly increasing trend (Sutton et al., 2016). Many studies discuss a wide range of technologies in addition to AI (Elliot et al., 2019). For example, Chen et al. (2016) and Locke et al. (2015) focus on interactive data or visual attention in decision-making or judgments. Differently, Kowalczyk and Buxmann (2015) and Schneider et al. (2015) emphasize more on analytics support. Other studies aim to provide more insights regarding big data, such as Vasarhelyi et al. (2015) and Warren et al. (2015).

When we focus on AI, several articles have discussed the potential implications of AI in more management-related contexts, such as a reduction of repetitive activities (Herbert et al., 2016) or help to change the business environment (Plastino & Purdy, 2018). For example, Schrage (2017) lists different paths for AI to be involved in automated business decisions. Other studies have discussed or argued for the potential benefits of AI. For example, Gulin et al. (2019) state that essential accountant services can be provided more efficiently to meet the customer's demands. In auditing, Almufadda and Almezeini (2021) perform a literature review of AI applications in auditing, while Zhang et al. (2022) propose an explainable AI in auditing. Bonsón et al. (2021) suggest that AI can produce benefits, but at the same time, it can bring risks and ethical challenges; the study is also the only one that we are aware of that focuses on AI disclosures in European countries. However, unlike our study, it focuses on AI activity and ethical approaches and the factors that influence disclosures. Overall, we find few empirical studies on AI disclosures or how AI brings firm value. One exception is Chen and Srinivasan (2022), which examines the disclosure of digital keywords in business descriptions in 10-K filings, finding that firms with digital transformation-related disclosures have higher market-to-book ratios. Although Chen and Srinivasan (2022) examine a broader range of digital transformations, we focus on firms' engagement in AI to provide more specific insights.

Although AI improves economic efficiency, it also poses new types of risks that adopting firms need to address (Taeihagh, 2021). First, unexpected situations or high-risk data in which AI has not been trained (i.e., corner cases) may cause damages to the business due to erroneous decisions (Ouyang et al., 2021; Taeihagh, 2021). These corner cases might even lead to fatal disasters if applied in auto vehicles, for example (Lim & Taeihagh, 2019). Because the machine learning process can be complex, it is difficult for humans to identify corner cases beforehand and to explain AI decisions afterward (Mittelstadt et al., 2016). Second, the responsibility and legal liability for the harm caused by AI decisions could be ambiguous. AI reduces human control; however, current legal frameworks may still treat AI as a tool controlled by human operators. Thus, unpredictable AI decisions may increase the risk of humans to exposure, who might not fully control AI decisions (Lim & Taeihagh, 2019; Taeihagh, 2021). Such ambiguity in responsibility may raise the compliance risk of firms, further deterring the development of AI. Third, because AI algorithms may process, store, and transmit a huge amount of confidential data, data privacy and security become critical issues (Stahl & Wright, 2018; Himthani et al., 2020). Handling confidential data may be subject to privacy laws and regulations, thus increasing the security and compliance risks of firms.

2.2 IT governance

IT governance ensures the effectiveness of IT utilization and can achieve the link between IT and business by the board of directors, executive management, and IT management (De Haes & Van Grembergen, 2004); this involves multiple scopes, including strategic alignment, risk management, resource management, value delivery, and performance measurement (Wilkin & Chenhall, 2010; Turel et al., 2019). For ensuring strategic alignment and the effectiveness of governance, the involvement of high-level roles in an IT-implementing firm is necessary to create firm value and mitigate risks. At the board level, because the directors oversee management and corporate operation, their involvement in IT can align IT with business strategies, facilitate collaboration among executives and management, and monitor performance, thus improving the decision-making of management and firm performance (Caluwe & De Haes, 2019). Benaroch and Chernobai (2017) show that operational IT failures indicate a lack of board-level IT governance, thus inducing firms to make the board more IT competent by assigning a CIO or CTO to the board or establishing an IT committee. Higgs et al. (2016) find that a mature IT committee can reduce security risk, as shown by fewer security breaches. Regarding the overall performance, Yayla and Hu (2014) show that IT awareness of the board, as proxied by the percentage of directors with IT experiences, is positively associated with Tobin's Q.

At the top management level, top management's competence also plays a crucial role in the effectiveness of IT governance and performance because the top management team establishes and executes the plans and processes regarding IT (Wilkin & Chenhall, 2010). For example, Kwon et al. (2013) and Haislip et al. (2021) find that firms with IT executives in their top management teams are less likely to report security breaches. Moreover, these studies find that the more risk-averse a CIO is, the less likely the firm is to have information security breaches.

2.3 Value relevance

According to the discounted cash flow model for firm value, a firm's current value is the net present value of investors' expected future cash flows based on currently available information. Peasnell (1982) incorporates accounting information into the discounted cash flow model; that is, the discounted future cash flows can be expressed by the current accounting book value and the present value of all expected future abnormal accounting earnings. By considering additional assumptions, Ohlson (1995) further extends the model that the current firm value is a function of the current book value, current earnings, and other information, which is hereafter called the Ohlson model. When investors perceive that certain information other than financial statements implies future abnormal returns, they discount the expected abnormal returns and reflect them into the current stock price.

Numerous studies have examined the value relevance of narrative disclosures because the information conveyed in narrative disclosures might not have been recognized in financial statements. These narrative disclosures include SEC filings about cybersecurity (Gordon et al., 2010), blockchain and cryptocurrency (Cheng et al., 2019; Yen & Wang, 2021), digital transformation (Chen & Srinivasan, 2022), and fintech-related patent documents (Chen et al., 2019). Regarding quantifying narrative disclosures, most studies use the dictionary approach (Gordon et al., 2010; Yen & Wang, 2021; Chen & Srinivasan, 2022), which is commonly used in the accounting domain and with less cost, while other studies manually identify the disclosures (Cheng et al., 2019). Yen and Wang (2021) further apply a topical model of LDA to analyze the themes of disclosures.

2.4 Hypothesis development

As AI has been applied and argued to benefit business functions, many new forms of risks resulting from AI implementation might decrease the benefits. Thus, investors might have the following concerns when evaluating a firm's AI implementation: First, the entry and development costs to establish AI systems and incorporate them into existing systems could be huge. Investors need to assess future incremental profits brought about by AI implementation to cover the costs, so they must collect sufficient information and incorporate it to make a more precise judgment. Second, firms must consider whether AI is mature enough to be applied in their business (Accenture, 2022) and whether executives and AI teams are competent enough to effectively implement the projects. Third, firms should consider whether their data quality is good enough to establish the machine learning model and continuously improve AI systems.

Although these factors are critical for successful current AI implementation or plan, the information required to make such an assessment might not have been reflected in the financial statements. Therefore, investors may incorporate information about a firm's AI implementation as conveyed in narrative disclosures. On the one hand, if investors perceive that AI implementation can generate future abnormal profits from AI disclosures, the abnormal profits that have not been recognized in financial statements will be discounted and reflected in higher current stock prices. On the other hand, investors might perceive a high risk of AI implementation from AI narrative disclosures. This risk might increase the uncertainty of future abnormal profits that can be brought about by AI implementation. In this case, the current stock price of the AI-implementing firm might not be higher or may even be lower than other firms. Based on the above discussions, we establish the following hypothesis without predicting direction:

Hypothesis 1: The stock prices of firms with AI disclosures differ from those without AI disclosures.

Because AI may improve operating efficiency and bring future profits, it also poses new forms of risk that firms need to address. Therefore, risk awareness of an AI-implementing firm may be considered by investors when evaluating the firm. Focusing on information security risk, Berkman et al. (2018) and Gordon et al. (2010) indicate that firm values are positively associated with security risk-related disclosures in SEC filings, showing that investors positively value a firm if it is aware of the risk it might confront. Similarly, if an AI-implementing firm discloses the risk factors related to AI applications in Item 1A risk factors in its SEC 10-K filings, we regard it as its risk awareness of adopting AI. Therefore, we establish an exploratory hypothesis about investors' evaluation of the awareness of risks regarding AI. In addition, because AI implementation yields various types of risk factors, we also explore the value relevance of different types of AI risk factors:

Hypothesis 2: The market values of firms with AI risk factor disclosures differ from those without AI risk factor disclosures.

The literature on IT governance has shown that board- and executive-level IT governance reduce IT-related risks and improve efficiency and performance (e.g., Benaroch & Chernobai, 2017; Haislip et al., 2021). Because AI implementation is complex in nature and poses new forms of risk, better IT governance should help reduce such risks. Thus, we expect that the association between firm value and different types of AI risk factors may depend on the firm's observable IT governance factors, as shown in the following exploratory hypothesis.

Hypothesis 3: The value relevance of AI risk factor disclosures depends on a firm's IT governance.

3. Research method

3.1 Empirical model

To test our hypothesis, we establish the following ordinary least squares (OLS) regression model based on Ohlson (1995):

$$Price_{it} = \beta_0 + \beta_1 AI_{it} + \beta_2 BookValue_{it} + \beta_3 NetIncome_{it} + \beta_4 Assets_{it} + \beta_5 Loss_{it} + industry\ fixed\ effects + year\ fixed\ effects + \epsilon_{it} \quad (1)$$

where $Price_{it}$ is the stock price one day after the 10-K filing date, and AI_{it} is an indicator that equals 1 if a 10-K includes the AI keywords and 0 otherwise. We also use $AIFreq_{it}$, the logarithm of the number of AI keyword appearances, as an alternative measure. According to Ohlson (1995), we include the book value at the end of the fiscal year ($BookValue_{it}$) and the net income of the fiscal year ($NetIncome_{it}$). Both variables are divided by the number of outstanding shares at the end of the fiscal year to address the scale effect (Barth & Clinch, 2009; Gordon et al., 2010; Song et al., 2010). To further address the scale effect, we control for $Assets_{it}$, which is the natural logarithm of total assets at the end of the fiscal year (Barth et al., 1996; Gordon et al., 2010). We also control for $Loss_{it}$, which is an indicator that equals 1 if the net income of the fiscal year is negative and 0 otherwise, to consider the asymmetry in the evaluation for positive and negative income (Berkman et al., 2018). All continuous variables are winsorized at 1 % and 99 % to eliminate the effect of any outliers. Industry and year fixed effects are included in the regression model, and standard errors are clustered by firm and year (Petersen, 2009). We summarize the variable definitions in Appendix A. According to Hypothesis 1, the estimated coefficient of AI_{it} (β_1) would be significantly positive (negative) if investors positively (negatively) value a firm's AI implementation.

To investigate the value relevance of a firm's awareness of AI-related risk factors based on Hypothesis 2, we establish the following OLS regression model:

$$Price_{it} = \beta_0 + \beta_1 AI_{it} + \beta_2 AIRisk_{it} + \beta_3 BookValue_{it} + \beta_4 NetIncome_{it} + \beta_5 Assets_{it} + \beta_6 Loss_{it} + industry\ fixed\ effects + year\ fixed\ effects + \epsilon_{it} \quad (2)$$

where $AIRisk_{it}$ is an indicator that equals 1 if the firm discloses one or more risk factors that include AI keywords in Item 1A of the 10-K filings in the fiscal year and 0 otherwise. As an alternative measure, we also use $AIRiskFreq_{it}$, which is the logarithm of the number of risk factors that include AI keywords. All other variables are defined in Eq. (1). Based on Berkman et al. (2018) and Gordon et al. (2010), if investors positively value the firm's awareness of AI-related risks, the estimated coefficient of $AIRisk_{it}$ (β_2) should be positive.

To further explore the different risk factors related to AI, we perform a topic analysis with the LDA approach on the AI-related risk factors in 10-K filings. We explain the LDA process in Section 3.2. We then replace the indicator of $AIRisk_{it}$ in Eq. (2) with the risk topic indicators.

For Hypothesis 3, we establish the following OLS regression model to investigate the moderating effect of IT governance on the value relevance of a firm's awareness of different AI-related risk factors:

$$Price_{it} = \beta_0 + \beta_1 AI_{it} + \beta_2 ITGovernance_{it} + \Sigma\beta_{3k} AIRiskTopick_{it} + \Sigma\beta_{4k} ITGovernance_{it} * AIRiskTopick_{it} + \beta_5 BookValue_{it} + \beta_6 NetIncome_{it} + \beta_7 Assets_{it} + \beta_8 Loss_{it} + industry\ fixed\ effects + year\ fixed\ effects + \epsilon_{it} \quad (3)$$

where $ITGovernance_{it}$ is an indicator of the board- and executive-level IT competence, which equals 1 if the firm's proxy statement (Form DEF-14A) includes any of the following keywords: chief information officer, chief technology officer, chief security officer, chief information security officer, AI, and their variations. We assume that the appearance of these keywords indicates the board or executives' involvement in IT or AI. $AIRiskTopick_{it}$ is an indicator that equals 1 if a firm discloses an AI-related risk factor that is classified as in *kth* topic by LDA and 0 otherwise. All other variables are defined in Eq. (1). For Hypothesis 3, the variables of interest are the interactions of $ITGovernance_{it}$ and $AIRiskTopick_{it}$. A positive (negative) estimated coefficient of the interaction indicates that investors value AI-related risk more positively (negatively) when the firm has better IT governance.

3.2 Topical analysis

To explore the theme of AI-related risk factors that a firm discusses in Item 1A of its 10-K filing, we perform a topic analysis with the LDA approach proposed by Blei et al. (2003). In LDA, a topic is defined as a list of words that can overlap between topics, and a document is a probabilistic distribution among topics (Blei et al., 2003; Blei, 2012). As the topics cannot be predefined and observed, LDA identifies the latent topics from the observable documents.

To prepare the input texts for LDA, we first extract the risk factors that include the AI keywords as the inputs. Each risk factor is identified by the subcaption of the risk factor. Next, we clean up the text by removing URLs, stop words,[1] numbers, punctuations, extra spaces, and so forth. To reduce dimensionality, we stem the words and only keep the word roots. We then convert the text inputs into a document–term matrix, where each element indicates the standardized term frequency of a unique word in an input text.

We next execute the LDA using the R software. In LDA, the number of latent topics needs to be predetermined, and we set it to three, here based on the algorithm proposed by Cao et al. (2009). To assign labels to the identified topics, we follow the suggestion of Sievert and Shirley (2014) to calculate the relevance ratio, which is the weighted average of a word's probability in the topic and its marginal probability among the whole corpus with the weight of 0.6, to rank the keywords in each topic. We then use the first-ranked keywords to label each topic. Specifically, topics 1 to 3 are labeled new technology market competition, business operations, and regulation and security. Appendix B presents the label and example keywords for each topic identified by LDA.

After LDA, each input text is presented as a probabilistic distribution of the three topics. For ease of interpretation, we assign each input text a topic based on the highest probability and establish dummy variables—$AIRiskTopic1_{it}$ to $AIRiskTopic3_{it}$—to indicate whether a firm's Item 1A includes AI-related risk factors assigned to the topic. Because a firm may mention more than one risk factor regarding AI, the values of the topical variables are not mutually exclusive for each observation. We then use the three topical indicators in Eqs. (2) and (3) to explore the value relevance of different topics of AI-related risk factors.

3.3 Sample

To establish our testing sample, we start by collecting all U.S. 10-K filings submitted between 1996 and 2021 that include "artificial intelligence" and its variations (hereafter

1 Because there is no dominant list of stop words, we adopt the list of generic stop words provided at https://sraf.nd.edu/textual-analysis/stopwords/.

AI keywords) from the SeekEdgar database. We set the sample collecting period starting in 1996 because this was the first year the U.S. SEC first launched its Electronic Data Gathering, Analysis, and Retrieval system (EDGAR) for firms to submit their filings. There are 736 10-K filings that include AI keywords. We next exclude 218 10-K filings that cannot be merged with stock price data in the CRSP database, leading to 518 10-K filings with AI keywords.

Next, we perform a PSM approach to find 10-Ks without AI disclosures from firms with similar firm characteristics (Rosenbaum & Rubin, 1983; Shipman et al., 2017). For each sample year, we run the following logistic regression model without replacement using all available observations in Compustat and CRSP to find matched 10-Ks without AI disclosures:

$$\Pr(AI_{it}) = \alpha_0 + \alpha_1 BookValue_{it} + \alpha_2 NetIncome_{it} + \alpha_3 Assets_{it} + \alpha_4 Loss_{it} + \epsilon_{it} \quad (4)$$

where all variables are as defined in Eq. (1). After running Eq. (4), we match each of the 518 10-K filings with AI disclosure with a 10-K filing without AI disclosure that has the nearest propensity score. The process results in 1,036 observations in our final sample.[2] Panel A of Table 1 summarizes the sampling process.

Panel B of Table 1 presents the covariate means of observations with and without AI disclosure (the AI and non-AI groups, respectively) before and after PSM. Before PSM, the means of $NetIncome_{it}$, $Assets_{it}$, and $Loss_{it}$ are significantly different between the AI and non-AI groups. All covariates become statistically indifferent in means after PSM, suggesting that our PSM process is valid.

Panel C of Table 1 presents the sample distribution by year. Overall, the number of 10-Ks with AI disclosure has largely increased since 2016, indicating the recent proliferating implementation of AI in business. The number becomes smaller in 2021 because the 10-Ks for fiscal year 2021 have not been completely submitted. There is no 10-K with AI disclosure from 2009 to 2012 in our sample because these observations cannot be matched to the CRSP database.

Table 1: Sample collection and distribution

Panel A. Sampling process

	# of firm–years
All 10-K filings reported from 1996 to 2021 including "artificial intelligence" and its variations	736
Less: cannot be merged with CRSP data	(218)
Subtotal	518
Matched group (10-Ks without "artificial intelligen*" selected by the 1-to-1 PSM)	518
Final PSM sample	1,036

2 The maximum of caliper of the PSM results is 0.003, suggesting no large differences in the covariates between an AI observation and its matched non-AI observation.

Panel B. Summary statistics of covariates in the PSM sample

Before PSM				
(N = 125,045)	Obs. with AI disclosure (N = 518)	Obs. without AI disclosure (N = 124,527)	Diff in mean	*t*-value
$BookValue_{it}$	10.453	10.440	0.013	(0.023)
$NetIncome_{it}$	0.952	0.719	0.233*	(1.801)
$Assets_{it}$	6.859	6.155	0.704***	(6.317)
$Loss_{it}$	0.477	0.339	0.138***	(6.260)

After PSM				
(N = 1,036)	Obs. with AI disclosure (N = 518)	Obs. without AI disclosure (N = 518)	Diff in mean	*t*-value
$BookValue_{it}$	10.453	10.548	-0.095	(-0.118)
$NetIncome_{it}$	0.952	0.968	-0.016	(-0.085)
$Assets_{it}$	6.859	6.874	-0.016	(-0.102)
$Loss_{it}$	0.477	0.469	0.008	(0.249)

Panel C. Frequency by fiscal year

Fiscal	Obs. with AI disclosure	Matched obs. without AI disclosure	Total
1996	2	2	4
1997	1	1	2
1998	1	1	2
1999	1	1	2
2000	3	3	6
2001	5	5	10
2002	2	2	4
2003	2	2	4
2004	2	2	4
2005	2	2	4
2006	1	1	2
2007	2	2	4
2008	2	2	4
2009	0	0	0
2010	0	0	0
2011	0	0	0

Fiscal	Obs. with AI disclosure	Matched obs. without AI disclosure	Total
2012	0	0	0
2013	2	2	4
2014	2	2	4
2015	3	3	6
2016	15	15	30
2017	51	51	102
2018	91	91	182
2019	123	123	246
2020	166	166	332
2021	39	39	78
Total	518	518	1,036

See Appendix A for variable definitions. The superscripts ***, **, and * represent statistical significance at the 1 %, 5 %, and 10 % levels, respectively, based on a two-tailed *t*-test. In parentheses, the *t*-values are given.

4. Empirical results

4.1 Descriptive statistics

Panel A of Table 2 presents the summary statistics of the PSM sample. On average, the stock price ($Price_{it}$) is 44.631 in our PSM sample. When we further divide the sample into the AI and non-AI groups, we find that the mean of $Price_{it}$ is significantly higher for the AI group than for the non-AI group ($p < 0.01$). This result indicates that investors evaluate firms with AI disclosure higher, primarily supporting our hypothesis. The raw value of the number of AI keyword appearances is 0.870 on average, with a maximum value of 10, indicating that some firms mention AI keywords more than once in their 10-K filings. Regarding the AI risk topic indicators, $AIRiskTopic1_{it}$ (new technology market competition) has the highest mean among the three indicators, suggesting that AI-implementing firms are more aware of the risks of market competition brought by the new technology development.

Panel B of Table 2 presents the Pearson correlation matrix of the variables. We first find that AI_{it} and $Price_{it}$ are significantly associated (0.177, $p < 0.01$), primarily supporting our hypothesis and suggesting that investors positively value firms' AI implementation presented in 10-Ks. Second, we find that the correlations between the control variables are high; the highest correlation is 0.635 between $BookValue_{it}$ and $NetIncome_{it}$, with $p < 0.01$. Although the high correlations among independent variables lead to a concern of multicollinearity in the multiple regression tests, the highest variance inflation factor (VIF) of the main regression test is 2.70, which does not exceed the threshold of 10. Thus, we do not find statistical evidence of a multicollinearity issue.

Table 2: Descriptive statistics of the sample

Panel A. Summary statistics and univariate tests

(N = 1,036)	Mean	S.D.	Min	P25	Mdn	P75	Max	Obs. with AI disclosure	Obs. without AI disclosure	Diff in mean
$Price_{it}$	44.631	51.137	0.375	7.382	25.185	61.625	184.859	53.677	35.585	18.092***
AI_{it}	0.500	0.500	0	0	0.500	1	1			
$AIFreq_{it}$ (raw)	0.870	1.229	0	0	0.500	1	10			
$AIFreq_{it}$	0.469	0.529	0	0	0.347	0.693	2.398			
$AIRisk_{it}$	0.046	0.210	0	0	0	0	1			
$AIRIskFreq_{it}$ (raw)	0.076	0.464	0	0	0	0	10			
$AIRIskFreq_{it}$	0.042	0.202	0	0	0	0	2.398			
$AIRiskTopic1_{it}$ (new technology market competition)	0.026	0.159	0	0	0	0	1			
$AIRiskTopic2_{it}$ (business operations)	0.019	0.138	0	0	0	0	1			
$AIRiskTopic3_{it}$ (regulation and security)	0.012	0.107	0	0	0	0	1			
$ITGovernance_{it}$	0.363	0.481	0	0	0	1	1			
$Book\ Value_{it}$	10.501	12.986	-4.404	0.512	5.966	15.363	64.511			
$Net\ Income_{it}$	0.960	2.989	-7.378	-0.691	0.078	2.190	10.340			
$Assets_{it}$	6.867	2.452	1.476	5.123	6.930	8.619	12.139			
$Loss_{it}$	0.473	0.500	0	0	0	1	1			

Panel B. Correlation matrix

	$Price_{it}$	AI_{it}	$AIRisk_{it}$	$ITGovernance_{it}$	$BookValue_{it}$	$NetIncome_{it}$	$Assets_{it}$	$Loss_{it}$
$Price_{it}$	1.000							
AI_{it}	0.177***	1.000						
$AIRisk_{it}$	0.117***	0.220***	1.000					
$ITGovernance_{it}$	0.199***	0.217***	0.101***	1.000				
$BookValue_{it}$	0.564***	-0.004	0.026	0.143***	1.000			
$NetIncome_{it}$	0.658***	-0.003	-0.009	0.111***	0.635***	1.000		
$Assets_{it}$	0.592***	-0.003	0.076**	0.148***	0.578***	0.544***	1.000	
$Loss_{it}$	-0.454***	0.008	0.012	-0.100***	-0.483***	-0.676***	-0.519***	1.000

See Appendix A for the variable definitions. The superscripts ***, **, and * represent statistical significance at the 1 %, 5 %, and 10 % levels, respectively, based on a two-tailed *t*-test.

4.2 Main results

Table 3 presents the OLS regression results of Eq. (1) for testing Hypothesis 1. In column (1), the coefficient of AI_{it} is significantly positive (15.239, $p < 0.01$), indicating that the AI disclosures in 10-Ks are positively associated with the firms' market values. When we use the alternative measure, $AIFreq_{it}$, the coefficient remains significantly positive; that is, firm market value is positively associated with the frequency of AI keywords. Overall, the results suggest that investors view a firm's AI implementation, here as proxied by the AI disclosures in their 10-Ks, as being able to bring in abnormal profits in the future, which is reflected in the current high stock price.

Regarding the control variables, the results show that stock price is positively associated with book value, net income, and total assets, which is consistent with the findings from the literature (Gordon et al., 2010; Berkman et al., 2018; Yen & Wang, 2021). However, we do not find a significant association between the market value and net loss.

Table 3: Main regression results for H1: AI disclosure

		(1)	(2)
Dependent var.:		$Price_{it}$	$Price_{it}$
AI_{it}	(H1)	15.239***	
		(4.547)	
$AIFreq_{it}$	(H1)		10.221**
			(2.460)
$BookValue_{it}$		0.635***	0.650***
		(3.426)	(3.451)
$NetIncome_{it}$		7.304***	7.329***
		(12.603)	(12.373)
$Assets_{it}$		6.983***	7.005***
		(6.984)	(6.585)
$Loss_{it}$		3.786	3.583
		(1.223)	(1.195)
Constant		-22.281	-21.758
		(-1.014)	(-1.013)
Observations		1,036	1,036
Adjusted R^2		0.580	0.572
Fixed effects		Ind./year	Ind./year

See Appendix A for the variable definitions. The superscripts ***, **, and * represent statistical significance at the 1 %, 5 %, and 10 % levels, respectively, based on a two-tailed *t*-test. In parentheses, the *t*-values based on the standard errors clustered at the firm and year levels are given (Petersen, 2009). We control for industry fixed effects based on FF48 industry classification.

Panel A of Table 4 presents the OLS regression results of Eq. (2) for testing Hypothesis 2. In column (1), the coefficient of AI_{it} remains positive (13.980, $p < 0.01$), which is consistent with the results in Table 3. The coefficient of the variable of interest, $AIRisk_{it}$, is also significantly positive (13.846, $p < 0.05$). When we use the alternative measure of the number of AI risk factors, *AIRiskFreq*$_{it}$, the results in column (2) still show a positive coefficient (15.813, $p < 0.05$). Overall, the positive coefficients of *AIRisk*$_{it}$ and *AIRiskFreq*$_{it}$ suggest that investors positively value a firm's awareness of the risks related to AI. The findings are similar to those of Berkman et al. (2018) and Gordon et al. (2010) that a firm's cybersecurity awareness has positive value relevance. AI implementation brings new types of risks.

To explore whether investors value the AI risk factors differently, we run Eq. (3) with the three AI risk factor topic indicators and present the empirical results in Panel B of Table 4. The coefficient of the first topic indicator (new technology market competition) is not statistically significant. However, the coefficient of the third topic indicator (regulation and security) is significantly positive (35.338, $p < 0.01$), and that of the second topic indicator (business operations) is also positive with weak significance (14.381, $p < 0.10$). The results suggest that, among the risk factors related to AI, investors place the most value on if the firm presents its awareness of risk related to regulation and security issues. The findings correspond to the discussion in Taeihagh (2021) that AI poses new forms of

Table 4: Main regression results for H2: Risk factors regarding AI

Panel A: With/without AI-related risk factor disclosures

		(1)	(2)
Dependent var.:		*Price*$_{it}$	*Price*$_{it}$
AI$_{it}$		13.980***	14.034***
		(3.976)	(4.095)
AIRisk$_{it}$	(H2)	13.846**	
		(2.277)	
AIRiskFreq$_{it}$	(H2)		15.813**
			(2.696)
BookValue$_{it}$		0.632***	0.631***
		(3.498)	(3.464)
NetIncome$_{it}$		7.352***	7.355***
		(12.751)	(12.883)
Assets$_{it}$		6.827***	6.802***
		(6.626)	(6.629)
Loss$_{it}$		3.640	3.521
		(1.211)	(1.190)
Constant		-20.716	-20.751
		(-0.919)	(-0.930)
Observations		1,036	1,036
Adjusted R^2		0.583	0.583
Fixed effects		Ind./year	Ind./year

See Appendix A for the variable definitions. The superscripts ***, **, and * represent statistical significance at the 1 %, 5 %, and 10 % levels, respectively, based on a two-tailed *t*-test. In parentheses, the *t*-values based on the standard errors clustered at the firm and year levels are given (Petersen, 2009). We control for industry fixed effects based on FF48 industry classification.

Panel B: Different topics of AI-related risk factor disclosure

		(1)
Dependent var.:		$Price_{it}$
AI_{it}		13.926***
		(4.072)
$AIRiskTopic1_{it}$	(H2)	-1.486
(new technology market competition)		(-0.185)
$AIRiskTopic2_{it}$	(H2)	14.381*
(business operations)		(1.789)
$AIRiskTopic3_{it}$	(H2)	35.338***
(regulation and security)		(3.424)
$BookValue_{it}$		0.654***
		(3.751)
$NetIncome_{it}$		7.151***
		(13.307)
$Assets_{it}$		6.863***
		(6.759)
$Loss_{it}$		3.296
		(1.084)
Constant		-21.332
		(-0.950)
Observations		1,036
Adjusted R^2		0.587
Fixed effects		Ind./year

See Appendix A for the variable definitions. The superscripts ***, **, and * represent statistical significance at the 1 %, 5 %, and 10 % levels, respectively, based on a two-tailed *t*-test. In parentheses, the *t*-values based on the standard errors clustered at the firm and year levels are given (Petersen, 2009). We control for industry fixed effects based on FF48 industry classification.

risk that require firms to address, including damage from corner cases, legal responsibility, and data privacy. Thus, AI-implementing firms showing their awareness of such risks may be able to convince investors about their performance and the effectiveness of AI implementation, which produces positive market value.

Table 5 presents the OLS regression results of Eq. (3) for testing Hypothesis 3. Column (1) presents the empirical results with the regression model with the IT governance indicator ($ITGovernance_{it}$) and its interaction terms with the three AI risk topic indicators, whereas column (2) presents the results, including the interaction terms of $ITGovernance_{it}$ and all control variables. The empirical results show that the coefficient of $AIRiskTopic2_{it}$ (business operations) is not significant in both columns, but that of $ITGovernance_{it}*AIRiskTopic2_{it}$ is significantly positive in columns (1) and (2) with different significance levels (24.684, $p < 0.10$, in column (1) and 37.192, $p < 0.01$, in column (2)). The results show that investors positively value firms' awareness of AI risk as it is related to business

Table 5: Main regression results for H3: IT governance

		(1)	(2)
Dependent var.:		$Price_{it}$	$Price_{it}$
AI_{it}		12.933***	13.406***
		(4.174)	(4.708)
$ITGovernance_{it}$		9.945***	3.219
		(3.739)	(0.253)
$AIRiskTopic1_{it}$		5.909	4.746
(new technology market competition)		(0.703)	(0.587)
$AIRiskTopic2_{it}$		2.638	0.609
(business operations)		(0.500)	(0.126)
$AIRiskTopic3_{it}$		41.724**	44.545***
(regulation and security)		(2.789)	(2.846)
$ITGovernance_{it}$*$AIRiskTopic1_{it}$	(H3)	-21.529	-25.672
		(-1.031)	(-1.190)
$ITGovernance_{it}$*$AIRiskTopic2_{it}$	(H3)	24.684*	37.192***
		(2.048)	(3.165)
$ITGovernance_{it}$*$AIRiskTopic3_{it}$	(H3)	-14.753	-30.131
		(-0.437)	(-0.859)
$BookValue_{it}$		0.595***	0.847***
		(3.638)	(3.580)
$NetIncome_{it}$		7.205***	6.170***
		(13.990)	(5.715)
$Assets_{it}$		7.053***	6.476***
		(7.080)	(7.678)
$Loss_{it}$		4.120	5.468
		(1.563)	(1.707)
Constant		-23.488	-29.860*
		(-1.226)	(-1.856)
$ITGovernance_{it}$*$Control\ vars.$		No	Included
Observations		1,036	1,036
Adjusted R^2		0.594	0.600
Fixed effects		Ind./year	Ind./year

See Appendix A for the variable definitions. The superscripts ***, **, and * represent statistical significance at the 1 %, 5 %, and 10 % levels, respectively, based on a two-tailed *t*-test. In parentheses, the *t*-values based on the standard errors clustered at the firm and year levels are given (Petersen, 2009). We control for industry fixed effects based on FF48 industry classification.

operations but only when the firm has better board- or executive-level IT governance, suggesting that AI implementation can bring additional value to the firm only if the firm has better IT governance, which can help the firm address the risk of AI-related business operations. Regarding other risk topics, the coefficient of $AIRiskTopic3_{it}$ (regulation and security) remains significantly positive in both columns, whereas the coefficient of $ITGovernance_{it}*AIRiskTopic3_{it}$ is not statistically significant. The results indicate that the positive evaluation of a firm's AI risk awareness about regulation and security is not conditional on whether the firm has better IT governance. That is, risk awareness about regulation and security is substantial for investors to assess whether a firm's AI implementation can bring value.

4.3 Additional tests

The first additional test is to extend Hypothesis 1 by exploring the value relevance of AI disclosures in different topics. Because firms may discuss their AI implementation from different perspectives (e.g., the current implementation and future plan, current product market, competition, financial performance, etc.), investors evaluate these discussions differently. To understand whether AI disclosures have different value relevance, we first extract 100 words before and after the appearance of an AI keyword in 10-Ks and perform the LDA approach, as described in Section 3.2. Based on the algorithm proposed by Cao et al. (2009), we set the number of latent topics to five, and we follow the suggestion of Sievert and Shirley (2014) to label the topics after performing LDA: technology, marketing and product, financial statement, governance, and healthcare. We then assign each text a topic based on the highest probability in the estimated distribution by LDA, where each topic is coded with a topic indicator ($AITopic1_{it}$ to $AITopic5_{it}$).

Table 6 shows the OLS regression results of Eq. (1) with the five topic indicators ($AITopic1_{it}$ to $AITopic5_{it}$). We find that the coefficient of $AITopic1_{it}$ (technology) is significantly positive (14.851, $p < 0.01$), indicating that the market values are positively associated with AI disclosures about technology. In addition, the coefficients of $AITopic2_{it}$ (marketing and product) and $AITopic4_{it}$ (governance) are also positive at different levels of significance (7.568, $p < 0.05$, and 9.392, $p < 0.10$), showing that the market values are positively associated with AI disclosures about marketing and product and are weakly associated with governance. We do not find statistical evidence that market values are associated with AI disclosures about financial statements and healthcare. Overall, the additional results based on LDA indicate that investors more positively value AI disclosures related to technology, products, and governance, suggesting that investors understand that AI technology, its related products, and governance can bring value to the firm.

The second additional test examines the moderating effect of IT intensity. Because investors may view IT intensity as a key success factor with fewer risks in the business (Dow et al., 2017), investors in firms in high IT intensity industries may not incrementally value the firms' implementation of AI. Thus, we additionally examine whether the positive association between firm values and AI disclosures is conditional on industry-level IT intensity. Specifically, we collect industry-level IT investment data from the U.S. Bureau of Economic Analysis and calculate the IT intensity following Mittal and Nault (2009). We then include the indicating variables of high and low industry-level IT intensity, $ITIntensity_{it}$, and its interaction with AI_{it} in Eq. (1).

Table 6: Additional regression results: Topical analysis of AI disclosure

		(1)
Dependent var.:		$Price_{it}$
$AITopic1_{it}$ (technology)	(H1)	14.581*** (3.330)
$AITopic2_{it}$ (marketing and product)	(H1)	7.568** (2.337)
$AITopic3_{it}$ (financial statement)	(H1)	1.869 (0.712)
$AITopic4_{it}$ (governance)	(H1)	9.392* (1.823)
$AITopic5_{it}$ (healthcare)	(H1)	3.853 (0.623)
$BookValue_{it}$		0.663*** (3.641)
$NetIncome_{it}$		7.275*** (13.139)
$Assets_{it}$		6.675*** (6.751)
$Loss_{it}$		3.557 (1.154)
Constant		-21.167 (-0.982)
Observations		1,036
Adjusted R^2		0.575
Fixed effects		Ind./year

See Appendix A for the variable definitions. The superscripts ***, **, and * represent statistical significance at the 1 %, 5 %, and 10 % levels, respectively, based on a two-tailed *t*-test. In parentheses, the *t*-values based on the standard errors clustered at the firm and year levels are given (Petersen, 2009). We control for industry fixed effects based on FF48 industry classification.

Table 7 presents the empirical results, where columns (1) and (2) present the empirical results without and with the interaction terms of $ITIntensity_{it}$ and all the control variables, respectively. We find that the coefficients of AI_{it} remain significantly positive in both columns (10.819, $p < 0.05$, and 9.776, $p < 0.05$, respectively), which is consistent with our main findings. However, the coefficients of $ITIntensity_{it}*AI_{it}$ in both columns are not statistically significant, indicating that investors value a firm's AI implementation positively, whether in high or low IT-intensive industries. The results suggest that investors might not treat IT intensity as an entry barrier or as a success factor in AI implementation.

Table 7: Additional regression results: Moderating effect of IT intensity

	(1)	(2)
Dependent var.:	$Price_{it}$	$Price_{it}$
AI_{it}	10.819**	9.776**
	(2.530)	(2.202)
$ITIntensity_{it}$	-2.808	-5.569
	(-0.804)	(-0.577)
$ITIntensity_{it}*AI_{it}$	5.562	6.784
	(1.000)	(1.182)
$BookValue_{it}$	6.922***	5.748***
	(5.580)	(5.124)
$NetIncome_{it}$	3.961	10.239***
	(1.026)	(3.100)
$Assets_{it}$	10.819**	9.776**
	(2.530)	(2.202)
$Loss_{it}$	-2.808	-5.569
	(-0.804)	(-0.577)
Constant	-21.802	-22.418
	(-1.049)	(-0.953)
$ITIntensity_{it}$*Control vars.	No	Included
Observations	901	901
Adjusted R^2	0.563	0.566
Fixed effects	Ind./year	Ind./year

See Appendix A for the variable definitions. The superscripts ***, **, and * represent statistical significance at the 1 %, 5 %, and 10 % levels, respectively, based on a two-tailed *t*-test. In parentheses, the *t*-values based on the standard errors clustered at the firm and year levels are given (Petersen, 2009). We control for industry fixed effects based on FF48 industry classification.

The third additional test investigates whether investors value the first and subsequent implementation of AI differently. Firms may confront higher uncertainty when first implementing AI, and such uncertainty may decrease with the maturity of implementation. Therefore, investors may value first-time and subsequent implementations differently. To examine this question, we measure the indicators of first-time and subsequent implementation of AI ($AIFirst_{it}$ and $AISubsequent_{it}$) by whether a firm mentions AI disclosures for the first time in its 10-K. Table 8 presents the empirical results of Eq. (1) with the two AI implementation indicators. We find that both coefficients $AIFirst_{it}$ and $AISubsequent_{it}$ are significantly positive (12.513 and 17.756, respectively, $p < 0.01$), which is consistent with our main results. We further perform a *t*-test on the difference between the two coefficients and find that the coefficient of $AISubsequent_{it}$ is larger than $AIFirst_{it}$ at the 10 % significance level. The results suggest that investors value subsequent AI disclosures more than first-time disclosures, which may be because subsequent AI disclosures indicate a relatively more mature development in AI and lower uncertainty of future performance.

Table 8: Additional regression results: First-time vs. subsequent implementation

	(1)
Dependent var.:	$Price_{it}$
$AIFirst_{it}$	12.513***
	(3.276)
$AISubsequent_{it}$	17.756***
	(5.569)
$BookValue_{it}$	0.637***
	(3.543)
$NetIncome_{it}$	7.329***
	(12.937)
$Assets_{it}$	6.964***
	(7.023)
$Loss_{it}$	3.930
	(1.237)
Constant	-26.477***
	(-3.291)
Diff. between the coefficients of $AISubsequent_{it}$ and $AIFirst_{it}$	5.243
p(Diff. = 0)	0.0719
Observations	1,036
Adjusted R^2	0.580
Fixed effects	Ind./year

See Appendix A for the variable definitions. The superscripts ***, **, and * represent statistical significance at the 1 %, 5 %, and 10 % levels, respectively, based on a two-tailed t-test. In parentheses, the t-values based on the standard errors clustered at the firm and year levels are given (Petersen, 2009). We control for industry fixed effects based on FF48 industry classification.

4.4 Robustness tests

We perform several robustness tests to verify our main results. The first robustness test uses the alternative evaluation dates of stock prices to ensure that investors have fully perceived the information conveyed in 10-K filings. Specifically, we alternatively measure $Price_{it}$ using the stock price three and seven days after the filing date as a robustness check. In the untabulated results of Eq. (1), here using the alternative $Price_{it}$, the coefficients of the variable of interest, AI_{it}, remain significantly positive, which is consistent with the main results. The estimated coefficients of AI_{it} are 15.037 and 15.003, respectively, both of which show $p < 0.01$ when $Price_{it}$ is set to three and seven days after the filing date. Overall, we do not find evidence that our main results are subject to the operational choice of the stock price's evaluation dates.

The second robustness test uses all available firm-year observations from Compustat and CRSP (the full sample) because our main results may be subject to the relatively limited PSM sample. To address this issue, we perform Eq. (1) using all available firm-year observations during the sample period. The alternative sample (full sample) consists of 125,045 observations. With the full sample, the untabulated results of Eq. (1) show that the coefficient of AI_{it} remains significantly positive (14.328, $p < 0.01$), which is consistent with the main results. Next, to capture potential omitted firm-level variables, we use a firm fixed effect model with the full sample for Eq. (1). The coefficient of AI_{it} remains significantly positive (11.257, $p < 0.01$) after controlling for the firm fixed effect. Finally, to address the fundamental differences in firm characteristics in the full sample, we perform an entropy balancing approach to reweight the non-AI group in the full sample (Hainmueller, 2012). After the reweighting, the means of the control variables are the same between the AI and non-AI groups in the full sample. The untabulated results using the full sample after entropy balancing are consistent with the main results, where the coefficient of AI_{it} is significantly positive (14.069, $p < 0.01$). Overall, we do not find evidence that our main results are subject to a limited PSM sample.

The final robustness test examines whether our main results are subject to the definition of AI disclosure. Although in the main test we consider only "artificial intelligence" and its variations as the AI keywords because many appearances of the acronym "AI" indicate item numbers only, we count the acronym as well when measuring $AIFreq_{it}$ in this robustness test. In the untabulated results of Eq. (1) using the alternative measure, we still find a significantly positive coefficient of $AIFreq_{it}$ (6.255, $p < 0.01$), which is consistent with the main results. We also find similar (untabulated) results using the full sample with industry fixed effects, firm fixed effects, and entropy balancing. Overall, we do not find evidence that our findings are subject to the operational definition of AI disclosures.

5. Concluding remarks

The present study examines whether firms' AI implementation brings value to firms from the investor perspective, that is, the value relevance of AI disclosures in the U.S. SEC 10-K filings. Our empirical results suggest that investors positively value firms with AI disclosures compared with those without AI disclosures. The results indicate that, after considering the benefits and costs of AI engagement, investors expect AI implementation will bring positive value for firms, as reflected in higher stock prices. Further investigating the AI-related risk factors in Item 1A and exploring the risk topics by LDA, we also find that AI-related risk factors are value relevant, specifically for those risk factors related to regulation and security; this suggests that investors value a firm's awareness of risks related to AI implementation. Finally, we find that when firms have better board- or executive-level IT governance, their risk factor disclosures regarding business operations are value relevant. Our empirical findings suggest that investors value a firm's AI implementation and AI-related risk awareness. In addition, IT governance plays a role in enhancing investor confidence regarding how firms address AI-related risks.

Our study provides empirical evidence for whether AI implementation can bring value to firms, given that it also yields new forms of risks (Taeihagh, 2021). Because investors consider expected future profits and perceived risks when assessing firm value, we aim to answer this question through an investor's viewpoint. Our findings provide implications for AI-implementing firms regarding the importance of risk awareness. That is, AI implementation may bring positive value only when firms are aware of the relevant risks. In addition, IT governance may also play a role in convincing investors about whether a firm is competent enough to address certain AI-related risks.

Our study has the following limitations: First, we search for the AI keywords in the whole 10-K filings, while disclosures in different sections or items in 10-Ks may be perceived by investors differently. These disclosures in different sections may imply AI implementation at different levels or scopes. Second, we limit our sample to SEC 10-K filings, which are more regulated, so that firms may be cautious about the AI-related information disclosed in SEC filings. Future research may consider exploring firms' AI disclosures from less regulated channels, such as press releases, new articles, social media, and so forth. Third, we use only the keyword "artificial intelligence" to search for AI disclosure because we aim to focus on firms' AI development instead of on a broader range of emerging technologies or digital transformations (e.g., automation, blockchain, business intelligence). Future research may consider a wide range of emerging technologies when investigating related research directions. Fourth, we consider only board- and executive-level IT governance, whereas IT governance covers a broader range, including processes, policies, employee training, and so forth. Because some scopes of IT governance might not be quantified by public disclosures, future studies may consider conducting interviews with executives or management to capture the different scopes of IT governance, thus examining how these scopes affect a firm's IT implementation differently.

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Appendix A: Variable definitions

Variable	Definition	Source
Dependent variables		
$Price_{it}$	The stock price one business day after the 10-K filing date	CRSP
Main independent variables		
AI_{it}	An indicator that equals 1 if a 10-K includes AI keywords ("artificial intelligen*", where * indicates variations) and 0 otherwise	SeekEdgar
$AIFreq_{it}$	The natural logarithm of the number of AI keyword appearances in a 10-K	SeekEdgar
$AIRisk_{it}$	An indicator that equals one if a firm discloses 1 or more risk factors that includes AI keywords in Item 1A of 10-K	SeekEdgar
$AIRiskFreq_{it}$	The natural logarithm of the number of risk factors including AI keyword in Item 1A of 10-K	
$AIRiskTopic1_{it}$ to $AIRiskTopic3_{it}$	Indicators that equal 1 if a firm disclose a risk factor including AI keywords that has been assigned as the first (new technology market competition), second (business operations), or third (regulation and security) topics identified by LDA, respectively, and 0 otherwise	
$ITGovernance_{it}$	An indicator of board- and executive-level IT competence, which equals 1 if the firm's proxy statement (Form DEF-14A) includes any of the following keywords: chief information officer, chief technology officer, chief security officer, chief information security officer, artificial intelligence, and their variations and 0 otherwise	SeekEdgar
Control variables		
$BookValue_{it}$	The book value of common equity divided by the number of outstanding shares at the end of the fiscal year	Compustat
$NetIncome_{it}$	The net income of the fiscal year divided by the number of outstanding shares at the end of the fiscal year	Compustat

Variable	Definition	Source
Assets$_{it}$	The natural logarithm of total assets at the end of the fiscal year	Compustat
Loss$_{it}$	An indicator that equals 1 if the net income of the fiscal year is negative and 0 otherwise	Compustat
Variables in additional tests		
AITopic1$_{it}$ to *AITopic5*$_{it}$	Indicators that equal 1 if the firm has a AI-related text (100 words before and after a AI keyword appearance) that are assigned as the first (technology), second (marketing and product), third (financial statements), fourth (governance), or fifth (healthcare) topics identified by LDA, respectively, and 0 otherwise	
ITIntensity$_{it}$	An indicator that equals 1 if the industry-level IT intensity is above the median in that year and 0 otherwise. Industry-level IT intensity is calculated as the sum of investment in computer and peripheral equipment, software, and communications, here as divided by total nonresidential fixed assets (Mittal & Nault, 2009).	U.S. BEA
AIFirst$_{it}$ (*AISubsequent*$_{it}$)	An indicator that equals 1 if the 10-K is (not) the first time to include the AI keywords for the firm and 0 otherwise	

Appendix B: Topic labels and keywords from LDA

We list the labels and example keywords of each latent topic identified by the LDA process, as follows: we label the topics by first ranking the keywords in each topic based on the weighted ratio suggested by Sievert and Shirley (2014) and then deciding the label of the topic based on top-rank keywords.

The below table lists the example keywords for the LDA on the AI-related risk factors in Item 1A, which is used for Eqs. (2) and (3) (Tables 4 and 5).

Variable	Label	Example keywords (stemmed)
AIRiskTopic1$_{it}$	New technology market competition	service, technolog, product, new, develop, competit, competitor, market, chang, custom, company, compet, busi, offer, abil
AIRiskTopic2$_{it}$	Business operations	platform, busi, result, oper, harm, use, acquisit, intellig, acquir, user, risk, affect, advers, content, brand
AIRiskTopic3$_{it}$	Regulation and security	data, regul, law, person, busi, inform, privacy, fund, require, protect, secur, invest, include, state, subject

The below table lists the example keywords for the LDA on the texts surrounding AI keywords in the whole 10-K, which is used for the first additional test (Table 6).

Variable	Label	Example keywords (stemmed)
$AITopic1_{it}$	Technology	custom, data, service, cloud, solute, analyst, enterpris, intellig, manag, provid, experi, busi, platform, enable, across
$AITopic2_{it}$	Marketing and product	technolog, advertis, market, client, consum, use, digit, new, may, search, product, platform, will busi, develop
$AITopic3_{it}$	Financial statement	company, statement, inc, finance, busi, agreement, note, subsidiary, acquisit, asset, stock, forward, consoled, oper, rad, item
$AITopic4_{it}$	Governance	comput, technolog, system, director, industry, company, board, intellig, market, high, applic, artifice, office, chip, includ
$AITopic5_{it}$	Healthcare	patient, health, cancer, clinc, diseas, drug, develop, hpe, test, medic, imag, diagnost, quantum, data, will, use

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