

An empirical study on digitalization's impact on operational efficiency and the moderating role of multiple uncertainties

Abstract

While many organizations are increasingly willing to invest in adopting digitalization in recent years, they might not be aware that different levels of uncertainty within and outside their organizations may impend digitalization's effectiveness. This study aims to empirically explore the performance impact from digitalization on organizations and the effect from uncertainty on the impact. More specifically, the objectives are pertinent to examining 1) the association between digitalization and operational efficiency and 2) the moderating effect of macro-level uncertainty, industrial-level uncertainty, and firm-level uncertainty on this association. Using a dataset collected from multiple sources employing innovative methodologies including natural language processing (NLP) to analyze digitalization announcements from Factiva and measuring operational efficiency based on the stochastic frontier approach (SFA), this study analyzes the impact from digitalization via 2,520 samples from 496 listed firms in North America during 2015-2021. The results show that digitalization significantly enhances operational efficiency, and this positive impact from digitalization is weakened by macro-level uncertainty and industrial-level uncertainty. Our findings provide researchers and practitioners with useful insights into digitalization's important role in enhancing operational efficiency and guidance indicating the business environments deserve extra attention so as to retain digitalization's positive impact.

Managerial Relevance Statement

Many managers remain hesitant to adopt digitalization within their organizations because of the numerous failure cases and limited managerial guidelines in the literature. This article shows the linkage between digitalization and operational efficiency. The managerial guidelines are that firms with a strategic goal of enhancing operational efficiency should invest more substantially in digitalization. Also, considering the differing digital technologies available today, organizations

should evaluate and adopt technologies with consideration on their relevancy to operational efficiency. Moreover, the impacts of different levels of uncertainty on digitalization's effectiveness in enhancing operational efficiency are crucial managerial considerations. Specifically, this article finds that macro- and industry-level uncertainties impede digitalization's effectiveness in enhancing operational efficiency. This offers managerial guidelines suggesting that organizations operate under such environments require extra foresight when scanning their business environments and flexibility in the relevant decisions. Specifically, organizations should maintain cautious to changes in their external environments after implementing digitalization and be prepared to adjust their strategies and decisions as necessary.

Keywords: digitalization, operational efficiency, uncertainty, NLP

1. Introduction

Firms increasingly consider digitalization essential for their survival in the era of Industry 4.0 and are willing to make relevant investments in digital technologies substantially. For instance, about 1.85 trillion dollars were poured into funding development of future digital technology in 2022, and the amount of global digital spending is predicted to reach 3.4 trillion dollars in the global environment in 2026 [1]. Indeed, many firms such as Facebook and Google have generated unparalleled value through such investments [2]. However, some other businesses did not achieve the expected outcomes from digitalization and took huge losses [3], where such failure was considered in relation to a lack of attention to changes in the environment or to the inability to assess future changes [4]. For instance, Blockbuster and Kodak's declines were attributed to the lack of foresight into changes in technologies relevant to their business contexts [2]. Similarly, one reason for Nokia's failure was its hesitation to upgrade to Android in the early 21st century in the face of high uncertainty in the mobile industry [5]. One important lesson implied from these failures is that success in the adoption of digitalization hinges on firms abilities to recognize the negative influence from environmental uncertainty and scan the relevant changes and challenges in their business environments on a regular basis. Although there have

been much discussion of the negative effect of uncertainty on businesses [6], the understanding concerning uncertainty's impact on digitalization remains unclear.

In practice, uncertainty is widely regarded as a negative factor for firms' performance. For instance, gubernatorial elections are often considered a critical form of uncertainty for firms in the US; many firms respond by reducing investments by 5%, whereas some firms more susceptible to uncertainty reduce their relevant investments by 15% [7]. In academia, uncertainty is also commonly believed to be negative for firms. For instance, policy uncertainty could negatively influence firms' investments [8] or motivate firms to hold more cash because of precautionary considerations [9]. However, some research suggests that uncertainty could be a favorable condition for firms and could lead to positive outcomes such as improved innovation [10] and enhanced IT ambidexterity capability and the resulted success [11]. One potential cause of these seemingly contrasting outcomes may be the presence of varying forms of uncertainty, which play distinct roles in business operations. Overall, there is a dearth of empirical evidence to substantiate the influence of uncertainty on the efficacy of digitalization efforts.

Scholars are interested in digitalization's effectiveness [12] but face challenges caused by a lack of measurement of digitalization based on second-hand data [13]. Prior research indicates that firms with higher levels of digital activities (e.g., digitalization strategic plan [14], blockchain adoption [15], and employees' digital literacy [16]) are associated with higher innovation [17], higher performance [14] and lower firm risk [18]. However, most of these studies utilize survey data or measure the adoption of digitalization with partial digital activities or based on investments, causing concern about the accuracy of the findings. Indeed, one conventional approach to measure digitalization is to count corporate announcements (Lam *et al.*, 2016), but this approach is often plagued by manual inconsistencies, time constraints, and human biases, resulting in potential data inaccuracies [19]. This paper attempts to address the problem by adopting a rigorous and advanced method, i.e., natural language processing (NLP), which is a form of the machine learning (ML) technique and is capable of

capturing required announcements from bigger databases and less structured writing in comparison with conventional methods.

In this study we test the relationship between digitalization and operational efficiency and the moderating effects of three levels of uncertainty (i.e., macro-level uncertainty (or economic policy uncertainty (EPU)), industrial-level uncertainty (IU), and firm-level of uncertainty (FU)) on this relationship. By studying 496 listed firms in North America from 2015 to 2021, we found that firms with higher digitalization levels performed better in operational efficiency. Our results also showed that different levels of uncertainty played different roles in the effect of digitalization on operational efficiency. EPU and IU hinder the enhancement of operational efficiency brought by digitalization; however, FU's moderating effect is insignificant. The three major contributions of this study are as follows: First, we measured digitalization adoption by processing objective announcement data with NLP, demonstrating the use of an advanced measurement method in text sources in the management context. Second, we verified digitalization's impact on operational efficiency. Third, we comprehensively examined the moderating effects of three levels of uncertainty on the link between digitalization and operational efficiency, thereby providing new insight to the body of knowledge on digitalization and uncertainty and to practitioners to enhance their efficiency enhancement effort via digitalization.

2. Theoretical background and hypothesis development

2.1 Theoretical background

Digitalization's rising influence in various domains has sparked considerable scholarly interest. Because it is a nascent field, most existing studies gravitate toward conceptual discussions and measurement debates; empirical research is somewhat limited due to a lack of direct secondary data [20]. Among the limited number of empirical studies, they tend to rely on the use of survey data for analysis. Table I summarizes studies on digitalization regarding its 1) definitions, 2) measurements,

and 3) performance outcomes. The review to be conducted below will also focus on these three aspects of digitalization in the literature.

Insert Table I around here

Because it is a relatively novel technological strategy, the comprehension of digitalization has evolved from obscurity to the formation of diverse interpretations. For example, many scholars have equated digitalization to the use of digital technologies for improving business processes and organizational management [21], while others have defined it from a socio-technical perspective as a process that integrates multiple technologies into aspects of business [22] or as involving a transformative process [23]. This ambiguity was significantly addressed when Verhoef distinctly differentiated these concepts and proposed that digitalization involves the use of digital technologies, whereas digital transformation is a revolutionary change brought by digital technologies in a company-wide context including the organizational culture [24]. This viewpoint has been increasingly accepted by the academic community. In the current study, digitalization refers to firms' application of digital technologies in their existing business processes. This broad conceptualization accurately describes the practical situation of firms rather than emphasizing the concept of transformation, which is mostly concerned with revolutionary changes [25].

Table I also indicates that no widely accepted measurement of digitalization is available, largely due to the scarcity of direct secondary data that can quantify the implementation level of this technology strategy. The methodologies of existing studies lean toward surveying or tracking the frequency of digitalization announcements. For instance, some researchers gauge digitalization based on how a company uses digital technologies to increase product value or to launch new business models [23]. Others look at the use of digital tools like social networks [26]. There are also

examinations on assessing a firm's digitalization capability [27, 28] or analyzing keyword frequencies in annual reports [20]. Despite these efforts, the quest for a widely accepted measurement remains ongoing.

The investigation into the effects of digitalization on performance outcomes has been diverse. Although direct empirical studies on digitalization are scarce, this body of literature has selected and summarized digitalization concepts that are similar to our definition of digitalization and has contributed to insights into outcomes such as firm performance [23], and total factor productivity [20]. These direct outcomes from digitalization could also be influenced by organizational factors. For example, although digitalization enhances firm performance, this advantage may be tempered by factors such as knowledge inertia [23]. Similarly, digital transformation can boost productivity but might concurrently impact other performance dimensions negatively [20], implying that the impact of digitalization on performance in different contexts is nuanced. To supplement this literature, new investigations into factors that strengthen the performance impact of digitalization on organizations should be conducted.

The multifaceted and volatile nature of the operational environment necessitates a more in-depth understanding of digitalization's performance impacts. The omnipresent uncertainty in general causes firms to grapple within operations [29]. Specifically, ignoring uncertainty can lead to substantial risks, potentially leading firms to misalign with shifting market demands [30], make suboptimal technological investments [31], and remain unresponsive to emergent competitive dynamics [32]. Consistent with the practice in the business context, the literature underscores the significant role of uncertainty in decision-making [33], and innovation strategy [34], etc. Obviously, the discourse surrounding uncertainty highlights its significance in operations, an importance that becomes even

more pronounced in the context of the new digital economy [35]. Digitalization, however, is not a monolithic entity but a layered technology strategy with implications across various strata of a firm [36]. It involves a firm's capability at different levels, such as sensing total market trends [37] and ensuring competitiveness within an industry [38]; thus, its effectiveness may vary significantly at different levels of uncertainty. In this study uncertainty is divided into three levels. First, EPU captures the unpredictability associated with government policies, and is a reflection of macro-economic and political instability [39], which often has long-term impacts on businesses on a broad scale and could affect a firm's long-term decisions on digitalization [40]. Second, IU relates to the unpredictability within industries that might spur firms to adopt digitalization to stand out in a volatile market [41] or that might undermine the effectiveness of digitalization efforts if businesses fail to keep up with competitors [42]. Finally, FU pertains to the internal unpredictability partly associated with fluctuations in performance that businesses face, which could hinder the smooth integration of resources with digitalization, thus affecting the potential of digitalization to achieve enhanced operational performance [43]. The variability and impacts posed by these distinct levels of uncertainty warrant further investigation into the role of uncertainty levels in digitalization's effectiveness. However, existing studies give scant attention to this critical research area.

2.2 Hypothesis development

Digitalization has become an inevitable element of competition in the era of Industry 4.0 [44]. This study adopts the resource-based view (RBV) to examine the effectiveness of digitalization in enhancing operational efficiency for organizations. Prior RBV research suggests that a firm's operational efficiency depends on its 1) resources, 2) routines, and 3) capabilities from the RBV perspective [45]. First, digitalization works as one strategic resource and is difficult to copy because it is supposed to be closely related to a firm's specific path or trajectory [46]. Path-dependence leads to

isolation mechanisms in firms' digitalization, hindering short-term imitation by competitors. Digitalization boosts operational efficiency by unifying tangible and intangible resources [45]. It optimizes access to customer data, improving understanding of their needs [47]. In addition, digitalization enables platforms and interfaces to facilitate integration of disparate yet complementary information, opening up new value creation opportunities [48]. Second, as an efficient instrument that influences actual processes, digitalization improves the efficiency of managerial routines [49] and is important to enhancing operational efficiency [45]. Third, digitalization effectively supports firms' development of their extended core capabilities [50], which are regarded as those core inter-organizational processes critical to firms' performance [51]. Thus, we develop the first hypothesis as follows:

H1: Digitalization improves firms' operational efficiency.

Firms nowadays operate in a highly uncertain environment [52]. The impact of uncertainty on firms is paradoxical. On the positive side, uncertainty could be a favorable environment for firms because it may stimulate firms to adopt more flexible strategies to adapt to changes and explore new market opportunities [53]. For example, firms may discover novel customer needs, products, or services, leveraging the full benefits of digitization and improving operational efficiency and competitiveness [54]. However, according to uncertainty management theory [33], uncertainty's negative impact may far outweigh its potential benefits in that it could expose firms to significant risks when they invest in digitalization [55]. For instance, firms may allocate substantial resources to digitalization, but because of unexpected changes in national policies, competitors' actions, or internal environments within firms, these investments may not yield the expected returns.

Considering the potentially conflicting impacts of uncertainty and firms' substantive investments in digitalization, a systematic investigation into the impacts of uncertainty on digitalization is warranted. To offer researchers and practitioners more exhaustive insights, we consider three levels of uncertainty facing firms, namely EPU, IU, and FU, in this study.

EPU is about broad societal, economic, and political fluctuations that can influence an entire industry. EPU directly affects firms' activities and performance [56] and brings additional risks or resource requirements to firms' operations, including the effect of digitalization on operational efficiency. Specifically, higher EPU will lead firms to retain fewer resources [57], which are the core input of digitalization's integrating function. Similarly, higher EPU will reduce their human capital [58], which is essentially important in digitalization's function relative to organizational routines. Empirical evidence shows that compensation is critical in attracting and retaining digitalization professionals [59] who positively impact organizational IT capabilities [60]. In addition, Nagar *et al.* (2019) asserted that during periods of heightened uncertainty, the information environment deteriorates, so there are not enough data for digitalization to identify and leverage complementary capabilities in creating value [61]. Accordingly, digitalization is unlikely to contribute as expected to the integration of resources to strengthen firms' routines and capabilities. With this logic, higher EPU is a negative factor in digitalization's contribution to firms' efficiency. We thus propose the following:

H2: A high level of EPU weakens the effectiveness of digitalization in enhancing operational efficiency.

IU refers to the unpredictability of various factors within industries [62]. Higher uncertainty within industries makes it difficult for firms to predict competitor behaviors [63], inducing a more uncertain business environment. In industries with lower uncertainty, firms can maintain steady production and face fewer rivals [10] while utilizing digitalization for resource allocation [10], maintaining stable routines [64] and improving firms' capabilities. Limited competition ensures that digitalization can function in a knowledge exchange, optimizing processes and sensing diverse resources. In contrast, the higher the IU is, the higher is the digitalization processing ability required by organizations. We thus propose the following:

H3: A high level of IU weakens the effectiveness of digitalization in enhancing operational efficiency.

Along with external uncertainties, internal uncertainty is also an indispensable challenge facing organizations [65]. Micro-level uncertainty in this study is reflected by FU, which refers to the unpredictability of factors impacting a firm's operations and performance [66]. First, firms with high FU are unlikely to have stable incomes and often suffer from high capital costs [67], underinvesting in digitalization and inhibiting digitalization's operational efficiency. Second, high FU creates volatile routines, complicating digitalization implementation [68], and firms may respond by giving up digitalization to avoid potential volatility in sales [69]. Lastly, high FU incurs costs, including reduced market value and increased capital costs, posing a dilemma for firms investing in digitalization technologies and developing the necessary capabilities. We thus propose the following:

H4: A high level of FU weakens the effectiveness of digitalization in enhancing operational efficiency.

3. Data collection and variable operationalization

To empirically test our hypotheses, we constructed a panel dataset on digitalization, operational efficiency, and the three levels of uncertainty from multiple sources to avoid common method bias [70]. We gathered digitalization data from Factiva by identifying 1,430 firms that had made at least one announcement about digitalization during 2015-2021. After matching the announcement data with data on variables concerning operational efficiency and uncertainty from two other databases, namely Compustat and the EPU index, we secured 2,520 samples from 496 firms. A flow chart summarizing the steps in the methodology of this study, including the development of this dataset comprising 2,520 samples, is shown in Figure 1.

Insert Figure 1 around here

3.1 NLP Analysis of digitalization announcements

To achieve better accuracy in the measurement of digitalization adoption, we analyzed digitalization announcements from Factiva using a ML technique called “topic modeling,” which is a major type of NLP. Topic modeling aids in revealing the primary themes or topics embedded in

unstructured documents such as texts on social media platforms.

First, aligning with the practical considerations of data collection and informed by the literature [24], digitalization in this study is defined as a broad concept that encompasses the use of numerous digitalization technologies or tools. With this broad definition, we derived key words to search for relevant digitalization announcements from the Factiva database. Appendix I gives the details of the announcement collection process.

After searching, gathering, and preprocessing the complete digitalization announcements from two sources within Factiva [71], the *Wall Street Journal*, and *Dow Jones Newswires*, we classified the announcements into five types, such that four of them represented types of genuine digitalization adoption in practice [72]. Table II shows example announcements of these four types of digitalization. Then, we analyzed the digitalization announcements with topic modeling steps consistent with the literature [73, 74]. Specifically, we adopted the latent Dirichlet allocation (LDA) model to reorganize the five types of digitalization into two topic clusters (e.g., digitalization announcements and non-digitalization announcements). The detailed process is presented in Appendix II. Note that the results obtained from the LDA model were also checked manually to achieve advantages such as scalability, discovery of hidden patterns, and consistency [75]. In short, the combination of LDA and manual checking ensured both efficiency and accuracy in this part of the data processing and analysis.

Insert Table II around here

With NLP, we collected 8,770 announcements by 1,430 firms from Factiva, covering firms that made at least one digitalization announcement in the period 2015 to 2021.

3.2 Variables Measurement

Digitalization. Through the process presented in Section 3.1, we obtained announcements on digitalization. We developed our data by standardizing the announcement numbers within different industries (j) based on the 2-digit SIC codes as follows:

Digitalization_{ijt}

$$= \frac{\text{Number of digitalization announcements}_{ijt} - \text{mean of number of digitalization announcements}_{jt}}{\text{Standard deviation of number of digitalization announcements}_{jt}} \quad (1)$$

Operational efficiency. Based on the literature [76], we adopted SFA to measure operational efficiency, offering a more comprehensive measurement of a firm's operational efficiency than the traditional single dimension indicator [45]. We calculated operational efficiency using a time varying model as follows:

$$\begin{aligned} \ln(\text{Operating Income})_{ijt} = & \beta_0 + \beta_1 \ln(\text{Number of Employees})_{ijt} \\ & + \beta_2 \ln(\text{Cost of Goods Sold})_{ijt} \\ & + \beta_3 \ln(\text{Capital Expenditure})_{ijt} \\ & + \varepsilon_{ijt} - \eta_{ijt}. \end{aligned} \quad (2)$$

After getting η_{ijt} , the inefficiency's corresponding frontier of operational efficiency in the same industry, we utilized Eq. (3) to calculate its operational efficiency, and further standardized operational efficiency with Eq. (4):

$$\text{Operational Efficiency}_{ijt} = 1 - \widehat{\eta_{ijt}} \quad (3)$$

$$\text{Operational Efficiency}_{ijt} = \frac{\text{Value of operational efficiency}_{ijt} - \text{Mean of value of operational efficiency}_{jt}}{\text{Standard deviation of value of operational efficiency}_{jt}} \quad (4)$$

EPU. EPU is reflected by the economic risk relative to undefined upcoming government policies and regulatory structures, and is measured by the BBD index provided by the EPU website of Baker, Bloom, and Davis [39].

IU. On the basis of the literature [77], we measured IU using Eq (5). Note that the four-firm concentration ratio is the combined market share of the four largest firms in an industry, expressed as a percentage [77].

$$IU = 1 - \text{Four-firm concentration ratio}. \quad (5)$$

FU. The literature on FU is sparse and mostly limited by data availability [78]. Furthermore, traditional measures, such as daily stock price volatility, have higher-frequency characteristics that may not capture the annual uncertainty faced by firms [79]. Therefore, our measurement of FU is

concerned with the realized or implied annual volatility of firm sales, and is obtained by computing the standard deviation of changes in earnings in sample firms as follows [80]:

$$FU = \sqrt{[\sum(\Delta E_{t+i+1} - E_{t+i} - \mu)^2 / 5]} , \quad (6)$$

where ΔE_{t+i+1} represents the earnings before extraordinary items for year $(t+i+1)$, where t denotes the initial year, and i ranges from 1 to 5, indicating the specific year within the 5-year period being analyzed.

Other variables. Table III provides a list of all the variables, their operationalization, and data sources.

Insert Table III around here

3.3 Summary Statistics and Correlations

The descriptions of our 2,520 samples are shown in Table III (see panels A and B). These sample firms operate in 49 industries with 2-digit SIC codes. Note that the top 20 industries are presented in panel C of Table IV. The descriptive and correlation analysis of the variables are presented in panels C and D of Table IV, respectively.

Insert Table IV around here

4. Model Development and Results Analysis

4.1 Model development

We developed an equation with firm operational efficiency as the dependent variable. Note that U presents EPU, IU, and FU, which are excluded in testing H1. Subscript i denotes the firm and subscript t denotes the calendar year:

$$\begin{aligned} \text{Operational Efficiency}_{i,t+1} &= \alpha_0 + \alpha_1 \text{Digitalization}_{it} + \alpha_2 U_{it} + \alpha_3 \text{Digitalization}_{it} \times U_{it} + \alpha_4 \text{Firm Size}_{it} \\ &+ \alpha_5 \text{Firm Age}_{it} + \alpha_6 \text{MarkettoRatio}_{it} + \alpha_7 \text{Firm Leverage}_{it} + \alpha_8 \text{R\&D Intensity}_{it} \\ &+ \alpha_9 \text{Firm Advertising Expense}_{it} + \sum_{k=1}^D \delta_k \text{IND}_k + \sum_{m=1}^Y \mu_k \text{YEAR}_m + \varepsilon_{it}. \end{aligned} \quad (7)$$

We lagged independent variables in the equations by a year because it takes time for firms to adjust the new operational modes brought by digitalization and for these modes to take effect on

operational efficiency [52, 73].

The analysis controls for six firm level variables, including firm size [81], firm age [81], leverage [52, 82], advertising expense [45], market-to-book ratio [52, 83] and firm R&D expenses [45]. To control for unobservable time and individual effects, the current analysis added the year- and firm-fixed effects in the regression models.

4.2 Baseline analysis

We constructed estimating models using Eq. (7) and illustrated the results of the fixed-effect (FE) model in Table V, and validated the results with robust t (columns 5–8) and bootstrap z statistics (columns 9–12[81]. We utilized robust t and bootstrap z statistics to address the possibility that the model may fail to meet standard regression assumptions, and we clustered all the standard errors at the firm level.

Insert Table V around here

The results in column (1) of Table V indicate that digitalization positively affects operational efficiency ($p < 0.001$), supporting H1. Then, the findings in column (2) show that EPU mitigates the enhancement effect of digitalization on operational efficiency ($p < 0.001$), supporting H2. Similarly, the findings in column (3) show that IU mitigates the enhancement effect of digitalization on operational efficiency ($p < 0.001$), supporting H3.

The findings in column (4) reveal that FU does not exhibit a significant moderating influence on the effectiveness of digitalization ($p > 0.05$), rejecting H4.

4.3 Endogeneity concerns analysis

The endogeneity issue that incorrect conclusions may result when one or more explanatory variables in a model are associated with the error item [84]. Generally, endogeneity can stem from causes such as reverse causality, sample selection bias, and omitted variables [84].

First, the issue of reverse causality pertains to the possibility that digitalization could be endogenously determined because firms with higher operational efficiency may have more

opportunities to adopt and capital to invest in digitalization. Under this situation, digitalization and the error term may be correlative, resulting in endogeneity. Based on prior studies [85], we used a one year lag of each digitalization and the control variables instead of their present values in Eqs (5), (6), and (7) to process the regression, which helps mitigate the potential endogeneity issue brought by reverse causality.

Second, there exists the possibility of sample selection bias in the data-collection process, so we employed the Heckman model [86] to address this potential issue. We constructed regression using Eq. (8) to estimate firms' profitability to adopt digitalization. We next estimated the inverse mills ratio (IMR) and then estimated Eq. (7) by controlling IMR:

$$\begin{aligned}
& \text{Probit} (Digitalization_{i,t} = 1) \\
& = \vartheta_0 + \vartheta_1 Firm\ Size_{it} + \vartheta_2 Firm\ Age_{it} + \vartheta_3 MarkettoRatio_{it} + \vartheta_4 Firm\ Leverage_{it} \\
& + \vartheta_5 R\&D\ Intensity_{it} + \vartheta_6 Firm\ Advertising\ Expense_{it} + \sum_{k=1}^D \varphi_k IND_k + \sum_{m=1}^Y \omega_k YEAR_m \\
& + \epsilon_{it}.
\end{aligned} \tag{8}$$

In Eq. (8), we stipulated that the digitalization level equals 1 if the focal firm i issued at least one digitalization announcement in year t ; the firm's size, firm's age, firm's market-to-ratio, firm's leverage, R&D expenses, and advertising expense are considered as variables that can affect the firm's profitability. After getting the IMR value, we controlled the IMR in the second step of the Heckman model. We report the Heckman results in Table VI.

Insert Table VI around here

The results show that the coefficient of digitalization remains significantly positive ($p < 0.001$), whereas the moderating effects of EPU ($p < 0.001$) and IU ($p < 0.001$) are still significantly negative, and the moderating effect of the coefficient of FU is the same, i.e., insignificant ($p > 0.1$). This evidence implies that the enhanced operational efficiency due to the inception of digitalization is stable.

Last, the issue of omitted variables is common in econometric models because it is impossible to make sure that a model can cover all the relevant variables. Referring to prior research on operational efficiency [45, 81], we considered that operational efficiency has the persistent influence of past

operational efficiency. We built a dynamic panel data (DPD) model using Eq. (9) as follows:

$$\begin{aligned} \text{Operational Efficiency}_{i,t+1} = & \beta_0 + \beta_1 \text{Operational Efficiency}_{i,t} + \beta_2 \text{Digitalization}_{i,t} + \beta_3 U_{i,t} + \\ & \beta_4 \text{Digitalization}_{i,t} \times U_{i,t} + \beta_5 \text{Firm Size}_{i,t} + \beta_6 \text{Firm Age}_{i,t} + \beta_7 \text{MarkettoRatio}_{i,t} + \beta_8 \text{Firm Leverage}_{i,t} + \\ & \beta_9 \text{R\&D Intensity}_{i,t} + \beta_{10} \text{Firm Advertising Expense}_{i,t} + \sum_{k=1}^D \varphi_k \text{IND}_k + \sum_{m=1}^Y \omega_k \text{YEAR}_m + \epsilon_{i,t}. \end{aligned} \quad (9)$$

Indeed panel D of Table IV indicates that the operational efficiency of a firm is very significantly associated with its performance in the previous year ($R = 0.408$, $p < 0.001$). Table VII reports the results of the DPD model, in which the findings are consistent, i.e., H1, H2, and H3 are supported, and H4 is rejected.

Inset Table VII around here

4.4 Robustness Checks

To test for robustness, we verified our hypothesis findings by conducting heterogeneity analysis. We considered both time and firm-type factors. Specifically, we first divided the samples into two groups, namely before COVID-19 and after COVID-19. To compare digitalization's effect on operational efficiency in these two groups, we reported the results of FE Models (1) to (8) in Table VIII. Then we further divided the samples into two groups based on firm-type, namely the B2B and B2C groups [87]. We report the results of FE Models (9) to (16) in Table VIII. Overall, all the model results in Table VIII indicate that the hypothesis findings are robust in all the groups.

Insert Table VIII around here

5. Discussion

5.1 Theoretical implications

First, this research extends the literature on digitalization in the Industry 4.0 era. Indeed, many prior studies have recognized the necessity of researching digitalization's impact on firm outcomes [26, 44]. Although data on direct measurement of digitalization are lacking, myriad studies have found positive contributions of specific digital instruments and activities on firm performance. For instance,

Lam *et al.* (2016) elucidated the advantages rendered by social media initiatives, Kozjek *et al.* (2018) highlighted the positive outcomes of integrating new digital processes, and Xiong *et al.* (2021) demystified the operational benefits of blockchain adoption. Cumulatively, these studies ratified the overwhelmingly positive imprint of specific facets of digitalization on business outcomes. Our research provides further empirical evidence with objective data on digitalization's positive impact from an operational perspective, generating new insights to the literature on digitalization and operations management.

Our examination on digitalization also contributes to enrich the empirical literature by employing NLP in the measurement. The survey data or objective data of specific technologies utilized in prior studies [89] are fraught with challenges, such as respondent biases [90] or accuracy concern because of the limited technologies covered in the measurement [91]. To improve the accuracy of the data of digitalization, this study employs NLP, a more advanced approach for soliciting insights from secondary data. Aligning with our study's reliance on the textual characteristic of announcements as a key source of digitalization, this methodological advancement allows for a more nuanced understanding of digitalization and demonstrates to researchers the use of a new approach for measuring a concept via unstructured and/or voluminous data.

Second, this study delves into the role of uncertainty as a critical context influencing the effectiveness of digitalization. Previous research on the relationship between uncertainty and digitalization has been inconclusive, with some studies suggesting positive effects [53] and others emphasizing negative consequences [33, 55]. Indeed, these mixed findings could be related to the assumption that uncertainty is a single-dimension factor. Our findings contribute to this ongoing debate by examining uncertainty at three levels, i.e., firm-, industrial- and macro-level uncertainty. We

demonstrated that uncertainty, except for FU, presents a significant challenge for organizations implementing digitalization strategies. Specifically, we revealed that EPU and IU pose significant challenges for organizations implementing digitalization strategies, whereas FU has a negligible effect. This result is in line with the notion that digitalization's impact is highly conditional and challenging to manage [92]. Overall, our results contribute to the literature on digitalization and uncertainty by offering empirical evidence of their interaction with respect to the outcome of operational efficiency.

5.2 Practical implications

Our study offers clear practical implications for businesses seeking to implement digitalization strategies to improve operational efficiency. These implications provide guidance on both whether and when (not) to pursue digitalization for firms.

First, our findings emphasize the importance of recognizing digitalization as a strategic tool for enhancing operational efficiency rather than merely viewing it as a generic method for imitating the practices of competitors. With this insight into the link between digitalization and operational efficiency, firms with the strategic goal of enhancing operational efficiency should invest substantially in digitalization. When selecting the specific technologies and considering the use of the resulting insights, extra attention should be paid to the potential technologies' relevancy to operational efficiency.

Second, our research highlights the need for managers to understand that digitalization's effectiveness is conditional. They should assess and identify the types of uncertainty their organizations face and adjust their digitalization strategies accordingly. Specifically, our results indicate that high levels EPU and IU are unfavorable for digitalization. With the recognition that it is inevitable that firms should continue to invest in digitalization, firms must be very cautious in the relevant actions and decisions. For instance, more sensitivity analysis on broader areas such as social, economic, or market changes should be carried out while making long-term investments concerning

digitalization. In addition, after making digitalization investments, firms must monitor their external environments closely and adjust their adoption strategies or relevant decisions accordingly.

6. Conclusions

Numerous studies have examined the outcomes of digitalization in various contexts. However, existent studies using objective data in the investigation are scant, and whether uncertainty provides a favorable [54] or unfavorable environment [88] for using digitalization to enhance operational efficiency is unclear. Our study employed NLP to analyze Factiva data to objectively measure digitalization and then to regress digitalization against operational efficiency, finding that digitalization enhances operational efficiency. In addition, we identified uncertainty as a highly relevant factor affecting the effectiveness of digitalization, and we comprehensively measured uncertainty at macro, industrial, and firm levels using objective data including the EPU index and Compustat. Our results indicate that different uncertainty levels influence digitalization's impact on operational efficiency differently. Unlike firm-level uncertainty, the other two levels of certainty pose significant challenges for organizations implementing digitalization strategies.

This research highlights the complex interplay between digitalization, operational efficiency, and uncertainty, providing valuable insights to the literature concerning digitalization, operational efficiency enhancement, and uncertainty. In addition, our findings offer valuable practical guidance for businesses aiming to harness the power of digitalization to improve operational efficiency. By understanding the context-specific nature of digitalization's effectiveness and tailoring their strategies to address different levels of uncertainty, organizations can better position themselves for success in an increasingly digital and uncertain business landscape.

Limitations and future research

There are at least three limitations in this research. First, our sample only covers listed companies

in North America. Although this sample helps us establish an important and relevant dataset, our findings may not be generalizable to firms in other contexts. Second, the endogeneity issue raised by omitted variables is also a great challenge to our research. We employed lagged variables, the Heckman model, and the generalized method of moments (GMM) to mitigate the possible endogeneity issues due to reverse causality, sample selection bias, and omitted variables, respectively. However, the use of GMM only addresses the endogeneity concerns in the relationship between digitalization and operational efficiency, without considering all three levels of uncertainty. Finally, we only tested the digitalization's effectiveness on operational efficiency, but it could also impact other important performance dimensions such as innovation, financial performance, and firm risks.

Future studies could verify the results developed in this study with a larger sample scope, such as unlisted firms in the US or listed firms in Asian or European countries. Furthermore, to tackle the endogeneity issue caused by potential omitted variables, future studies should prioritize the identification of strictly exogenous instrumental variables, a solution that is widely considered to be effective for testing endogeneity due to omitted variables. Finally, future research may provide extra empirical evidence on the performance implications of digitalization with respect to different performance outcomes and to different moderating factors such as supply chain complexity or innovation capability.

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Appendix I

We used broad search terms including “digit!” (to capture any word that starts with “digit,” such as “digitalization,” “digitalise,” or “digital”) and a number of relevant verbs (such as “adopt” and “implement”) to ensure the announcements identified were pertinent to making changes or adopting new practices. One key parameter that needed to be determined was the number of words between “digit!” and the relevant verb. Following the approach of Dotzel and Shankar (2019), we experimented with setting this parameter from 8 to 12 and manually inspected the outcomes. The results indicated that a search specifying no more than ten words between “digital” and the relevant verb was the most effective setting to obtain relevant announcements accurately.

With this setting and the search terms discussed above, we input the following to Factiva,

“(digit or digits or digitization or digitalization or digitalisation or digitize or digitise or digital or digitally or AI or big data or cloud or blockchain or internet of things) near 10 (construct or constructs or constructing or constructed or construction or adopt or adopts or adopted or adopting or adoption or use or uses or using or used or usage or usages or utilize or utilizes or utilizing or utilized or utilization or develop or develops or developing or developed or development or exploit or exploits or exploiting or exploiting or exploitation or apply or applies or applying or applied or application or equip or equips or equipping or equipped or equipment or establish or establishes or establishing or established or establishment).”

This search resulted in 81,310 announcements. We then followed the steps of Shankar and Parsana (2022) to employ LDA, which is an ML algorithm particularly useful for analyzing large volumes of text data, to classify files into different groups with distinct digitalization types. We also supplemented the LDA analysis with manual inspection to ensure accuracy in the classification.

We also paid attention to make sure we collected announcements from accurate sources. Factiva is a comprehensive database comprising data from various sources. This study followed prior literature (e.g., Hendricks and Singhal, 2003) to gather announcements from two major sources, namely Dow

Jones and the *Wall Street Journal*. To ensure the accuracy of the data from these two sources, we compared the search results of Dow Jones and the *Wall Street Journal* against those from the whole Factiva database (see Figure 2). The number of digitalization announcements in Factiva showed a linear trend and maintained a steady increase over the years. In contrast, trends in Dow Jones and the *Wall Street Journal* were more consistent with practice—the jump in 2013 is partly related to the proposition of “Industry 4.0” that promotes the rapid development of digitalization; the valleys in 2019 and 2020 are consistent with the outbreak of COVID-19, supporting the accuracy and representativeness of the data from these two resources.

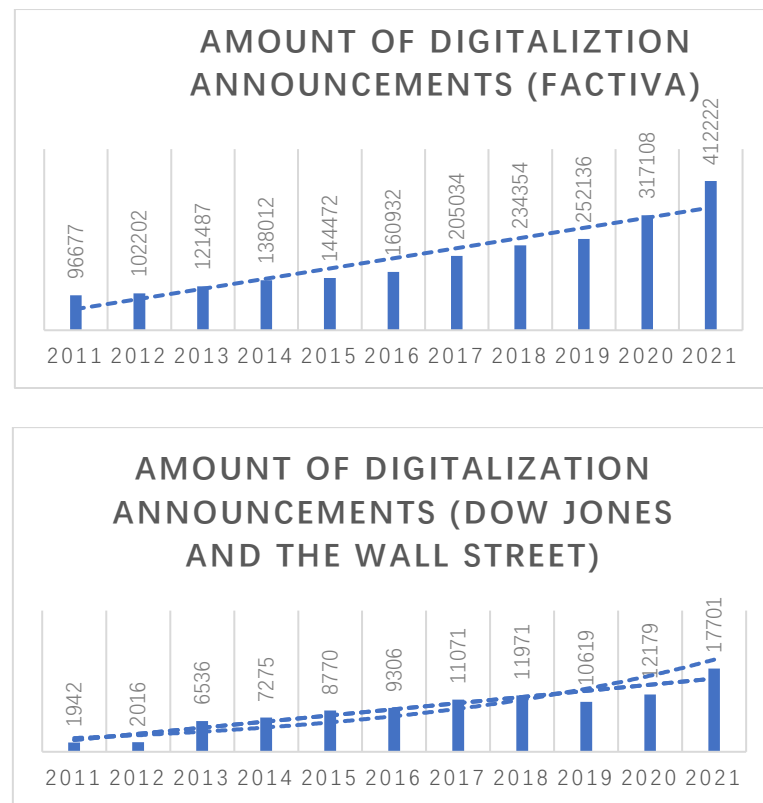


Figure 2. Trends of digitalization announcements from Factiva (all sources), Dow Jones and the *Wall Street Journal*

Appendix II

We completed a four-stage collection process [71, 73] to develop the digitalization data. The details are presented in Table IX.

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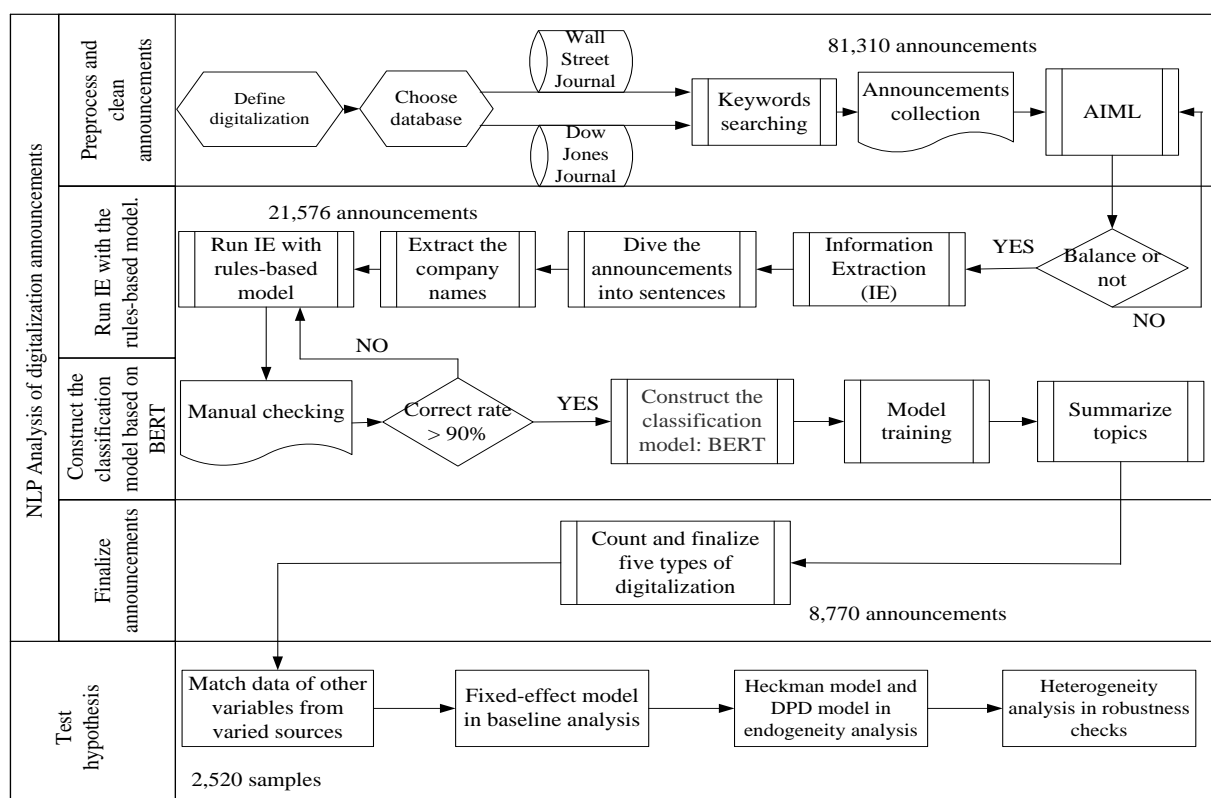


Figure 1. Flow chart summarizing the steps in research methodology

Table I Studies on digitalization

Digitalization literature	Content	Reference
Definition	Digitalization is the use of digital technologies to transform business processes and organizational management.	[23]
	Digitalization is a broad sociotechnical procedure that encompasses the fusion of various technologies into everyday societal activities.	[22]
	Digitalization is a broad concept that encompasses the use of numerous tools.	[26]
	Digitalization involves the increased use of digital technologies and their integration and cross-fertilization in the firm's products and inbound and outbound activities.	[72, 93]
	Digitalization refers to the application of IT or digital technologies to transform traditional business processes.	[24]
Measurement	Survey data (leveraging digital tools to understand customers, guide operational choices, increase the added-value of products and services and introduce novel business models).	[23]
	Survey data (the use of simple digital tools that are accessible to any firm, including social network updates, the corporate use of digital tools and social networks, and training in new digital tools)	[26]
	Survey data (evaluations of companies' digital capabilities)	[27]
Performance output	Keyword occurrences in annual reports representing the indicators of digital transformation	[20]
	Digitalization positively correlates with firm performance; however, this association is negatively influenced by knowledge inertia	[23].
	Digitalization notably impacts performance, serving as a mediator between information technology and performance outcomes.	[27]
	Digital transformation can significantly increase total factor productivity but decrease firm performance.	[20]

Table II Samples of digitalization

Category	Firm's name	Date	Samples of digitalization announcement
Use information and communication platforms of the second-party firm	SeABank	29-Dec-2021	SeABank enhances digital banking experiences with Google Cloud. Southeast Asia Commercial Joint Stock Bank (SeABank, stock code SSB) has chosen Google Cloud as its primary cloud provider to enhance the service quality and customer experiences delivered on its SeAMobile/SeANet digital banking platform.
	Armis	28-Dec-2021	Armis selects Radware to deliver cloud security for AWS.
	Green-GO Digital	23-Dec-2021	Sequans Communications S.A. (NYSE: SQNS), a leading provider of cellular IoT chips and modules for massive and broadband IoT, announced that Green-GO Digital is using its Cassiopeia CB410L CBRS module to connect its new Beltpack Sports wireless intercom communications device.
Cooperate with other firms to co-construct digital infrastructures or platforms	Ardonagh and Mphasis	23-Dec-2021	Expanding on this, in 2021, Mphasis and Ardonagh agreed to set up a shared services entity to service middle and back-office functions while applying digital transformation.
	Phunware and PrimusTech	23-Dec-2021	Phunware announces partnership with PrimusTech to integrate mobile smart solutions in Asia.
	Borqs and Cheyin	22-Dec-2021	Borqs and Cheyin's cooperation plans to develop the smart digital cockpit market by deploying Qualcomm's integrated and scalable automotive solutions, including but not limited to the R&D and manufacturing of in-vehicle-infotainment systems, intelligent cockpit systems, intelligent assisted driving systems and other products based on the Qualcomm technology platform.
Extend the firm's business to the digitalization field through acquisition	Sage	21-Dec-2021	Sage acquired Brightpearl. This acquisition accelerates Sage's strategy for growth, including scaling Sage Intact, broadening the value proposition for mid-sized businesses, and expanding Sage's digital network.
	Oracle Corp.	21-Dec-2021	Oracle Corp. on Monday announced its largest deal ever, a roughly \$28.3 billion purchase of electronic-medical-records company Cerner Corp. that vaults the business-software giant deeper into health-care technology. With this acquisition, Oracle's corporate mission expands to assume the responsibility to provide our overworked medical professionals with a new generation of easier-to-use digital tools that enable access to information via a hands-free voice interface to secure cloud applications.
	MCAP Acquisition Corporation	22-Dec-2021	MCAP Acquisition Corporation ("MCAP"; Nasdaq: MACQ), a special purpose acquisition company sponsored by an affiliate of Monroe Capital LLC ("Monroe Capital"), today announced the completion of its business combination (the "Business Combination") with AdTheorent Holding Company, LLC ("AdTheorent" or the "Company"), a leading programmatic digital advertising company using advanced machine learning technology and privacy-forward solutions to deliver measurable value for advertisers and marketers.
Develop digital technology by the company (and use it in the production or operation)	Mobiquity Technologies, Inc.	29-Dec-2021	Mobiquity Technologies, Inc. (NASDAQ: MOBQ; the "Company"), a leading provider of next-generation advertising, today announced a new end-user feature for MobiExchange (www.mobiexchange.com), the Company's SaaS platform for digital advertising and data services.
	Brain+	29-Dec-2021	Brain+ has developed a set of digital medicine technologies, which enable the Company to create a unique and differentiated product offering.
	EchoPark	22-Dec-2021	EchoPark is...and is already making its mark by earning the 2021 Consumer Satisfaction Award from DealerRater, expanding its Owner Experience Centers, developing an all-new digital ecommerce platform, and focusing on growing its brand nationwide.
	LiveFreely	22-Dec-2021	LiveFreely announces the Apple Watch version of "BUDDY," the predictive AI-driven digital health assistant for seniors and their loved ones.
	The Bank of Mexico	31-Dec-2021	Central banks need to move quickly to develop new forms of money and fully operable digital currencies amid the growing use of crypto assets and the risks they entail.

Table III Variable measurement

Variable	Measurement	Source	Reference
Independent Variable			
Digitalization	Annual firm-level count of digitalization announcements	Factiva	[73]
Dependent Variables			
Operational Efficiency	A firm's efficiency (relative to its industry peers with the same four-digit SIC code) in transforming operational inputs, i.e., EMP, CGS, and CEX, into operational output, i.e., OI, based on stochastic frontier estimation	Compustat	[45] [52]
Moderating Variables			
EPU	Policy uncertainty is measured with the BBD index developed by Baker <i>et al.</i> , a monthly index that is transferred into annually data with mean value.	EPU	[39]
IU	IU = 1-four-firm concentration ratio. A higher value of the (1-ratio) implies more competitors and a higher level of uncertainty within the industry.	Compustat	[10][77]
FU	Standard deviation of change in earnings [SD ($\Delta Et + 1, t + 5$)] is calculated based on the change in earnings before extraordinary items over the previous year for years $t + 1$.	Compustat	[92][80]
Control variables			
Market-to-Book Ratio	A firm's market value of equity divided by book value of equity.	Compustat	[52][83]
Firm Leverage	A firm's total debt divided by total assets.	Compustat	[52, 82]
Firm Size	A firm's total assets based on a logarithmic transformation.	Compustat	[52, 76]
Firm Age	Number of years since the firm's initial public stock offering	Compustat	[45]
Firm R&D expenses	A firm's ratio of expenditures on research and development divided by the firm's sales	Compustat	[45]
Firm Advertising Expense	Expenses associated with marketing a firm's brands, products, or services via media outlets	Compustat	[45]

Table IV. Descriptive statistics of sample firms and variables correlations

Panel A: Percentage of industry based on 2-digit SIC codes			
2-digit SIC code	Firm Frequency	Industry	Firm percentage
73	878	Business services	34.8%
36	196	Electronic and other electric equipment	7.8%
35	177	Industrial machinery and equipment	7.0%
48	131	Communications	5.2%
38	122	Instruments and related products	4.8%
60	122	Depository institutions	4.8%
28	112	Chemical and allied products	4.4%
37	58	Transportation equipment	2.3%
62	50	Security and commodity brokers, dealers, exchanges, and services	2.0%
87	49	Engineering, accounting, research, management, and related services	1.9%
63	48	Insurance carriers	1.9%
67	42	Holding and other investment offices	1.7%
59	40	Miscellaneous retails	1.6%
61	36	Non-depository credit institutions	1.4%
50	34	Wholesale trade e-durable goods	1.3%
99	26	Non-classifiable establishments	1.0%
13	25	Oil and gas extraction	1.0%
27	25	Printing, publishing, and allied industries	1.0%
58	25	Eating and drinking places	1.0%
78	19	Motion pictures	0.8%
Other SIC codes	305	Other industries	12.1%
Total	2520		100%

Panel B: Percentage of announcements from industry based on sectors

Sector	Percentage
I. Services	41.4%
D. Manufacturing	31.9%
H. Finance, insurance, and real estate	11.4%
E. Transportation, communications, electric, gas and sanitary services	7.3%
G. Retail trade	4.2%
F. Wholesale trade	1.8%
B. Mining	1.1%
C. Construction	0.1%
A. Agriculture, forestry, and fishing	0.0%

Panel C: Industry groups of samples

Industry Group	Description	Firm	Percentage
01–19	Agriculture, mining, and construction	44	1.7%
20–23, 27	Other non-durable manufacturing	53	2.1%
26, 28, 29	Process manufacturing	138	5.5%
36–38	High-tech manufacturing	376	14.9%
24,25, 30–35, 39	Other durables	213	8.5%
40–48	Transportation and communications	169	6.7%
49	Utilities	18	0.7%
50–59	Retail and wholesale	160	6.3%
60–69	Financial institutions	319	12.7%
70–99	Services and others	1032	41.0%
Total		2520	100.0%

Panel D Descriptive analysis and correlation matrix of variables

Variable	Obs	Mean	Sd.	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) Operational efficiency _{i,t+1}						1.000											
(2) Operational efficiency _{i,t}	2289	.922	.038	0	.983	0.408	1.000										
						(0.000)											
(3) Digitalization _{i,t}	2289	.516	1.399	0	21	0.108	0.041	1.000									
						(0.000)	(0.087)										
(4) EPU _{i,t}	2289	182.04	61.118	142.396	464.243	0.027	0.012	0.034	1.000								
						(0.259)	(0.599)	(0.162)									
(5) IU _{i,t}	2289	.823	.206	.257	1	-0.040	-0.032	-0.006	-0.005	1.000							
						(0.093)	(0.178)	(0.809)	(0.823)								
(6) FU _{i,t}	2289	.365	.481	.01	4.246	0.075	0.068	-0.004	0.028	0.098	1.000						
						(0.002)	(0.004)	(0.872)	(0.240)	(0.000)							
(7) Firm Size _{i,t}	2289	6.284	2.205	0	12.111	-0.152	-0.150	0.152	0.004	-0.071	-0.053	1.000					
						(0.000)	(0.000)	(0.000)	(0.865)	(0.003)	(0.024)						
(8) Firm Age _{i,t}	2289	21.399	11.349	5	79	-0.041	-0.041	0.075	0.030	-0.015	-0.102	0.320	1.000				
						(0.086)	(0.081)	(0.002)	(0.203)	(0.523)	(0.000)	(0.000)					
(9) Leverage _{i,t}	2289	.101	24.329	-776.587	315.847	-0.014	-0.011	0.000	0.014	0.013	-0.010	0.063	-0.014	1.000			
						(0.564)	(0.644)	(0.994)	(0.564)	(0.576)	(0.677)	(0.007)	(0.555)				
(10) Market/book rat. _{i,t}	2289	-.512	108.708	-	283.929	-	-0.006	0.015	-0.155	0.025	0.006	0.036	-0.006	0.122	1.000		
			4466.67			0.009											
						(0.695)	(0.791)	(0.537)	(0.000)	(0.293)	(0.787)	(0.133)	(0.786)	(0.000)			
(11) Advertising exp _{i,t}	2289	231.819	758.979	0	8709.748	0.017	0.005	0.208	0.048	-0.037	-0.006	0.464	0.163	0.017	0.017	1.000	
						(0.478)	(0.820)	(0.000)	(0.041)	(0.122)	(0.804)	(0.000)	(0.000)	(0.480)	(0.474)		
(12) R&D intensity _{i,t}	2289	417.478	1676.461	0	27573	0.061	0.087	0.348	0.028	-0.005	0.082	0.377	0.216	0.010	0.017	0.471	1.000
						(0.010)	(0.000)	(0.000)	(0.238)	(0.828)	(0.001)	(0.000)	(0.000)	(0.679)	(0.477)	(0.000)	

Table V. The impact of digitalization on operational efficiency under different levels of uncertainty (FE model)

Variable	(1) Operational efficiency _{<i>i,t+1</i>}	(2) Operational efficiency _{<i>i,t+1</i>}	(3) Operational efficiency _{<i>i,t+1</i>}	(4) Operational efficiency _{<i>i,t+1</i>}	(5) Operational efficiency _{<i>i,t+1</i>} (robust <i>t</i>)	(6) Operational efficiency _{<i>i,t+1</i>} (robust <i>t</i>)	(7) Operational efficiency _{<i>i,t+1</i>} (robust <i>t</i>)	(8) Operational efficiency _{<i>i,t+1</i>} (robust <i>t</i>)	(9) Operational efficiency _{<i>i,t+1</i>} (bootstrap <i>z</i>)	(10) Operational efficiency _{<i>i,t+1</i>} (bootstrap <i>z</i>)	(11) Operational efficiency (bootstrap <i>z</i>)	(12) Operational efficiency (bootstrap <i>z</i>)
Digitalization _{<i>i</i>}	.0047*** (4.24)	.00069 (0.50)	.0048*** (4.38)	.0046*** (4.17)	.0047*** (3.27)	.0007 (0.27)	.0048** (3.45)	.0046*** (3.36)	0.0047** (3.25)	.0007*** (0.25)	.0048*** (4.08)	.0045** (3.33)
EPU _{<i>i,t</i>}		.0067 (1.52)				.0067 (1.47)				.0067 (1.29)		
IU _{<i>i,t</i>}			-.0026** (-2.66)				-.0026* (-1.75)				-.0026* (-1.85)	
FU _{<i>i,t</i>}				.0014 (1.31)				.0014* (2.15)				.0014 (2.08)
Digitalization _{<i>i,t</i>} ×EPU _{<i>i,t</i>}		-.0117*** (-4.63)				-.0117* (-2.49)				-.0117* (-2.16)		
Digitalization _{<i>i,t</i>} ×IU _{<i>i,t</i>}			-.0049*** (-4.62)				-.0049* (-2.30)				-.0049* (-2.33)	
Digitalization _{<i>i,t</i>} ×FU _{<i>i,t</i>}				-.0010 (-1.13)				-.0010 (-1.02)				-.0011 (-0.93)
Firm Size _{<i>i,t</i>}	-.0029*** (-5.09)	-.0028*** (-5.07)	-.0028*** (-5.14)	-.0029*** (-5.08)	-.0029*** (-6.98)	-.0028*** (-6.91)	-.0029*** (-6.69)	-.0029*** (-7.07)	-0.0028*** (-6.98)	-.0028*** (-6.97)	.0029*** (-6.84)	-.0029*** (-6.91)
Firm Age _{<i>i,t</i>}	-.0001 (-0.52)	-.0001 (-0.77)	-.0001 (-0.42)	-.0001 (-0.51)	-.0001 (-0.29)	-.0001 (-0.42)	-.0000 (-0.23)	-.0001 (-0.28)	-.0001 (-0.29)	-.0001 (-0.40)	.0000 (-0.23)	-.0001 (-0.28)
Leverage _{<i>i,t</i>}	-.0001 (-0.67)	-.0001 (-0.76)	-.0001 (-0.69)	-.0000 (-0.66)	-.0000 (-1.60)	-.0001* (-1.82)	-.0000 (-1.63)	-.0001 (-0.73)	-.00000 (-1.60)	-.0000 (-0.78)	.0000 (-0.67)	-.0000 (-0.70)
Market/book rat. _{<i>i,t</i>}	-2.91e-06 (-0.34)	-9.15e-07 (-0.11)	-2.58e-06 (-0.30)	-2.85e-06 (-0.33)	-2.91e-06 (-1.79)	-9.15e-07 (-0.22)	-2.58e-06 (-1.49)	-2.85e-06 (-0.51)	-2.91e-06 (-1.79)	-9.15e-07 (-0.12)	-2.58e-06 (-0.41)	-2.85e-06 (-0.51)
Advertising expense _{<i>i,t</i>}	3.47e-06* (2.10)	3.23e-06* (1.96)	3.30e-06* (2.01)	3.57e-06* (2.16)	3.47e-06* (1.37)	3.23e-06 (1.34)	3.30e-06 (1.36)	3.57e-06 (1.31)	3.47e-06 (1.37)	3.23e-06 (1.28)	3.30e-06 (1.31)	3.57e-06 (1.35)
R&D intensity _{<i>i,t</i>}	1.10e-06 (1.45)	8.66e-07 (1.14)	1.02e-06 (1.34)	1.17e-06 (1.50)	1.10e-06 (0.85)	8.66e-07 (0.69)	1.02e-06 (0.83)	1.17e-06 (0.84)	1.10e-06 (0.85)	8.66e-07 (0.70)	1.02e-06 (0.83)	1.17e-06 (0.80)
Year-fixed effect	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry-fixed effect	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Constant	.9427*** (115.68)	.9473*** (109.44)	.9410*** (116.15)	.9431*** (115.71)	.9427*** (194.57)	.9473*** (180.84)	.9410*** (189.07)	.9431*** (192.66)	.9427*** (186.17)	.9473*** (166.33)	.9410*** (183.38)	.9431*** (185.01)
R ²	0.1599	0.1706	0.1733	0.1613	0.1599	0.1706	0.1733	0.1613	0.1599	0.1706	0.1733	0.1613
Adjusted R ²	0.1345	0.1446	0.1473	0.1350					0.1345	0.1446	0.1473	0.1350
F value	6.31	0.0000	0.0000	0.0000						0.0000	0.0000	0.0000
Wald chi2									4649.59	4277.01	3948.34	4465.30
Observations	1744	1744	1744	1744	1744	1744	1744	1744	1744	1744	1744	1744

Note: robust *t* statistics in parentheses in columns (5–8), bootstrap *z* statistics in parentheses in columns (9–12). **p* < 0.05, ***p* < 0.01, ****p* < 0.001 *t*-statistics are in parentheses.

Table VI. Results of Heckman correction

Variable	(1)	(2)	(3)	(4)
	Operational efficiency _{<i>i,t+1</i>}	Operational efficiency _{<i>i,t+1</i>}	Operational efficiency _{<i>i,t+1</i>}	Operational efficiency _{<i>i,t+1</i>}
Digitalization _{<i>i</i>}	.0048*** (4.33)	.0008 (0.57)	.0049*** (4.45)	.0047*** (4.17)
IMR	.0034* (2.00)	.0034* (2.04)	.0025 (1.51)	.0034* (1.99)
EPU _{<i>i,t</i>}		.0074 (1.52)		
IEU _{<i>i,t</i>}			-.0025* (-2.54)	
FEU _{<i>i,t</i>}				.0013 (1.14)
Digitalization _{<i>i,t</i>} ×EPU _{<i>i,t</i>}		-.0117*** (-4.63)		
Digitalization _{<i>i,t</i>} ×IU _{<i>i,t</i>}			-.0048*** (-4.50)	
Digitalization _{<i>i,t</i>} ×FU _{<i>i,t</i>}				-.0013 (-1.14)
Firm Size _{<i>i,t</i>}	-.0033*** (-5.09)	-.0033*** (-5.47)	-.0032*** (-5.34)	-.0033*** (-5.46)
Firm Age _{<i>i,t</i>}	.0001 (-0.52)	.0001 (0.42)	.0001 (0.45)	.0001 (0.62)
Leverage _{<i>i,t</i>}	-.0000 (-0.62)	-.0000 (-0.70)	-.0000 (-0.65)	-.0000 (-0.60)
Market/book rat. _{<i>i,t</i>}	-2.54e-06 (-0.29)	-6.94e-07 (-0.08)	-2.32e-06 (-0.27)	-2.47e-06 (-0.29)
Advertising expense _{<i>i,t</i>}	5.14e-06** (2.78)	4.91e-06** (1.96)	4.57e-06* (2.48)	5.26e-06* (2.83)
R&D intensity _{<i>i,t</i>}	1.75e-06* (2.12)	1.54e-06* (1.86)	1.51e-06 (1.84)	1.87e-06 (2.19)
Year-fixed effect	YES	YES	YES	YES
Industry-fixed effect	YES	YES	YES	YES
Constant	.9268*** (81.50)	.9317*** (80.54)	.9290*** (82.10)	.9272*** (81.21)
R ²	0.1618	0.1706	0.1744	0.1633
Observations	1744	1744	1744	1744

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ t -statistics are in parentheses.

Table VII. The impact of digitalization on operational efficiency under different levels of uncertainty (DPD model)

Variable	(1) Operational efficiency _{it+1}	(2) Operational efficiency _{it+1}	(3) Operational efficiency _{it+1}	(4) Operational efficiency _{it+1}	(5) Operational efficiency _{it+1} (robust t)	(6) Operational efficiency _{it+1} (robust t)	(7) Operational efficiency _{it+1} (robust t)	(8) Operational efficiency _{it+1} (robust t)	(9) Operational efficiency _{it+1} (bootstrap z)	(10) Operational efficiency _{it+1} (bootstrap z)	(11) Operational efficiency (bootstrap z)	(12) Operational efficiency (bootstrap z)
Operational efficiency $_{it}$.3252*** (13.42)	.3275*** (13.61)	.3215*** (13.34)	.3244*** (13.39)	.3252* (2.44)	.3276** (2.43)	.3215* (2.45)	.3244* (2.43)	.3252* (2.26)	.3276* (2.25)	.3215* (2.26)	.3244* (2.25)
Digitalization _i	.0045*** (4.30)	.0003 (0.24)	.0046*** (4.45)	.0045*** (4.24)	.0045** (3.27)	.0003 (0.13)	.0046** (3.49)	.0045** (3.38)	0.0045** (3.24)	.0003 (0.12)	.0046** (4.08)	.0045** (3.34)
EPU $_{it}$.0056 (1.35)				.0056 (1.40)				.0056 (1.25)		
IU $_{it}$			-.0019* (-2.66)				-.0026* (-1.61)				-.0019* (-1.69)	
FU $_{it}$.0012 (1.13)				.0011* (1.85)				.0012 (1.77)
Digitalization $_{it}$ ×EPU $_{it}$		-.0123 *** (-4.63)				-.0124** (-2.65)				-.0123* (-2.32)		
Digitalization $_{it}$ ×IU $_{it}$			-.0048*** (-4.72)				-.0048* (-2.39)				-.0047* (-2.42)	
Digitalization $_{it}$ ×FU $_{it}$.0009 (-1.01)				-.0010 (-0.92)				-.0009 (-0.86)
Firm Size $_{it}$	-.0020*** (-3.66)	.0019 *** (-3.61)	-.0020*** (-3.67)	-.0020*** (-3.66)	-.0020*** (-4.68)	-.0019*** (-4.52)	-.0020*** (-4.59)	-.0020*** (-4.60)	-0.0020*** (-4.46)	-.0020*** (-4.31)	.0020*** (-4.37)	-.0020*** (-4.35)
Firm Age $_{it}$	-.0000 (-0.36)	-.0001 (-0.60)	-.0000 (-0.29)	-.0001 (-0.36)	-.0000 (-0.19)	-.0001 (-0.30)	-.0000 (-0.15)	-.0000 (-0.18)	-.0000 (-0.18)	-.0001 (-0.29)	.0000 (-0.14)	-.0000 (-0.18)
Leverage $_{it}$	-.0000 (-0.54)	-.0000 (-0.64)	-.0000 (-0.57)	-.0000* (-0.53)	-.0000 (-1.78)	-.0000* (-2.08)	-.0000* (-1.82)	-.0000* (-1.71)	-.00000 (-0.56)	-.0000 (-0.61)	.0000 (-0.53)	-.0000 (-0.54)
Market/book rat. $_{it}$	-2.38e-06 (-0.29)	6.15e-08* (0.01)	-2.22e-06 (-0.27)	-2.85e-06 (-0.28)	-2.38e-06* (-1.66)	6.15e-08 (0.01)	-2.22e-06 (-1.45)	-2.33e-06* (-1.67)	-2.38e-06 (-0.41)	-6.15e-07 (0.01)	-2.22e-06 (-0.35)	-2.33e-06 (-0.41)
Advertising expense $_{it}$	2.92e-06 (1.86)	2.68e-06 (1.72)	2.76e-06 (1.77)	3.57e-06 (1.91)	2.92e-06* (1.24)	2.68e-06 (1.22)	2.76e-06 (1.22)	3.01e-06 (1.28)	2.92e-06 (1.22)	2.68e-06 (1.20)	2.76e-06 (1.20)	3.01e-06 (1.26)
R&D intensity $_{it}$	1.42e-07 (0.20)	-1.20e-07 (-0.17)	6.89e-08 (0.10)	1.17e-06 (0.28)	1.42e-07 (0.11)	-1.20e-07 (-0.09)	6.89e-08 (0.06)	2.10e-07 (0.15)	1.42e-06 (0.10)	-1.20e-07 (-0.09)	6.89e-06 (0.05)	2.10e-06 (0.14)
Year-fixed effect	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry-fixed effect	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Constant	.6328 *** (25.99)	.6345*** (26.00)	.6346*** (26.20)	.6340 *** (26.03)	.6328 *** (5.05)	.6345*** (4.98)	.6346*** (5.14)	.6340*** (15.05)	.6328*** (4.64)	.6345*** (4.60)	.6346*** (4.71)	.6340*** (4.65)
R ²	0.2408	0.2526	0.2521	0.2418	0.2408	0.2526	0.2521	0.2418	0.2408	0.2526	0.2521	0.2418
Adjust R ²	0.2174	0.2287	0.2282	0.2175					0.2174	0.2287	0.2282	0.2175
F value	10.31	10.57	10.54	9.97						0.0000	0.0000	0.0000
Wald chi2									5312.22	4833.66	4815.33	5142.43
Observations	1744	1744	1744	1744	1744	1744	1744	1744	1744	1744	1744	1744

Note: robust *t* statistics in parentheses in columns (5), (6), (7), and (8), bootstrap *z* statistics in parentheses in columns (9), (10), (11), and (12). **p* < 0.05, ***p* < 0.01, ****p* < 0.001 t-statistics are in parentheses.

Table VIII. Heterogeneity analysis—the impact of digitalization on operational efficiency before vs. after COVID-19 and B2B VS. B2C (fixed effects model)

Variable	Operational efficiency _{<i>i,t+1</i>}															
	Before Covid-19					After Covid-19					B2B			B2C		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Digitalization _{<i>i</i>}	.0052* (2.29)	-0.0074 (-1.29)	.0041* (1.85)	.0052** (2.31)	.0036** (3.09)	.0011 (0.86)	.0042*** (3.59)	.0038** (3.17)	.0043** (3.41)	-0.0003 (-0.19)	.0048*** (3.78)	.0043** (3.37)	.0079* (2.28)	.0040 (1.92)	.0096** (2.73)	.0072* (2.04)
EPU _{<i>i,t</i>}		.0101 (1.14)				.0052 (1.08)				.0019 (0.36)				.0300* (2.37)		
IU _{<i>i,t</i>}			-0.0022** (-1.21)				-0.0031** (-2.87)				-0.0032** (-2.78)				-0.0028 (-0.27)	
FU _{<i>i,t</i>}				.0021* (1.04)				.0013 (1.02)				.0009 (0.75)				.0010 (0.21)
Digitalization _{<i>i,t</i>} ×EPU _{<i>i,t</i>}		-0.0242* (-2.38)				-0.0106*** (-4.38)				-0.0128*** (-4.07)				-0.0153*** (-2.72)		
Digitalization _{<i>i,t</i>} ×IU _{<i>i,t</i>}			-0.0058** (-2.63)				-0.0045 (-4.01)				-0.0057*** (-4.73)				-0.0067* (-2.02)	
Digitalization _{<i>i,t</i>} ×FU _{<i>i,t</i>}				-0.0033 (-2.04)				.0004 (0.33)				.0009 (-0.85)				-0.0047 (-0.76)
Firm Size _{<i>i,t</i>}	-0.0031 (-3.00)	-0.0033** (-3.15)	.0004* (-1.85)	-0.0032** (-3.06)	-0.0027*** (-4.35)	-0.0026*** (-4.27)	-0.0028 (-4.43)	-0.0032*** (-1.37)	-0.0025*** (-3.67)	-0.0025*** (-3.66)	-0.0025*** (-3.68)	-0.0025*** (-3.69)	-0.0048 (-3.31)	-0.0051*** (-3.57)	-0.0049** (-3.35)	-0.0047** (-3.30)
Firm Age _{<i>i,t</i>}	-0.0004 (-1.84)	-0.0004 (-2.18)	.0031 (-3.05)	-0.0004 (-1.84)	.0001 (1.21)	.0001 (1.09)	.0002 (1.37)	.0001 (1.24)	-0.0001 (-0.85)	-0.0001 (-0.91)	-0.0001 (-0.84)	-0.0001 (-0.85)	.0000 (0.17)	-0.0002 (-0.69)	.0001 (0.29)	.0000 (0.18)
Leverage _{<i>i,t</i>}	-0.0000 (-0.30)	-0.0000 (-0.35)	-0.0000 (-0.29)	-0.0000 (-0.30)	-0.0000 (-0.10)	-0.0000 (-0.25)	-0.0000* (-0.20)	-0.0000 (-0.12)	-6.77e-06 (-0.14)	-0.0000 (-0.25)	-8.61e-06 (-0.17)	-5.93e-06 (-0.12)	-0.0002 (-0.52)	.0001 (-0.39)	-0.0002* (-0.64)	-0.0003 (-0.79)
Market/book rat. _{<i>i,t</i>}	-0.0000 (-0.27)	-0.0000 (-0.46)	-0.0000 (-0.60)	-0.0000 (-0.52)	-7.87e-07 (-0.10)	1.28e-06 (0.17)	-1.08e-07 (-0.01)	-8.00e-07 (-0.10)	-7.88e-07 (-0.08)	3.04e-06 * (0.31)	-2.17e-07 (-0.02)	-7.86e-07 (-0.08)	-5.27e-07 (-0.02)	-1.94e-06 (-0.06)	1.13e-06 (0.04)	6.82e-06 (0.21)
Advertising expense _{<i>i,t</i>}	8.55e-06 (1.84)	8.33e-06 (2.36)	8.09e-06 * (2.29)	8.60e-06 (2.43)	9.41e-07 (0.55)	9.04e-07 (0.54)	9.94e-07 (0.59)	9.00e-07 (0.53)	4.29e-06 (2.39)	4.20e-06 (2.35)	3.99e-06 * (2.25)	4.39e-06 (2.44)	.0000* (2.06)	.0000* (1.99)	.0000* (1.97)	.0000 * (2.07)
R&D intensity _{<i>i,t</i>}	2.44e-06 (1.50)	2.08e-06 (1.28)	2.66e-06 (1.64)	3.29e-06 (1.95)	8.01e-07 (1.02)	4.82e-07 (0.62)	5.80e-07 (0.75)	6.59e-07 (0.82)	8.76e-07 (1.07)	6.39e-07 (0.78)	7.07e-07 (0.87)	9.55e-07 (1.14)	7.97e-06 (0.84)	6.96e-06 (0.74)	.0000 (1.07)	8.44e-06 (0.88)
Year-fixed effect	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry-fixed effect	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Constant	.9459*** (64.22)	.9548*** (59.12)	.9381*** (98.82)	.9464*** (98.00)	.9406*** (104.13)	.9444*** (99.10)	.9392*** (104.99)	.9409*** (103.98)	.9402*** (50.03)	.9412*** (92.88)	.9381*** (98.82)	.9405*** (98.00)	.9438*** (49.69)	.9722*** (44.39)	.9340*** (49.56)	.9550*** (15.05)
R ²	0.1568	0.1646	0.1667	0.1627	0.2093	0.2246	0.2278	0.2102	0.1273	0.1389	0.1476	0.1282	0.4125	0.4288	0.3502	0.4141
Adjust R ²	0.1004	0.1061	0.1084	0.1040	0.1696	0.1840	0.1873	0.1688	0.0941	0.1048	0.1138	0.0936	0.3448	0.3585	0.2429	0.3421
F value	2.78	2.81	2.86	2.77	5.27	5.53	5.63	5.08	3.84	4.06	4.36	3.70	6.08	6.11	3.26	5.75
Observations	719	719	719	719	1025	1025	1025	1025	1284	1284	1284	1284	339	339	339	339

Note: **p* < 0.05, ***p* < 0.01, ****p* < 0.001 *t*-statistics are in parentheses.

Table IX. Steps of digitalization data collection using NLP

Steps	Description
Stage 1: Preprocess and clean announcements	<ul style="list-style-type: none"> ► Tokenize the corpus in whitespaces. ► Convert each character to its lowercase form. ► Remove numbers at the beginning or end of the sentence or passage. ► Remove stop words. ► Remove punctuations, single character words, and very high frequency words that offer little inference. ► Lemmatize all words.
Stage 2: Run information extraction (IE) with the rules-based model.	<ul style="list-style-type: none"> ► Extract the companies' names. ► Opt for a rules-based model, using text documents of the characteristics and structures to find rules for extraction. ► Construct the regular expression to classify the digitalization announcements into five types that are distinct in the announcements. <ul style="list-style-type: none"> Type 1: A company announced acquisition of another company to obtain new expertise of digital technologies. Type 2: A company announced the appointment of a senior manager to carry out specific digitalization-related tasks or with an emphasis on their prior experience in digitalization. Type 3: A company announced development or launched new digital technologies. Type 4: A company announced co-design or co-development with third parties in digital technologies. Type 5: Other announcements that were obtained through the approach in Appendix I but could not be clarified into Types 1 to 4. In this classification, the levels of restrictions are controlled carefully to make sure announcements only fall correctly into their corresponding types of categories. <ul style="list-style-type: none"> ► Match each sentence of the announcements with regular expression to gain short but information-rich paragraphs, thereby reducing the data volume and enabling the manual checking process. ► Manually check half the classified announcements and correct the errors identified. The five groups of checked and corrected announcements serve the training purposes in the subsequent stage.
Stage 3: Construct the classification model based on a pre-trained language model: BERT	<ul style="list-style-type: none"> ► Split the dataset by randomly assigning 90% and 10% to the training set and validation set, respectively. ► Train the classification model by the BERT model and linear layers using the training data set. ► Test the classification model by using the validation data set and evaluate the result's accuracy. <p>The accuracy in the result is considered unsatisfactory because the number of Type 5 announcements is markedly higher than any of the other four types of announcements, making the learning process ineffective.</p> <ul style="list-style-type: none"> ► To address this problem, data were reclassified into two groups. Group 1 comprises announcements of Types 1 to 4 whereas Group 2 comprises announcements of Type 5. We used this classification of data to retrain the classification model by BERT and linear layers. The result of this classification model achieved an accuracy rate of 91.667%.
Stage 4: Finalize announcements	<ul style="list-style-type: none"> ► Employ the announcements of Group 1 as the data to reflect the digitalization variable of this study.