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4 authors:

Yong Suk Lee
University of Notre Dame

Taekyun Kim
Korea Advanced Institute of Science and Technology

Sukwoong Choi
University at Albany, The State University of New York

Wonjoon Kim
Korea Advanced Institute of Science and Technology

When Does AI Pay Off?: AI-Adoption Intensity, Complementary Investments, and R&D Strategy

Yong Suk Lee, Keough School of Global Affairs, University of Notre Dame[*]
Taekyun Kim, School of Business and Technology Management, KAIST
Sukwoong Choi, Sloan School of Management, MIT
Wonjoon Kim, School of Business and Technology Management, KAIST

Abstract: This paper examines how high-tech venture performance varies with AI-adoption intensity. We find that firm revenue increases only after sufficient investment in AI, and the benefits of AI adoption are greater at firms that also invest in complementary technologies and pursue internal R&D strategy. Specifically, AI adoption at low levels does not suggest significant revenue growth, but, as the intensity of AI adoption increases revenue growth occurs. We find that such performance gains from adoption is larger among firms that invest in complementary technologies such as cloud computing and database systems. Moreover, the positive relationship between AI adoption intensity and revenue growth is stronger among firms that pursue a more exclusive R&D strategy specific to the venture.

Keywords: artificial intelligence, high-tech ventures, firm performance, complementary investment, R&D strategy

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Declaration of Interest Statement

The authors of this paper have no interest to declare.
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[*] Lee: Corresponding author. Keough School of Global Affairs, University of Notre Dame, 3171 Jenkins Nanovic Halls, Notre Dame IN 46556 USA (Email: yong.s.lee@nd.edu)

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Abstract: This paper examines how high-tech venture performance varies with AI-adoption intensity. We find that firm revenue increases only after sufficient investment in AI, and the benefits of AI adoption are greater at firms that also invest in complementary technologies and pursue internal R&D strategy. Specifically, AI adoption at low levels does not suggest significant revenue growth, but, as the intensity of AI adoption increases revenue growth occurs. We find that such performance gains from adoption is larger among firms that invest in complementary technologies such as cloud computing and database systems. Moreover, the positive relationship between AI adoption intensity and revenue growth is stronger among firms that pursue a more exclusive R&D strategy specific to the venture.

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1. Introduction

Artificial intelligence (AI) is increasingly being adopted in firms around the world, with its prevalence only expected to increase further. In fact, AI is widely accepted as the newest general-purpose technology (GPT) (Goldfarb, Taska, & Teodoridis, 2020; Tratjenberg, 2019), following major technological innovations such as information technology (IT), computers, and electricity. Since AI was first established in computer science in the mid-twentieth century, the development and application of AI have rapidly expanded only in the past decade. Massive investments in AI have occurred recently, and organizations are in the midst of adopting and exploring the best ways to use AI for their purposes. Thus, AI has the potential to change the way we innovate, do business, and organize and to affect all aspects of the economy (Cockburn, Henderson, & Stern, 2019).

Scholars have started to examine how AI could affect the economy (Acemoglu et al., 2020; Brynjolfsson et al., 2021, 2019; Chalmers et al., 2020; Farboodi et al., 2019; Mihet & Philippon, 2019), but most studies are theoretical due to the lack of firm-level data (Brynjolfsson & Mitchell, 2017; Seamans &

Raj, 2018), and empirical papers have generally focused on the effect of AI on the labor market (Agrawal et al., 2019; Grennan & Michaely, 2019; Webb, 2020) or on listed firms (Kim et al., 2021). Despite the importance of new ventures for economic growth (Lee 2018), and technological innovation for entrepreneurial opportunities (Eckhardt & Shane 2011), we still know surprisingly little about whether AI has made high-tech ventures more productive and, if so, when or why.

In this study, we aim to shed light on the effects of AI adoption on high-tech venture performance. We first theorize how AI adoption could improve firm performance, and we examine the relationship between the intensity of AI adoption in high-tech ventures and their performance. Given that complementary investments and organizational changes have been important in new technology's successful contribution to firm performance, complementary tangible and intangible assets will likely be important for firms to reap the benefits from AI adoption (Felten et al., 2019). Accordingly, we examine whether a firm's investment in different technologies and research and development (R&D) strategy complement AI adoption.

To do so, we use a novel survey and administrative data on high-tech ventures in South Korea, where AI adoption has accelerated but with considerable variation across firms. We construct the extent of AI adoption based on the rate of natural language processing (NLP), computer vision (CV), and machine learning (ML) in the production or development of goods and services. Our survey also contains information on investment in various technologies, including database systems and cloud computing, as well as the firms' strategies and characteristics at the time of the survey (2019) and a base year.

We find that AI adoption is associated with higher revenue growth but only at high levels of adoption. At low levels of adoption, whether firms are simply testing the technology or are at adoption levels below 25%, we do not find performance benefits from AI adoption. This finding is consistent with the literature that finds that the productivity benefits of new technologies often do not appear in the initial stages of adoption but appear in the later stages of adoption, when firms invest in complementary technologies and make complementary organizational and strategy changes (Jovanovic & Rousseau, 2005; Bresnahan, 2010; Majumdar et al., 2010).

We also find that the positive relationship between higher levels of AI adoption and revenue growth is significant at firms that invest in complementary technologies, such as database systems and cloud computing. Compared with previous GPTs, AI is unique in that the technology is a software algorithm that analyzes data, and the utility of such an algorithm is inevitably tied to the amount of data and the ability to process the data. Hence, technologies such as database or cloud computing complement AI adoption. In addition, we find that the positive relationship between higher levels of AI adoption and revenue growth is significant at firms that pursue firm-specific internal R&D strategy. This finding suggests that firms benefit from AI-related R&D specifically tailored to each firm's unique business environment and needs.

We believe that this paper provides initial empirical evidence consistent with the delayed performance benefits of AI. Though we can only measure the intensity of adoption, which doesn't necessarily imply timing of adoption, intensity and time of adoption are likely highly correlated since adoption intensity is generally low at earlier stages of adoption and tends to increase with time. Though studies have examined the delayed productivity benefits of new technologies such as electrification, automobiles, computers, IT, and robotics (Brynjolffson, 1993; David, 1990; Brynjolffson et al., 2019; Chung & Lee, 2021), our paper is among the first to find a similar pattern for AI.

The paper proceeds as follows. In section 2, we develop our hypotheses regarding the potential benefits of AI adoption and complementary investments. Section 3 discusses our survey and the data. Section 4 discusses the empirical strategy, and section 5 presents our results. Section 6 concludes.

2. Literature and Hypotheses

AI describes a broad set of computing techniques with the capacity to perform functions that would ordinarily require human intelligence. These functions include the application of NLP, CV, and ML technologies, including but not limited to chatbots, text generation, object and facial recognition, autonomous driving, and recommendation engines. As Agrawal et al. (2018) highlight, the key feature of AI is that its predictions can be directly adopted and accepted by humans or, with some adjustments, into the organization's decision-making process. Accordingly, the potential benefits from AI are the automation of cognitive tasks such as categorization, perception, and problem solving, which have widespread applications in a variety of business and government settings. In addition, AI algorithms have the unique ability to self-improve their predictive power through repeated training and to ultimately perform highly cognitive tasks. For example, pharmaceutical firms have introduced AI techniques to assist in drug discovery in the early stages of R&D by suggesting possible molecular syntheses (Lou & Wu, 2020). Banks have applied AI techniques to better manage risks, by predicting fraud and the likelihood of loan defaults (Deloitte, 2018).

Consequently, AI could enhance productivity via at least three important mechanisms. First, it can liberate workers from existing tasks and enable them to perform more productive, specialized, and new tasks. By performing repetitive cognitive tasks, AI can allow workers to focus on tasks in which people have a comparative advantage (Acemoglu & Restrepo, 2018). For example, chatbots and voicebots have replaced customer service workers in retail, banking, health care, and many other industries (Brynjolfsson et al., 2021; Deloitte, 2018). In some cases, firms may even decide to substitute away from human labor to AI-based systems to mitigate labor costs and boost productivity. This displacement can enable firms to invest more in core competencies and potentially enhance firm competitiveness.

Second, AI can reduce the error and bias that often accompany human judgment. Because errors and biases can negatively affect productivity, adopting AI could enhance productivity (Tversky & Kahneman, 1974; Cowgill, 2019). For example, CV can diagnose certain diseases with less error than people and assist doctors in making accurate diagnoses and providing better prescriptions (Gulshan et al., 2016). Relatedly, AI-based systems are already improving the accuracy and efficiency of diagnosis and treatment across various specializations (Wang et al., 2019). Although the data that AI use may be biased because the data are themselves a product of human decision, Cowgill (2019) shows that when human decisions are sufficiently noisy and inconsistent, AI can offer less biased and better recommendations than people can.

Lastly, by processing complex and large datasets, AI can provide new ways to solve problems, as well as business opportunities. For example, trained with a large volume of player data, AlphaGo outperformed Go players by implementing new sequences, instead of the traditional sequences that people had considered superior for hundreds of years (Singh et al., 2017). In other words, AI can detect patterns from large volumes of structured and unstructured data, which would not be possible with heuristics alone, and ultimately enable decision-makers to discover new solutions. Relatedly, retailers are using AI to provide personalized product recommendations, logistics companies are using ML algorithms to minimize product backlogs and speed up deliveries, and banks are using AI-based risk-assessment algorithms to expand lending to new customers. Thus, AI's data-driven algorithms reduce the overhead costs of entering new markets (Aghion et al., 2019; Babina et al., 2020) and enable firms to expand more readily across different markets (Goldfarb et al., 2019; Klinger et al., 2018; Trajtenberg, 2019).

In short, AI can improve productivity through multiple mechanisms, such as enabling workers, reducing error and bias, discovering new processes, and reducing fixed costs in entry and expansion. Hence, we predict that AI adoption is positively associated with increases in firm performance.

Hypothesis 1a. AI adoption is positively associated with firm performance.

However, merely introducing AI in existing businesses is unlikely to generate productivity gains. New technologies such as AI realize their productive market potential when both tangible investment (e.g., equipment, software, and infrastructure) and intangible investment (e.g., business and technology development processes, organizational restructuring, and worker training) are made (Brynjolffson et al., 2019). Previous studies have found that industries experienced output declines due to various adjustment costs and learning delays after the introduction of GPTs (Atkeson & Kehoe, 1993; Hornstein & Krusell, 1996; Jovanovic & Nyarko, 1994; Greenwood & Yorukoglu, 1997; Jovanovic & Rousseau, 2005). In the case of AI, significant research and time are required for a firm to identify AI opportunities in its business, operation, technology development, and production processes (McKinsey, 2017). Furthermore, firms that adopt AI require organizational adaptations or changes before they transform the core or peripheral parts of their businesses. For example, the process of using AI in business at firms requires frequent interaction between people and machines (Ransbotham et al., 2020), because most business processes involve complex tasks, and algorithms are therefore not readily available (Raisch & Krakowski, 2021). This iterative process of mutual learning demands significant efforts and resources to improve productivity gains from AI utilization.

In addition, the market mismatch between the supply and demand of skilled workers can hinder productivity gains in the early stages of GPT adoption (Jovanovic & Rousseau, 2005). A long line of research has found that physical capital and skilled labor are more complementary than physical capital and unskilled labor (Griliches, 1969; Duffy et al., 2004; Goldin & Katz, 1998; Franck & Galor, 2017). New technologies increase the relative earnings of skilled workers, because demand outweighs supply in the early stages of adoption, as was the case for electrification (in 1890–1918) and IT (Jovanovic & Rousseau, 2005). In the case of AI, a key challenge that firms face today is the difficulty in finding skilled workers who can implement AI (McKinsey, 2017), and this mismatch between the demand and supply of skilled AI workers likely delays the productivity gains for firms.

Hence, for the adoption of AI to become productive, it will require significant complementary investments in both tangible and intangible assets, including co-invention of new products and business models, business-model redesign, and human capital investment. Productivity growth may initially be underestimated, and the productivity benefits will occur later when corresponding and necessary business transformations are made. This pattern emerged with prior GPTs (Bresnahan & Trajtenberg, 1996; Brynjolffson, 1993; David, 1990), and similar patterns are expected to hold for AI as well (Brynjolffson et al., 2019). Thus, we hypothesize the following:

Hypothesis 1b. The positive association between the rate of AI adoption and firm performance occurs with some delay. That is, at the early stages of adoption, when adoption rates are low, AI may not provide productivity benefits. However, the benefits may start to accrue later, when adoption rates are higher.

Hitt & Brynjolfsson (1997) emphasized the importance of complementary assets in explanation for substantial variations in returns when firms adopt new innovations. They explain that firms with higher performance also adopt complementary technologies as well as organizational practices. In line with it, previous studies have documented productivity and performance premiums from the adoption of complementarities (Aral et al., 2012; Tambe et al., 2012). This notion that complementary assets are crucial to the adoption of new technologies is not new (Felten et al., 2019). But different types of technologies may have different complementarities.

IT has been found to be complementary in demand across different technological components (Arora et al., 2010), and this technological complementarity shapes firms' strategies and increases barriers to entry (Bresnahan & Greenstein, 1999). For example, complementarity between operating systems and enterprise software (Kretschmer 2005), routers and switches (Chen and Forman 2006), 56K models by ISPs (internet service providers) and ISDN adoption (Augereau and Greenstein 2001), word processing and spreadsheet software (Scott 1997), and IT infrastructure and e-commerce capability (Zhu 2004) have shown the consumption of one IT technology affects the returns to investment for another (Arora et al., 2010). One IT technology enables the effective use of the other technology by coordinating the flow of information and resources within the integrated system, which in turn affects the firm's market performance. In other words, technological complementarities can affect a firm's ability to adjust or enhance the use of innovative techniques and eventually the firm's market performance. Likewise, firms that are slow to adopt complementary products or technologies will fall behind the frontier in terms of technology adoption and implementation (David, 1991).

In this regard, because AI is an algorithm based on training data in large databases, the quality of outcomes generated by AI is closely tied to data collection, data management, and computing capabilities. New and large datasets can vitalize new AI businesses. For example, commercial AI facial-recognition software was developed when the government released data on images of people (Beraja et al., 2020). In addition, many high-tech companies use cloud-computing resources such as Amazon Web Services (AWS), IBM, and Microsoft Azure to access high computational power that can handle big data and run AI algorithms. In other words, the application of AI needs complementary technological investments (Brynjolfsson et al., 2019), and the level and quality of complementary technology investments influences the firms' productivity benefits from adopting AI. If a firm has access to large amounts of data and high-power computing systems for its AI application, that firm could more effectively benefit from adopting AI.

Hypothesis 2. The positive relationship between AI adoption and firm productivity is stronger when firms invest in complementary technologies, especially technologies related to big-data processing and high-power computing.

R&D is fundamental to the commercialization of new technologies. Some firms pursue R&D in house by hiring the researchers and investing in the capital needed to conduct R&D. Other firms collaborate with research institutes or universities to conduct R&D activity or even outsource their R&D. Which R&D strategy a firm chooses not only represents the nature of the firm's business strategy but also directly affects firm performance. Cohen and Levinthal (1989), in their theory of "absorptive capacity," emphasize the importance of the accumulated stock of knowledge to effectively scan, screen, and absorb external know-how (Griffith et al., 2004). In this regard, internal and external R&D are complementary (Cassiman & Veugelers, 2006), and internal knowledge creation, including know-how, can increase the marginal return to external knowledge sourcing.

As R&D costs have increased, firms have expanded the scale and scope of external sourcing of knowledge (Berchicci, 2013; Katz, 1986) through joint R&D activities, licensing, R&D outsourcing, company acquisition, or hiring of qualified researchers with relevant knowledge (Arora & Gambardella, 1990; Cockburn & Henderson, 1998). However, outsourcing of knowledge (R&D) can dilute firm-specific resources and capabilities if firms rely on generic external knowledge that competitors can access (Grimpe & Kaiser, 2010). In addition, outsourcing of knowledge can also deteriorate the firm's integrative capabilities that are essential to developing internal innovation capabilities (Helfat & Raubitschek, 2000; Weigelt, 2009). In fact, internal R&D is critical for a firm to create sufficient absorptive capacity that can enhance the complementarity between internal R&D and external sourcing of knowledge (Lokshin et al., 2008).

AI is still at a relatively early stage in terms of how the technology is developed and embedded in the firm's business, organizational, operational, and production processes. In many cases, firm-specific internal resources and capabilities may not yet be mature enough to generate complementarity with the external outsourcing of AI knowledge. The McKinsey Global Institute (2018) finds only 21% of responding companies report that AI is embedded in their business units or functions, and many still lack the fundamental strategies to map AI to opportunities, data sourcing, and skilled AI workers.

When firms introduce a new technology, such as AI, the nature of the technology influences the mode of R&D. As noted above, the successful introduction of AI depends not only on maintaining large datasets but also on having high computational power that can analyze such data. Firms might seek to implement AI and train their own databases and enhance their internal processes (e.g., marketing and sales and IT operations). The use of internal data by a firm often raises issues about privacy and secrecy, particularly when the data can be accessed by other firms or institutes (Tucker, 2019). Accordingly, the firms are unlikely to risk exposing their database to and sharing it with external organizations and might choose to analyze it internally.

Moreover, protecting algorithms that build the company's AI systems through patents and copyrights is difficult (Trippe, 2020), whereas copying them is relatively easy. Hence, firms that develop their own AI systems tend to be reluctant to disclose proprietary information and share or expose how their algorithms work. Thus, firms that have the capacity to do so prefer to hire talented AI experts and scientists to conduct R&D internally. Indeed, McKinsey (2017) indicates that large technology companies, such as Amazon, Apple, Baidu, and Google, spent 90% of their AI-related budget on internal R&D and recruiting AI talents and only 10% on AI acquisitions. Thus, we argue that pursuing a firm-specific internal R&D strategy, rather than a collaborative and external R&D strategy, can more effectively create productivity benefits from AI adoption.

Hypothesis 3. The positive relationship between AI adoption and firm productivity is stronger when a firm pursues an internal R&D strategy.

3. The Data

3.1 Data and sample

We conducted a survey of high-tech ventures based on a list of 1,248 companies that were randomly selected and given to us by the Ministry of SMEs and Startups. We sent out surveys to all companies in the list and over three months in 2019, we collected 300 responses (i.e., a response rate of approximately 24%). The geographic distribution of the respondent firms was representative of all high-tech ventures, according to data from the Ministry of SMEs and Startups[1]. In addition, the respondent firms in the sample were representative of all high-tech ventures with respect to their revenue across regions, in accordance with statistics from the Korean Statistical Information Service (KOSIS)[2].

The survey examines various aspects of firms' AI adoption and business strategies divided into six sections: (1) firm profile, (2) business strategy, (3) innovation and technology adoption, (4) AI adoption, (5) financing, and (6) demographics of the owners. In particular, the survey covers the extent to which firms adopted AI technologies in the production or development of their goods and services, which has been difficult to obtain in most other data sources. The survey also asks about the level of AI adoption in terms of NLP, CV, and ML, and the level of prior technology adoption, such as database systems and cloud computing. Moreover, the survey also asks a set of questions that evaluate how firms perceive the benefits from adopting AI in various aspects of their business processes, including development, marketing, and customer service. Another valuable component of the survey is information on firm R&D strategy, where we asked respondents to rate the degree to which their firm pursues an internal development versus a collaboration strategy.

[1] Our sample is representative of the population of interest in view of the fact that, of the 300 ventures that responded to our survey, 65.4% (68.3%) are in Seoul/Gyeonggi-do, 14.4% (13%) are in Daejeon/Chungcheong-do, 11.2% (12.7%) are in Gyeongsang-do, 6.5% (4.7%) are in Jeolla-do, 1.9% (1.0%) are Gangwon-do, and 0.6% (0.3%) are in Jeju-do.

[2] Our sample is representative of the population of interest in view of the fact that, of the 275 (due to missingness in revenue data) ventures that responded to our survey, generated similar amount of revenue: \$0.44 million (\$0.43 million) in Seoul/Gyeonggi-do, \$0.36 million (\$0.32 million) in Daejeon/Chungcheong-do, \$0.35 million (\$0.38 million) in Gyeongsang-do, \$0.31 million (\$0.27 million), and \$0.25 million (\$0.27 million) in Gangwon-do and Jeju-do.

Among the 300 firms, our core empirical sample focuses on firms that were created in 2015 or before. We include this restriction because we only observe the intensity of AI adoption in 2019 (the survey year), and firms generally started adopting AI after 2015, so we assume that AI adoption in 2015 was 0%. Most Korean ventures that use AI started adoption after the historical Go match between Lee Se-dol and AlphaGo. When the Korean Go Master lost, interest in AI spiked among Korean entrepreneurs which led to a surge in new AI-based startups while mobile app and general software-based startups declined. According to the Ministry of SMEs and Startups, among all startups, AI and big data startups accounted for only 432 ventures (1.6% of all high-tech startups) in 2013-2016, but then explosively increased to 2,376 ventures (8.8% of all high-tech startups) in 2017-2020. Similarly, venture capital investment in AI startups increased from 1.7% ($40 million) of total investments in 2017 to 18.5% ($316 million) of total investment in 2020. Considering this trend, assuming that AI adoption in 2015 was at zero seems a reasonable approximation. However, we also perform analyses without this restriction in our robustness check.

Focusing on firms created in 2015 or before reduces the sample to 211 firms, and we drop 37 observations because of missing responses to questions on firm characteristics such as firm valuation and AI intensity. In addition to the survey data, we also collected the venture's financial data including revenue data from the Small Business Status Information System, known as SMINFO (http://sminfo.mss.go.kr) run by the Ministry of SMEs and Startups. This government database provides data on industry classification, establishment year, CEO information, location, history of certifications, as well as recent five years of financial data such as revenue, current asset, and debt. Thus, this data enables us to accurately measure financial performance and also cross-check the basic information with our survey. We drop 14 ventures whose revenues were not observable in SMINFO because of business closure. Based on these restrictions, our final sample includes 160 firms. To ensure the representativeness of our final sample, we use the Kolmogorov-Smirnov (K-S) two-sample test to compare the sample of 160 and the full sample (Westphal & Bednar, 2005; Petrenko et al., 2019). The test results indicate no statistically significant differences in terms of firm-level (e.g., revenue growth, firm age, business stage, valuation, funding) and CEO-level variables (e.g., age, gender, prior experience) or industry and region.

3.2. Variable description

Table 1 presents the summary statistics of the key variables. In terms of industry distribution, about 26% of the ventures are in the software industry, 17% are in the pharmaceutical industry, including medical devices, and 10% are in the mobile IT industry. These ventures together account for more than 50% of the full sample. The average firm age is about 3.6 years, and in general, their current business stage is between early profit generation and growth. Approximately 54% of the firms have adopted some type of AI technology, whether NLP, CV, or ML.

------Insert Table 1 about here------

Independent variable

AI-adoption intensity. Our key explanatory variables are the AI technologies that the ventures use in their business processes for the production or development of products and services: (1) natural language processing (NLP, i.e., speech and pattern recognition and chatbots), (2) computer vision (CV, i.e., imaging tagging, image recognition), and (3) machine learning (ML, i.e., recommendation and prediction). To minimize confusion, we explicitly explained and provided examples of each technology. Then, we asked respondents to rate their level of adoption in each of the three AI technologies (1 = no adoption, 2 = testing stage, 3 = 0%-5%, 4 = 5%-25%, 5 = 25%-50%, and 6 = 50% or more).[3] Because firms often use these AI technologies in conjunction with each other, we construct our key AI adoption intensity measure with the maximum value in the three technologies.

Moderating variables

Complementary technologies. As noted in the literature (Brynjolfsson et al., 2019), the adoption of other technologies can create variation in the benefits of AI adoption through technological complementarity. In this vein, we asked respondents to state the level of adoption in database systems and

[3] The values we use to measure adoption intensity were recently used by Beede et al. (2020) and Zolas et al. (2021).

cloud computing in their business process of production or development of products and services, similar to how we asked about AI intensity. We then created a binary variable for each technology, which equals 1 for firms that adopted any of the technologies by more than 5%, and 0 otherwise.

R&D strategy. To gauge a firm's R&D strategy, we asked managers to indicate where their firms' strategies lie along a seven point scale where 1 corresponds to a firm-specific internal R&D strategy that emphasizes independent development by internal talents and 7 corresponds to a collaborative R&D strategy with external partners [i.e., universities and public institutions]. We converted the responses to a binary variable indicating internal R&D strategy, where 1 to 4 are coded as 1, and 0 otherwise.

Dependent variables

We used the *average revenue growth rate* as a measure of firm performance. The economics literature examines firm performance using a variety of metrics including labor productivity (revenue per employee), profitability (net operating profit to capital employed), tobin's q (the ratio of the firm's stock market value to it's capital stock), and revenue growth (Bloom and Van Reenen 2010). Since our focus is on small and medium sized high-tech ventures, of which many are not listed firms and do not publically report financial statements, we use revenue growth as our main outcome as revenue measures are more readily available for emerging firms. As noted above we were able to collect data on revenue from SMINFO, in particular, the most recent five years of revenue (2015-2019). The average annual revenue growth rate was measured as $\frac{\log \mathrm{Y}_{2019} - \log \mathrm{Y}_t}{2019 - t}$, where *t* represents the establishment year for firms established after 2015, and 2015 otherwise. Accordingly, $\log \mathrm{Y}_{2019}$ is the firm's revenue in 2019, and $\log \mathrm{Y}_t$ is revenue in the establishment year *t* for firms established after 2015, and revenue in 2015 otherwise.

Control variables

We control for a number of firm and owner characteristics that the literature has shown are related to firm performance. First, we control for firm age, measured as the age since the establishment year. We also account for the different types of business models. We asked respondents to state the firm's current business model (B2C, B2B, B2G, etc.) and included the responses as dummy variables. To control for a firm's different growth stages, we incorporate the current business stage, using dummy variables for *before profit generation*, *early profit generation*, *growth*, *near IPO*, and *IPO*. In addition, we included a control variable for the firm's valuation, by including dummy variables that correspond to approximately \$0-0.5 million, \$0.5–1 million, \$1–2 million, \$2–5 million, \$5–10 million, and above \$10 million. We use the valuation by venture capital and other financial institutions if the venture was not listed on the market, and on stock prices if the venture was listed on the stock exchange. Lastly, to control for previous IT capital investments, we use the firm's adoption of enterprise resource planning (ERP) systems within their business. We create a binary variable for the ERP adoption, which equals 1 for firms that adopted ERP technologies by more than 5%, and 0 otherwise.

In addition, research shows that owner characteristics strongly influence firm performance (Lindquist et al., 2015; Eesley & Lee, 2020). We capture these effects with several owner-related variables indicating gender and prior experience of the owner as well as the owner's age. Moreover, we also account for differences in specific firm types, including dummy variables for an independent venture, spinoffs from either domestic or foreign firms, lab-based ventures, and joint ventures.

Taking into consideration the time-varying firm characteristics, we also control for a set of variables in the year the firm was established, or 2014 if earlier. We control for the initial size of the venture, measured by dummy variables indicating the number of total employees at the time of the firm's establishment, namely, 5–10, 11–15, 15–20, 21–30, and above 30. Firm performance can also vary in the extent to which firms receive subsequent funding, which we account for using the amount of funding received from various sources at the time of the firm's establishment.[4] We specifically asked respondents to fill in the year of

[4] The funding module consists of funding from the following: (1) friends, family, and angel investors; (2) accelerators and incubators; and (3) domestic and foreign venture capital.

funding and the amount of funding received for each funding source. Finally, we add industry dummies[5] as well as venture location[6] to all our specifications.

3.3. Descriptive statistics

Table 2 presents descriptive statistics by the level of AI adoption. Firms that have a higher level of AI adoption tend to be smaller and younger than firms that have not adopted AI technologies. Moreover, firms with a higher valuation are likely to adopt AI technologies more intensively. This difference is large between firms with no AI adoption and firms with AI adoption of more than 50%. Firms founded by younger CEOs and CEOs with prior startup experiences are likely to adopt AI technologies more intensely. Notably, across all levels, AI adoption is correlated with database and cloud-computing adoption. Lastly, turning to our main outcome, average revenue growth, we observe significant differences in performance between firms that did adopt AI technologies and firms that did not, particularly firms with adoption levels of 25% or more.

------Insert Table 2 about here------

4. Empirical Framework

We present the framework of the revenue growth regressions we use in the empirical analysis. Consider the following equation which represents a general relationship between AI-adoption intensity and firm performance:

$$y_{it} = \beta \mathrm{AI}_{it} + \mathbf{X_{it}} \cdot \boldsymbol{\delta} + \varepsilon_{it}, (1)$$

where y_{it} measures firm revenue for firm *i* in year *t*, and AI_{it} represents the intensity of AI adoption by firm *i* in year *t*. The control variable vector $\mathbf{X_{it}}$ includes a host of firm-level and owner-level variables,

[5] Specifically, we include machine & materials, pharmaceuticals, software, mobile IT, logistics, energy, smart systems, augmented reality/virtual reality, automobiles, and so on.
[6] We add capital cities (Seoul and Gyeonggi-do), Daejeon, where R&D clusters are located, and the other remaining cities as dummy variables.

including firm age, firm size, growth stage of the firm, valuation of the firm, industry, and location of the firm, and various owner characteristics (age, gender, serial entrepreneur). Although we include many control variables, omitted variables may exist that are related to both the firm's AI-adoption intensity and firm performance. The presence of omitted variables will lead to bias in the coefficient estimate on AI adoption in equation (1). To mitigate this concern, we control for unobserved firm-fixed effects by performing a first-differenced regression at the firm level, as follows:

$$\Delta y_{i,2015-2019} = \beta_1 AI_{i,2019}^{testing} + \beta_2 AI_{i,2019}^{0-5} + \beta_3 AI_{i,2019}^{5-25} + \beta_4 AI_{i,2019}^{25-50} + \beta_5 AI_{i,2019}^{50+} +$$

$$\mathbf{W_{i,2015}}\boldsymbol{\gamma} + \mathbf{X_i}\boldsymbol{\delta} + u_{it}. \ (2)$$

$\Delta y_{i,2015-2019}$ measures firm *i*'s change in log revenue between 2015 and 2019. $AI_{i,2019}^{k}$ is a dummy variable representing the intensity of AI adoption by firm *i* in 2019, where *k* represents the level of adoption: testing but not adopting, 0%–5%, 5%–25%, 25%–50%, or 50% or more. $\mathbf{X_i}$ represents firm and owner characteristics, and $\mathbf{W_{i,2015}}$ is the set of firm characteristics in 2015, which are based on retrospective questions we pose in the survey. The $AI_{i,2019}^{k}$ variables are intended to capture the change in AI adoption, which as we discussed in the data section, is based on the very likely assumption that AI adoption was 0% in 2015 or earlier. Hence, the adoption level in 2019 can be considered as the change in the level of AI adoption. The assumption is reasonable because AI adoption among high-tech ventures in South Korea was fairly recent. AI adoption has been slightly slower in South Korea than in the US, where AI adoption generally began after 2016 in Korea. This assumption limits the sample to firms that were created in 2015 or before. We also examine results using different years, for example, 2014 and 2016, as the cutoff in Online Appendix Tables A2 and A3.

Equation (2) presents the growth regressions used in the analysis, and the coefficient estimates on AI adoption (i.e., β_1 to β_5) represent the difference in average annual revenue growth rates at different adoption levels compared with no adoption. If AI adoption increases firm performance, we would expect the coefficient estimates on high AI-adoption-intensity levels (e.g., β_4 and β_5) to be greater than the estimates on zero or low levels of adoption. If a lag exists in the benefits of AI as we hypothesized, the coefficient estimates at low levels of adoption may not be significantly different from zero but turn positive and significant at higher levels of adoption. If something akin to a so-called J-curve effect exists, in which adoption of AI initially results in lower performance through adjustment costs, we may find that some coefficient estimates are negative at low levels of adoption. The growth regressions do not resolve all potential sources of endogeneity, but with the rich set of control variables, the results do provide convincing insights into how AI-adoption affects firm performance.

5. Results

5.1. Determinants of AI adoption by intensity

We first examine firm and owner characteristics associated with AI-adoption in Table 3. We perform an ordered logit regression, in which the outcome variable is an ordinal variable from 1 to 6 that corresponds to the different AI adoption levels: no adoption, testing, 0%-5%, 5%-25%, 25%-50%, and 50% or more (column (1)). We also run ordinary least squares (OLS) regressions in which each outcome variable represents the cumulative level of AI adoption (columns (2)-(5)). Several interesting patterns emerge. First, firms with high valuations are more likely to adopt AI more intensively, but the effect on valuation is not necessarily linear. As columns (4) and (5) indicate, firms with a relatively low valuation ($1 million–$5 million) are significantly more likely to adopt AI intensively (at or above 25%), as well as firms with a high valuation ($10 million or more). The results suggest that newer firms with the more potential for growth are likely to adopt AI intensively, along with the more established firms. However, this U-shaped pattern is not necessarily a size effect. The coefficient estimates on all the firm-size dummy variables are negative in column (1). Note that the missing category is firms with a size of 10 or less. So, larger firms are less likely to adopt AI intensively relative to smaller firms. Also, estimates on firms with a size of 41 or more are large and negative throughout and significant (at the 10% level) in column (5).

Firm type is significantly related to AI-adoption intensity. Spinoffs from other companies are less likely to adopt AI, but lab-based spinoffs are more likely to adopt AI intensively. CEOs with prior entrepreneurship experience, that is, serial entrepreneurs, are more likely to adopt AI intensively. We do not find that younger CEOs are more likely to adopt AI intensively, which may be due to the correlation between CEO age and firm valuation or size. Finally, firms that have adopted database systems and cloud computing are more likely to adopt AI more intensively.[7]

------Insert Table 3 about here------

5.2. AI-Adoption Intensity and Firm Performance

We examine how revenue growth is related to AI adoption, focusing on any level of AI adoption. Table 4, column (1), examines any AI technology, and columns (2) to (4) examine each specific AI technology (NLP, CV, and ML). All regressions control for the full set of control variables, namely, the base controls (firm age, business-development level, finance level, prior technology adoption and owner characteristics), initial-year controls, industry-fixed effects, and region-fixed effects.

The results indicate average annual revenue growth is about 30 percentage points higher for AI adopters than for non-adopters. If we examine each AI technology separately, the effect ranges from 32.4 percentage points (ML) to 45.8 percentage points (NLP). The effects are all statistically significant at the 1% level, and the R-squared of each regression hovers around 0.5. The larger magnitudes in columns (2) to (4) are likely due to firms that often incorporate more than one AI technology.[8]

------Insert Table 4 about here------

We next examine how the intensity of AI adoption is related to firm performance. Table 5 presents the regression results, and Figure 1 plots the coefficient estimates. The estimates represent the difference in the firm's annual growth rates at different levels of adoption relative to non-adopting firms. As Figures 1a-1d illustrate, the firm's average annual revenue growth rate generally increases with higher levels of AI

[7] We also examine results from a logit regression that correspond to columns (2)-(5) in Online Appendix Table A1. The results between the ordinary least squares (OLS) and logit regressions are qualitatively similar. However, given the multiple fixed effects included in the estimation equation, we focus on the OLS results.
[8] In our sample of 160, 6, 13, and 8 firms exclusively adopted NLP, CV, and ML, respectively; 2, 10, and 8 firms adopted both NLP & CV, NLP & ML, and CV & ML, respectively. Lastly, 36 firms reported that they adopted all three AI technologies.

adoption, and the relationship becomes significant at higher levels of adoption, namely, 25%-50% or 50% or more.

However, low levels of AI adoption or the testing stages of AI technologies do not generate revenue growth. These findings are consistent with Hypotheses 1a and 1b and show that there may be delayed productivity gains from AI adoption.[9] There could be several reasons behind delayed productivity gains. At the early stages of AI adoption, firms often need to adjust or reorganize their business practices to use AI productively. Firms may also recognize the need to make complementary investments, such as R&D, AI-specific human capital, data, and cloud computing, at the early stages of adoption. After the complementary investments and reorganization are in place, firms might start to reap the benefits of AI.

------Insert Table 5 about here------

------Insert Figure 1a-1d about here------

5.3. AI adoption and complementary investments

We next examine whether the relationship between AI-adoption and revenue growth is more pronounced at firms that make complementary investments. As we discussed in Section 2, the unique aspects of AI as an algorithmic technology motivates us to focus on two potentially complementary technology investments, namely, in database and cloud computing, and R&D strategy.

Table 6 presents results after we split the sample based on database and cloud-computing adoption. We find that 83 out of 160 firms invested in these technologies. The pattern between AI-adoption intensity and revenue growth in Table 5 occurs only among firms that adopt these technologies. Figure 2 illustrates the results by plotting the coefficient estimates between the two samples for any AI technology (which corresponds to the results in Table 5, column (1)). The jump at 25% adoption or higher is evident only at firms that invest in these technologies.

[9] We also examined results when we use the 2019 revenue, rather than changes, as the dependent variable in all of our regressions. We use this value as measure as a proxy for labor productivity because we do not have accurate information on the number of employees of each firm. The results are consistent with our main specifications and are presented in the Online Appendix A4-A9

In Table 7, we test whether the differences in Figure 2 and Table 6 are statistically meaningful. We pool the two samples together and conduct a regression analysis that includes a dummy variable indicating AI adoption at 25% or more, a dummy indicating whether the firm adopted database and cloud computing, and the interaction term between the two. As column (1) indicates, the interaction term is positive at 0.637 with a standard error of 0.175. Revenue growth is 63.7 percentage points higher among firms that additionally invest in these complementary technologies than at firms that intensively adopt AI technology (at 25% or higher) without investing in database and cloud computing. These findings are consistent with Hypothesis 2. AI is an algorithm based technology that trains on large databases and the performance of AI is closely tied to data collection, data management, and computing capabilities. Indeed our results indicate that firms that have access to large amounts of data and high-power computing systems for its AI applications more effectively benefit from adopting AI. The pattern is generally the same across each specific AI technology, with complementarity being most pronounced for ML, followed by CV and then NLP. The weaker interaction effect between NLP and database systems and cloud computing might imply that NLP need different technology complementarity. For example, some researchers indicate that current NLP algorithms could be further improved by applying other ML algorithms and developing new optimization methods (Iandola et al., 2020).

------Insert Table 6 about here------

------Insert Figure 2 about here------

------Insert Table 7 about here------

We next examine the complementarity between AI adoption and R&D strategy. Some firms engage in more open and collaborative R&D, whereas others pursue a more secretive and firm-specific R&D strategy. The latter strategy may be more suitable for proprietary databases and algorithms and more responsive to the reorganization needs of the firm's unique production processes and business strategy. Table 8 presents the results after we split samples between those that pursue a firm-specific internal R&D strategy and those that pursue a more open and collaborative R&D strategy. Comparing columns (1) to (4), we find a positive relationship between higher levels of AI adoption, and revenue growth is significant among firms that adopt more firm-specific internal R&D strategies. The estimates in columns (5) to (8) indicate that a positive association also exists at firms that pursue external R&D collaboration, but the estimates are not precise. Figure 3 illustrates this point as well. The coefficient estimates between the two groups are similar but significant only for the subsample of firms pursuing internal R&D strategies. Moreover, when we examine the results for each AI technology, the relationship is more consistent among firms that adopt internal R&D strategies. The interaction-term analysis in Table 9 also illustrates this point. Column (1) indicates that AI adoption of 25% or more is associated with revenue growth that is 53.9 percentage points higher. The table shows revenue growth that is 39.9 percentage points higher among firms adopting an internal R&D strategy. When we examine each technology separately, we always find a positive interaction term, and the estimate is the largest for ML. These findings are consistent with Hypothesis 3 and indicate that firms that pursue internal R&D strategies are more likely to be productive at using algorithms and data that are often proprietary and firm-specific.

------Insert Table 8 about here------

------Insert Figure 3 about here------

------Insert Table 9 about here------

Lastly, we examine the potential mechanisms through which AI adoption at higher levels might result in revenue growth in Table 10. We asked firm managers how their firms would use AI to contribute to their products and services. Managers at firms that adopt AI at higher levels expected improvement in their products and services, marketing and sales, and customer support. These are all key aspects that contributs to firm revenue. Though we are unable to test how these aspects changed with AI adoption, the findings in Table 10 suggest that AI adoption, and the more intense adoption of AI, may contribute to revenue growth by improving the firms' products and services, marketing and sales, and customer support.

------Insert Table 10 about here------

6. Conclusion

Despite the rapid increase in AI adoption among firms, evidence on how AI adoption affects firm performance is relatively scant. Moreover, the decline in productivity despite technological progress in recent years has puzzled scholars studying technology and productivity. In this paper, we examine how AI adoption affects firm performance at high-tech ventures. In particular, we investigate how firm performance varies depending on the AI adoption level and which firm strategies are complementary to AI-adoption intensity.

We find that AI adoption at low levels is initially unrelated to revenue growth, but as the level of AI adoption increases, revenue growth increases significantly. Moreover, such delayed productivity gains occur at ventures that invest in complementary technologies, such as cloud computing and database systems, and pursue firm-specific internal R&D strategy. The latter point suggests that AI contributes to firm performance when its R&D is well tailored and integrated into the business. In sum, our findings show that firm performance increases with the level of AI adoption, but only after sufficient investment in AI technology has been made. Moreover, the benefits of AI adoption become more salient when complementary technology investments and R&D are made.

The productivity gains from AI will likely become more evident as adoption continues to increase. Our findings suggest that the performance benefits from AI adoption will likely differ across firms depending on whether they invest in complementarities, including technological complementarities, such as database systems and cloud computing, and intangible investments, such as R&D strategy. Many firms, especially smaller firms without the technical capabilities of large companies, are still exploring how to incorporate AI into their businesses. At the same time, governments around the world are encouraging AI development and adoption. In 2016, the US announced its AI initiative to pursue policies to expand its AI-related R&D workforce and funding (Agrawal et al., 2016), and in 2019, the president signed an executive order regarding the national strategy on AI to maintain national competitiveness.[10] Similar efforts are being

[10] https://www.whitehouse.gov/ai/executive-order-ai/.

pursued in many countries, including China, South Korea, and the member countries of the European Union. Although such AI initiatives abound, little research concretely addresses the challenges that firms face in terms of AI adoption and the productivity benefits of AI. Our findings may help firms and policymakers understand which attributes are associated with high levels of AI adoption and when and how companies can obtain the productivity benefits from adopting AI.

More specifically, countries that pursue an AI policy would benefit by concurrently pursuing policies that develop cloud computing and that expand and facilitate firms' and entrepreneurs' access to it. Cloud computing incurs substantial costs, especially for small and young firms, and access limitations can hinder the adoption and productive development of AI. Major cloud-computing service providers in the US, such as Amazon Web Services and Microsoft Azure, offer free cloud credits to startups and university researchers (Marks, 2018). By incorporating cloud computing into national AI strategies, countries could help develop an ecosystem that enables productive AI adoption.

Another key policy component is AI education and training. Currently, the demand for AI researchers far exceeds the supply, and the relatively few AI researchers are mostly recruited by larger tech companies at a high premium (Metz, 2017; Tilley, 2017). Younger and smaller firms that cannot afford to pay comparable wages to these skilled workers are falling behind in terms of AI adoption and commercialization. In particular, when the internal R&D strategy is complementary to AI adoption, as we find in our study, the supply of technical workers well versed in AI is critical for the productive use of AI by smaller firms.

Our study is not without limitations, and future research can build upon our findings. First, we consider AI the combination of specific learning algorithms (NLP, CV, and ML) with respect to technology (Babina et al., 2020), because of the nature of our research question. However, future studies can investigate the effects of different aspects of AI; for example, they could examine which types of AI are "human-enhancing innovations" and which are "human-replacing innovations" (Trajtenberg, 2019). Alternatively, future research can examine the different applications of AI across different industries. The major innovations in AI in business are not in refining existing algorithms to perform slightly better than the previous iterations, but in how those algorithms are applied to businesses. In fact, most patents related to AI are related to how the technology is applied (Webb 2020). Hence, future studies can examine the productivity benefits based on different AI applications in different industries. The literature has made headway in some sectors, such as finance (Choi et al. 2020; Fuster et al. 2019, 2020; Bartlett et al. 2019), but analysis has yet to catch up to many more areas of AI application.

Second, we explore a variety of other potential complementarities, but the two we highlight in the paper, namely, complementary technology investment and R&D strategy, are the ones that were most significant in our data. However, other intangible investments, especially those related to human resource management, business organization, production strategy, and so on, may also be important complementarities in different contexts. A fruitful next step would be to study other firms (e.g., listed firms, firms in developing countries) and other potential complementarities, such as financial capabilities, human resource management and organizational structure and practices (Powell & Dent-Micallef, 1997; Bennett & Levinthal, 2017).

Lastly, the impact of AI will likely evolve over time and become more nuanced. AI as a GPT is still in its nascent stage. In this paper, we examine its performance benefits at high-tech ventures in Korea. However, AI will become more advanced, widespread, and diverse. The impact of AI on firms and people will evolve accordingly. As Agrawal et al. (2018) underscore, AI is primarily a prediction machine, and our analysis is based on an AI system whose primary role in business is to assist managers and workers through prediction. However, AI's ultimate goal is artificial general intelligence (AGI), a machine that can perform all the same tasks as people. Whether we will achieve AGI, and how long doing so might take, is unknown. However, human efforts to obtain AGI will continue, and the process will create new dimensions and applications for AI. An ultimate understanding of the impact of AI will require researchers to examine the new capabilities as it evolves.

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Figures and Tables

Figure 1a. Any AI

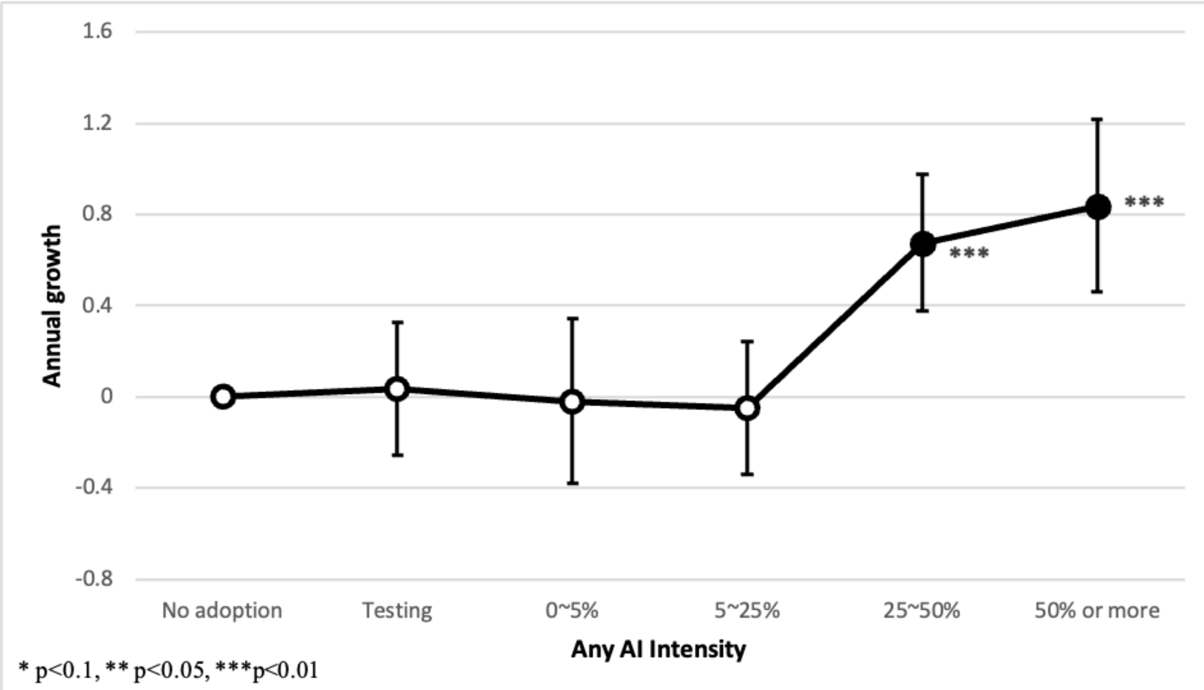

Figure 1b. NLP

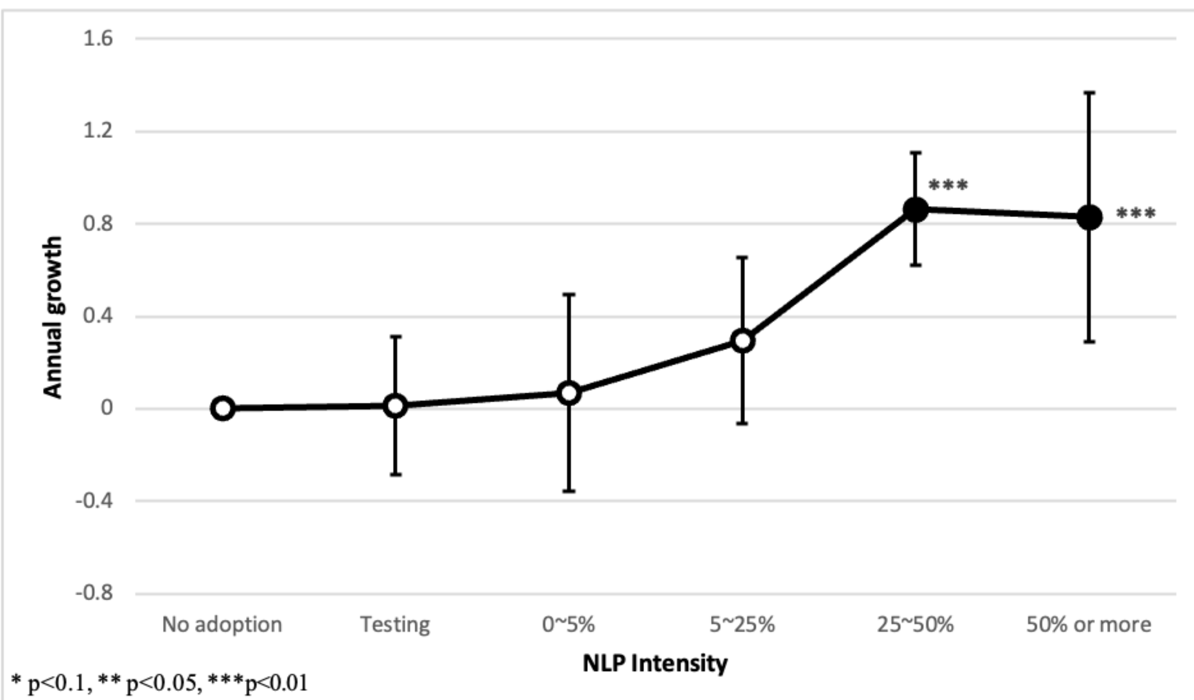

Figure 1c. CV

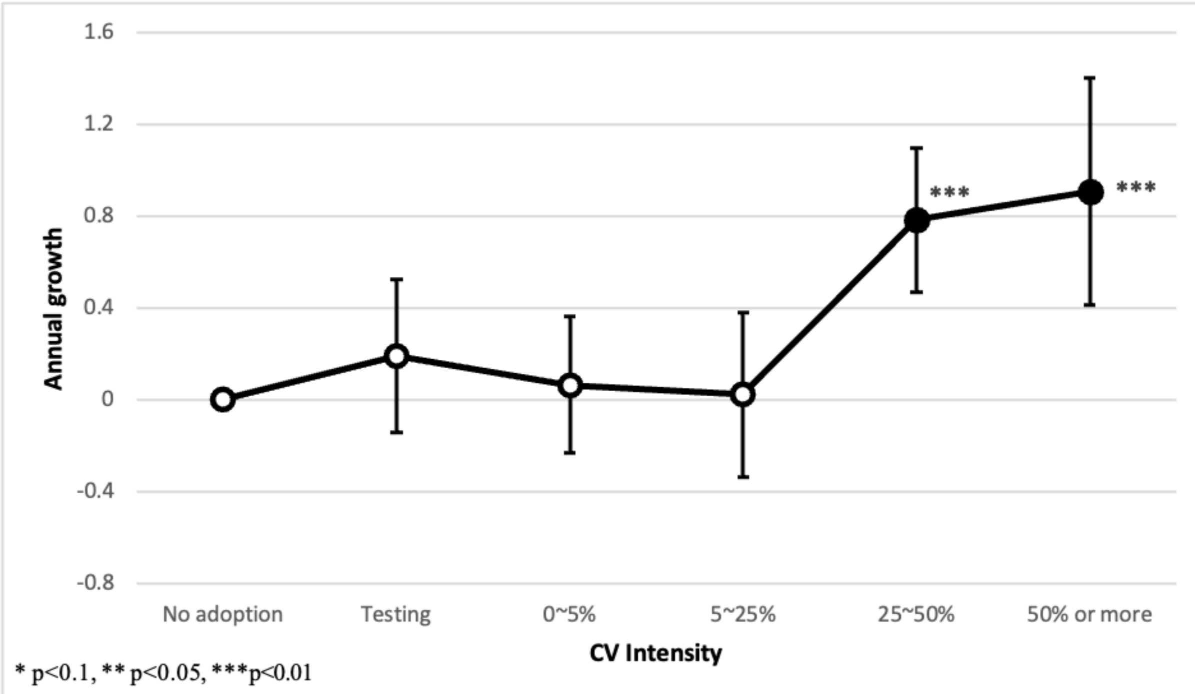

Figure 1d. ML

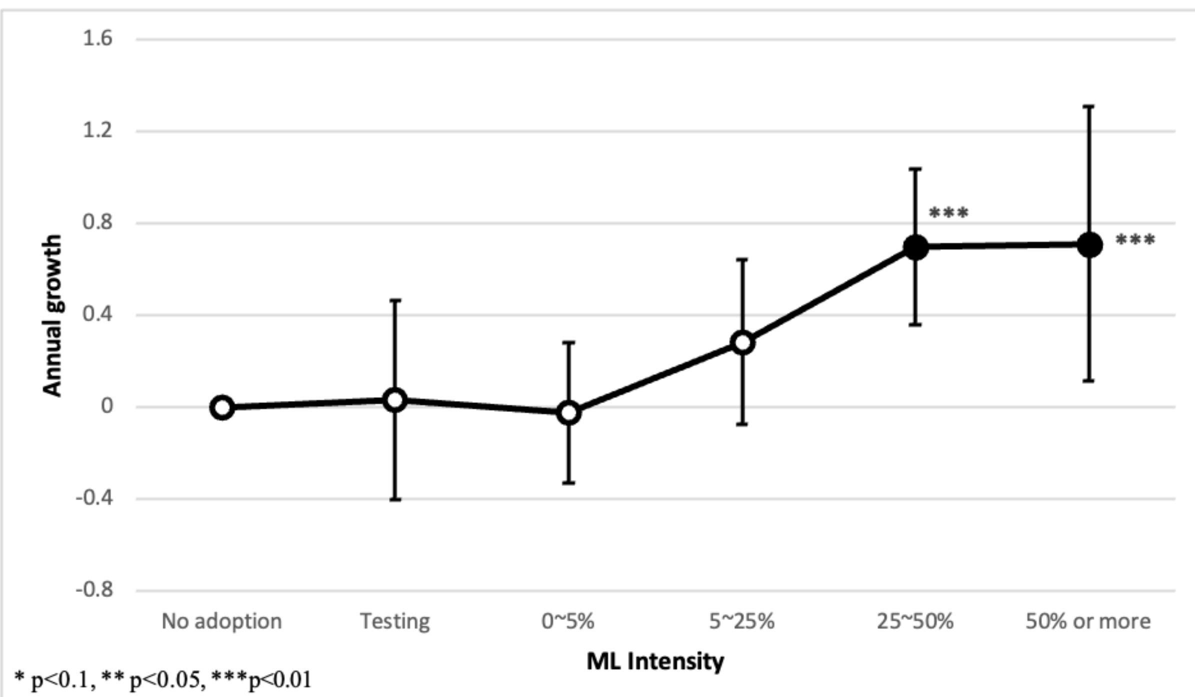

Figure 2. Technology complements

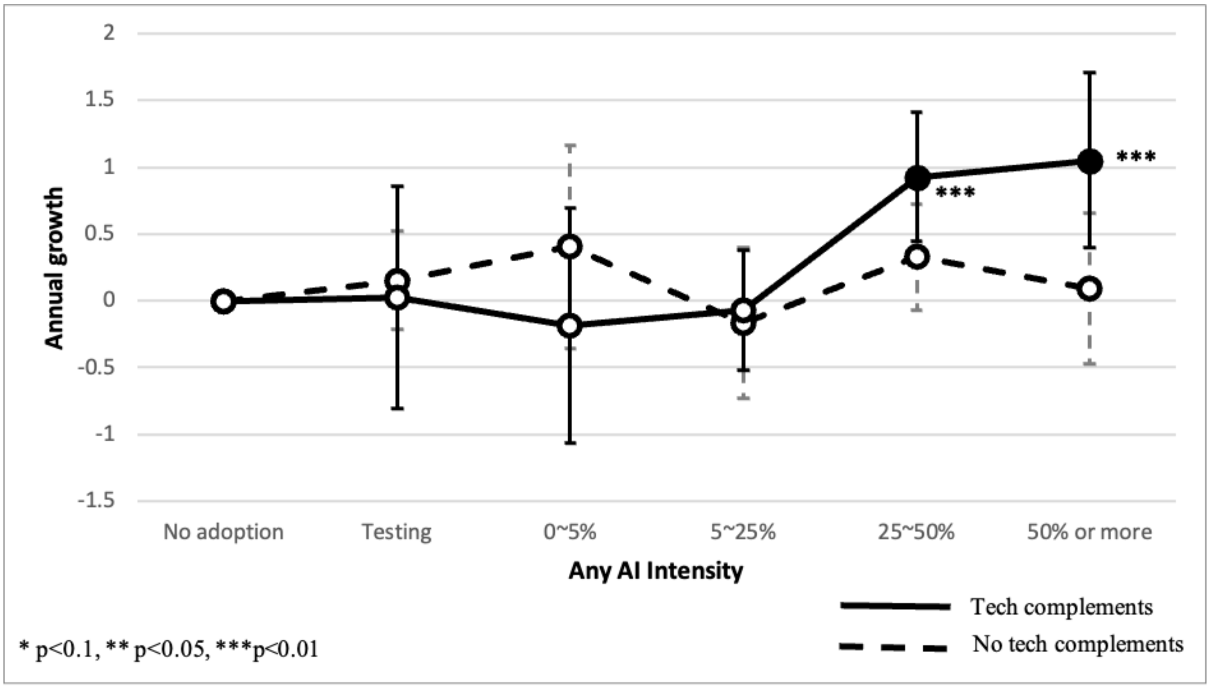

Figure 3. R&D complements

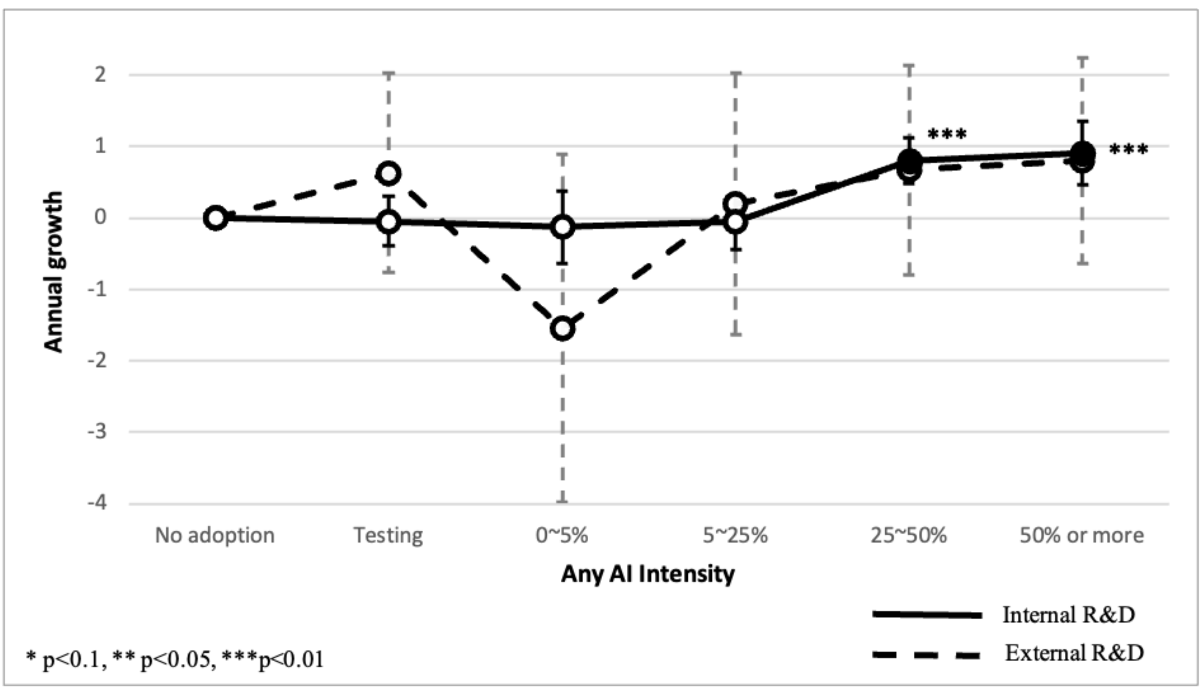

Table 1. Summary statistics

Variable	Obs.	Mean	Std. Dev.	Min.	Max.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1. Annual growth	160	1.458	.565	-.248	3.222	1																		
2. AI intensity	160	2.856	1.984	1	6	0.54*	1																	
3. NLP intensity	160	2.081	1.682	1	6	0.52*	0.70*	1																
4. CV intensity	160	2.144	1.697	1	6	0.49*	0.74*	0.42*	1															
5. ML intensity	160	2.188	1.687	1	6	0.51*	0.74*	0.64*	0.54*	1														
6. Business stage	160	2.487	.761	1	4	-0.02	-0.03	-0.01	-0.01	-0.05	1													
7. Firm valuation	160	3.894	1.452	2	6	0.12	0.10	0.02	0.07	0.19*	-0.03	1												
8. Business model	160	1.681	.628	1	4	-0.04	0.02	-0.01	0.10	0.09	-0.04	0.07	1											
9. Firm size	160	1.925	1.226	1	5	-0.08	-0.11	-0.13	-0.10	-0.01	0.34*	0.40*	0.12	1										
10. Firm age	160	3.612	4.41	1	22	-0.20*	-0.13	-0.06	-0.10	-0.14	0.36*	0.05	0.09	0.33*	1									
11. CEO gender	160	.912	.283	0	1	0.12	0.11	0.02	0.17*	0.07	0.02	0.21	-0.02	-0.06	0.04	1								
12. CEO age	160	38.794	8.143	20	63	-0.18*	-0.24*	-0.23*	-0.12	-0.25*	-0.06	0.01	0.13	0.01	-0.11	0.03	1							
13. CEO's prior experience	160	.256	.438	0	1	0.10	0.06	0.07	0.02	0.10	-0.17*	0.09	-0.02	-0.20*	-0.22*	0.13	0.06	1						
14. Firm type	160	1.3	.815	1	4	-0.17*	-0.07	-0.12	-0.06	0.01	-0.19*	0.21*	0.00	0.17*	0.03	0.01	0.23*	-0.18*	1					
15. Ln(Funding)	160	.154	.524	0	3.600	0.15	-0.00	-0.11	0.08	0.04	-0.15	0.12	0.10	0.11	-0.11	0.04	0.05	-0.08	0.21*	1				
16. Database adoption	160	.594	.493	0	1	0.29*	0.40*	0.34*	0.30*	0.36	0.18*	-0.05	-0.08	-0.07	0.03	0.06	-0.30*	-0.01	-0.15	-0.00	1			
17. Cloud-computing adoption	160	.506	.502	0	1	0.18*	0.44*	0.38*	0.33*	0.33	-0.09	-0.00	-0.02	-0.17*	-0.06	0.00	-0.14	0.12	-0.07	-0.05	0.56*	1		
18. ERP adoption	160	0.575	0.496	0	1	0.19*	0.10	0.16	0.18*	0.12	0.30*	-0.05	-0.07	0.12	0.09	0.09	-0.02	-0.07	-0.03	-0.05	0.27*	0.04	1	
19. R&D strategy	160	3.788	1.746	1	7	0.02	0.23*	0.07	0.17*	0.19*	-0.08	-0.01	0.10	-0.07	-0.03	0.04	-0.06	-0.07	0.04	-0.01	0.08	0.27*	-0.10	1

Note: * statistical significance at the 5% level.

Table 2. Descriptive statistics (by the intensity of any AI adoption)

	No adoption	Testing stage	0-5%	5-25%	25-50%	50%	Total
Annual growth	1.221	1.276	1.340	1.205	1.902	2.070	1.458
	(0.040)	(0.144)	(0.175)	(0.103)	(0.102)	(0.132)	(0.045)
Business stage	2.500	2.615	2.000	2.526	2.536	2.381	2.488
	(0.089)	(0.241)	(0.447)	(0.177)	(0.120)	(0.176)	(0.060)
Firm valuation	3.851	3.462	4.200	3.579	3.929	4.476	3.894
	(0.176)	(0.386)	(0.917)	(0.345)	(0.257)	(0.289)	(0.115)
Business model	1.689	1.538	1.600	1.579	1.857	1.619	1.681
	(0.072)	(0.144)	(0.245)	(0.116)	(0.152)	(0.129)	(0.050)
Firm size	4.041	4.000	4.400	3.684	3.857	3.667	3.925
	(1.232)	(1.581)	(1.140)	(1.157)	(1.146)	(1.197)	(1.226)
Firm age	4.284	3.000	3.400	3.632	2.214	3.524	3.613
	(0.574)	(0.734)	(0.927)	(1.117)	(0.444)	(1.139)	(0.349)
CEO gender	0.892	0.846	1.000	0.895	0.929	1.000	0.913
	(0.036)	(0.104)	(0.000)	(0.072)	(0.050)	(0.000)	(0.022)
CEO age	41.014	40.231	32.200	36.632	34.929	38.762	38.794
	(0.992)	(2.453)	(2.478)	(1.734)	(1.324)	(1.285)	(0.644)
CEO's prior experience	0.216	0.385	0.400	0.211	0.214	0.381	0.256
	(0.048)	(0.140)	(0.245)	(0.096)	(0.079)	(0.109)	(0.035)
Firm type	1.392	1.077	1.600	1.263	1.036	1.429	1.300
	(0.105)	(0.077)	(0.600)	(0.168)	(0.036)	(0.235)	(0.064)
Ln(Funding)	0.171	0.043	0.000	0.093	0.302	0.055	0.154
	(0.069)	(0.036)	(0.000)	(0.052)	(0.142)	(0.029)	(0.041)
Database adoption	0.392	0.538	0.600	0.895	0.750	0.857	0.594
	(0.057)	(0.144)	(0.245)	(0.072)	(0.083)	(0.078)	(0.039)
Cloud-computing adoption	0.270	0.462	0.600	0.789	0.786	0.714	0.506
	(0.052)	(0.144)	(0.245)	(0.096)	(0.079)	(0.101)	(0.040)
ERP adoption	0.514	0.615	1.000	0.526	0.607	0.667	0.575
	(0.058)	(0.140)	(0.000)	(0.118)	(0.094)	(0.105)	(0.039)
R&D strategy	3.392	3.769	3.200	4.263	4.214	4.333	3.788
	(0.194)	(0.469)	(0.583)	(0.404)	(0.335)	(0.410)	(0.138)

Notes: Standard errors are in parentheses.

Table 3. Determinants of AI adoption by intensity

	(1)	(2)	(3)	(4)	(5)
			Any AI adoption (OLS)		
Variables	Ologit	0% or more	5% or more	25% or more	50% or more
Firm age	0.004	0.001	-0.001	-0.005	0.009
	(0.046)	(0.008)	(0.008)	(0.007)	(0.006)
Firm valuation ($1-2 million)	0.695	0.009	0.036	0.170**	0.118**
	(0.469)	(0.087)	(0.086)	(0.077)	(0.052)
Firm valuation ($2-5 million)	0.333	0.038	0.039	0.102	0.109*
	(0.413)	(0.082)	(0.084)	(0.081)	(0.057)
Firm valuation ($5-10 million)	0.397	-0.019	-0.002	0.114	0.102*
	(0.456)	(0.081)	(0.081)	(0.081)	(0.058)
Firm valuation ($10 million and up)	1.631***	0.174	0.140	0.198*	0.269***
	(0.602)	(0.110)	(0.094)	(0.103)	(0.074)
Firm size (11-20)	-0.653*	-0.068	-0.085	-0.046	-0.125***
	(0.380)	(0.070)	(0.071)	(0.075)	(0.046)
Firm size (21-30)	-0.503	-0.079	-0.106	-0.070	-0.061
	(0.607)	(0.105)	(0.100)	(0.099)	(0.066)
Firm size (31-40)	-0.287	0.043	-0.057	0.009	0.027
	(0.670)	(0.122)	(0.123)	(0.122)	(0.092)
Firm size (41 or more)	-0.875	-0.136	-0.135	-0.079	-0.201*
	(1.156)	(0.149)	(0.155)	(0.149)	(0.113)
CEO gender	0.309	0.092	0.070	0.103	0.064
	(0.499)	(0.094)	(0.094)	(0.079)	(0.045)
CEO age	0.005	-0.004	0.001	-0.001	0.003
	(0.022)	(0.003)	(0.003)	(0.003)	(0.002)
CEO's prior experience	0.620*	0.054	0.025	0.035	0.095*
	(0.372)	(0.070)	(0.070)	(0.068)	(0.053)
Firm type (spinoffs)	-1.525**	-0.119	-0.099	-0.176**	-0.056
	(0.723)	(0.099)	(0.094)	(0.082)	(0.057)
Firm type (lab-based)	-0.190	0.001	-0.051	-0.045	0.134*
	(0.565)	(0.094)	(0.090)	(0.093)	(0.077)
ln(Funding)	-0.427	-0.019	-0.009	-0.022	-0.060*
	(0.371)	(0.045)	(0.045)	(0.048)	(0.033)
Database system adoption	0.730*	0.164**	0.193***	0.006	0.036
	(0.408)	(0.072)	(0.074)	(0.069)	(0.047)
Cloud-computing adoption	1.197***	0.191***	0.193***	0.163**	-0.003
	(0.389)	(0.073)	(0.072)	(0.066)	(0.046)
ERP adoption	0.088	0.046	-0.006	0.034	-0.003
	(0.322)	(0.061)	(0.060)	(0.056)	(0.043)
Constant cut1	1.425				
	(1.295)				
Constant cut2	1.870				
	(1.290)				
Constant cut3	2.065				
	(1.289)				
Constant cut4	2.842**				
	(1.292)				
Constant cut5	4.646***				
	(1.306)				
Constant		0.255	0.0856	0.0793	-0.222*
		(0.218)	(0.215)	(0.215)	(0.132)
Observations	253	253	253	253	253
R-squared		0.453	0.436	0.390	0.360
Pseudo R-squared	0.221				
Business model	Yes	Yes	Yes	Yes	Yes
Current business stages	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes	Yes	Yes
Region-fixed effects	Yes	Yes	Yes	Yes	Yes

Notes: All regressions controls for business stages, firm valuation, business model, firm age, firm size, CEO gender, CEO age, CEO’s prior experience, firm type, the amount of funding, database system, cloud-computing adoption, ERP adoption, and industry and region fixed effects. The results of current business stage and business model are not shown in the table. Robust standard errors are in parentheses. ***, **, and * statistical significance at the 1%, 5%, and 10% level.

Table 4. AI adoption and firm performance

	(1) Any AI revenue growth	(2) NLP revenue growth	(3) CV revenue growth	(4) ML revenue growth
AI adoption	0.288**	0.458***	0.354***	0.324***
	(0.120)	(0.109)	(0.113)	(0.113)
Observations	160	160	160	160
R-squared	0.491	0.548	0.511	0.507
Base control variables	Yes	Yes	Yes	Yes
Initial year controls	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes	Yes
Region-fixed effects	Yes	Yes	Yes	Yes

Notes: Base controls include business stages, firm valuation, business model, firm age, CEO gender, CEO age, CEO's prior experience, firm type, database system, cloud-computing adoption, and ERP adoption. Initial-year controls include firm size and the amount of funding. The control variables include fixed effects for 12 industries and 3 regions. Robust standard errors are in parentheses. ***, **, and * statistical significance at the 1%, 5%, and 10% level.

Table 5. AI intensity and firm performance

	(1) Any AI revenue growth	(2) NLP revenue growth	(3) CV revenue growth	(4) ML revenue growth
Testing	0.035	0.013	0.192	0.031
	(0.148)	(0.151)	(0.170)	(0.222)
Adopt 0%-5%	-0.018	0.069	0.065	-0.023
	(0.185)	(0.217)	(0.152)	(0.156)
Adopt 5%-25%	-0.049	0.296	0.024	0.284
	(0.149)	(0.184)	(0.183)	(0.182)
Adopt 25%-50%	0.675***	0.866***	0.783***	0.700***
	(0.153)	(0.124)	(0.161)	(0.173)
Adopt 50% or more	0.839***	0.829***	0.908***	0.711**
	(0.193)	(0.275)	(0.253)	(0.305)
Observations	160	160	160	160
R-squared	0.658	0.647	0.614	0.573
Base control variables	Yes	Yes	Yes	Yes
Initial year controls	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes	Yes
Region-fixed effects	Yes	Yes	Yes	Yes

Notes: Base controls include business stages, firm valuation, business model, firm age, CEO gender, CEO age, CEO's prior experience, firm type, database system, cloud-computing adoption, and ERP adoption. Initial-year controls include firm size and the amount of funding. The control variables include fixed effects for 12 industries and 3 regions. Robust standard errors are in parentheses. ***, **, and * statistical significance at the 1%, 5%, and 10% level.

Table 6. Hypothesis 2 (AI intensity with tech complements) heterogeneity

Variables	(1) Any AI revenue growth	(2) NLP revenue growth	(3) CV revenue growth	(4) ML revenue growth	(5) Any AI revenue growth	(6) NLP revenue growth	(7) CV revenue growth	(8) ML revenue growth
	No prior complementary technology				Prior complementary technology			
Testing	0.153	0.336	0.064	0.333	0.025	-0.328	0.724	-0.050
	(0.186)	(0.198)	(0.217)	(0.219)	(0.423)	(0.426)	(0.454)	(0.627)
Adopt 0-5%	0.405	0.687	0.537	0.278	-0.185	-0.085	-0.049	0.198
	(0.388)	(0.482)	(0.433)	(0.339)	(0.447)	(0.471)	(0.407)	(0.329)
Adopt 5-25%	-0.166	0.495	0.793	0.330	-0.072	0.505	-0.074	0.293
	(0.287)	(0.380)	(0.601)	(0.364)	(0.229)	(0.305)	(0.251)	(0.229)
Adopt 25-50%	0.328	0.484	0.355	0.194	0.926***	0.972***	0.963***	1.047***
	(0.203)	(0.435)	(0.307)	(0.254)	(0.247)	(0.253)	(0.295)	(0.295)
Adopt 50% or more	0.094	0.499	-0.107	-0.263	1.049***	1.111***	1.338***	1.681***
	(0.288)	(0.514)	(0.359)	(0.436)	(0.334)	(0.403)	(0.479)	(0.517)
Observations	77	77	77	77	83	83	83	83
R-squared	0.766	0.797	0.788	0.764	0.790	0.733	0.750	0.731
Base control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Initial-year controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Base controls include business stages, firm valuation, business model, firm age, CEO gender, CEO age, CEO's prior experience, firm type, and ERP adoption. Initial-year controls include firm size and the amount of funding. The control variables include fixed effects for 12 industries and 3 regions. Robust standard errors are in parentheses. ***, **, and * statistical significance at the 1%, 5%, and 10% level.

Table 7. Hypothesis 2 (AI intensity with tech complements) interaction

Variables	(1) Any AI revenue growth	(2) NLP revenue growth	(3) CV revenue growth	(4) ML revenue growth
Complementary tech	0.015	0.102	0.175	0.047
	(0.102)	(0.103)	(0.106)	(0.110)
Any AI (25% or more)	0.281*			
	(0.153)			
Any AI (25% or more) X Complementary tech	0.637***			
	(0.175)			
NLP (25% or more)		0.535**		
		(0.267)		
NLP (25% or more) X Complementary tech		0.284		
		(0.294)		
CV (25% or more)			0.444*	
			(0.230)	
CV (25% or more) X Complementary tech			0.464*	
			(0.250)	
ML (25% or more)				0.011
				(0.249)
ML (25% or more) X Complementary tech				0.798***
				(0.275)
Observations	160	160	160	160
R-squared	0.700	0.641	0.638	0.597
Base control variables	Yes	Yes	Yes	Yes
Initial-year controls	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes	Yes
Region-fixed effects	Yes	Yes	Yes	Yes

Notes: Base controls include business stages, firm valuation, business model, firm age, CEO gender, CEO age, CEO's prior experience, firm type, and ERP adoption. Initial-year controls include firm size and the amount of funding. The control variables include fixed effects for 12 industries and 3 regions. Robust standard errors are in parentheses. ***, **, and * statistical significance at the 1%, 5%, and 10% level.

Table 8. Hypothesis 3 (AI intensity with R&D) heterogeneity

Variables	(1) Any AI revenue growth	(2) NLP revenue growth	(3) CV revenue growth	(4) ML revenue growth	(5) Any AI revenue growth	(6) NLP revenue growth	(7) CV revenue growth	(8) ML revenue growth
	Internal development				External collaboration			
Testing	-0.046	-0.068	0.124	-0.190	0.630	0.037	0.583	-2.003
	(0.177)	(0.159)	(0.249)	(0.204)	(0.709)	(1.084)	(0.410)	(1.004)
Adopt 0-5%	-0.129	0.212	-0.048	-0.038	-1.549	-0.956	0.796	-1.045
	(0.258)	(0.309)	(0.388)	(0.183)	(1.243)	(0.538)	(0.446)	(0.656)
Adopt 5-25%	-0.060	-0.114	0.083	0.242	0.194	-0.457	1.276**	0.972
	(0.193)	(0.264)	(0.206)	(0.208)	(0.933)	(0.513)	(0.450)	(0.462)
Adopt 25-50%	0.805***	0.804***	0.732***	0.763***	0.669	1.374**	1.176**	0.769
	(0.163)	(0.145)	(0.215)	(0.196)	(0.747)	(0.382)	(0.391)	(0.483)
Adopt 50% or more	0.904***	1.095***	1.027**	1.399***	0.795	-2.518*	2.145***	0.836
	(0.227)	(0.214)	(0.489)	(0.494)	(0.733)	(1.110)	(0.369)	(0.518)
Observations	100	100	100	100	60	60	60	60
R-squared	0.850	0.860	0.781	0.820	0.948	0.975	0.989	0.978
Base control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Initial year controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Base controls include business stages, firm valuation, business model, firm age, CEO gender, CEO age, CEO's prior experience, firm type, database system, cloud-computing adoption, and ERP adoption. Initial-year controls include firm size and the amount of funding. The control variables include fixed effects for 12 industries and 3 regions. Robust standard errors are in parentheses. ***, **, and * statistical significance at the 1%, 5%, and 10% level.

Table 9. Hypothesis 3 (AI intensity with R&D) interaction

Variables	(1) Any AI revenue growth	(2) NLP revenue growth	(3) CV revenue growth	(4) ML revenue growth
R&D	0.037	-0.013	0.106	0.100
	(0.133)	(0.095)	(0.095)	(0.100)
Any AI (25% or more)	0.539***			
	(0.133)			
Any AI (25% or more) X R&D	0.399**			
	(0.167)			
NLP (25% or more)		0.561***		
		(0.180)		
NLP (25% or more) X R&D		0.357		
		(0.219)		
CV (25% or more)			0.734***	
			(0.172)	
CV (25% or more) X R&D			0.140	
			(0.225)	
ML (25% or more)				0.386**
				(0.184)
ML (25% or more) X R&D				0.588**
				(0.239)
Observations	160	160	160	160
R-squared	0.682	0.644	0.616	0.594
Base control variables	Yes	Yes	Yes	Yes
Initial-year controls	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes	Yes
Region-fixed effects	Yes	Yes	Yes	Yes

Notes: Base controls include business stages, firm valuation, business model, firm age, CEO gender, CEO age, CEO's prior experience, firm type, database system, cloud-computing adoption, and ERP adoption. Initial-year controls include firm size and the amount of funding. The control variables include fixed effects for 12 industries and 3 regions. Robust standard errors are in parentheses. ***, **, and * statistical significance at the 1%, 5%, and 10% level.

Table 10. Possible mechanisms

Variables	(1) Improvement of service or products	(2) Improvement of marketing and sales	(3) Improvement of customer support
Testing	-	-	-
Adopt 0%-5%	0.232	0.275	0.490
	(0.681)	(0.716)	(0.626)
Adopt 5%-25%	0.638	0.688	1.089**
	(0.461)	(0.490)	(0.425)
Adopt 25%-50%	0.806*	0.881*	0.967**
	(0.423)	(0.457)	(0.391)
Adopt 50% or more	0.857*	0.999*	0.994**
	(0.493)	(0.529)	(0.451)
Observations	123	123	123
R-squared	0.290	0.348	0.284
Base control variables	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes
Region-fixed effects	Yes	Yes	Yes

Notes: Base controls include business stages, firm valuation, business model, firm age, CEO gender, CEO age, CEO's prior experience, firm type, database system, cloud-computing adoption, and ERP adoption. Initial-year controls include firm size and the amount of funding. The control variables include fixed effects for 12 industries and 3 regions. Robust standard errors are in parentheses. ***, **, and * statistical significance at the 1%, 5%, and 10% level.