Artificial Intelligence, CEO Turnover, and Directional Change in Firm Innovation

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Abstract

We examine the role of artificial intelligence (AI) in facilitating a change in innovation directions after a leadership change. Using patent data for firms that have gone through a CEO turnover, we find that firms with greater AI investment are more successful in changing their innovation directions. The effect of AI is driven principally by the continued development of innovation in areas that are modestly different from the past. Further analyses show that this effect is likely due to firms with AI investment that can enable strategic change in cultivating culture of exploring frontiers in innovation and managing R&D. A new CEO can direct more resources to the acquisition of employees with greater technological capabilities such as AI skills to facilitate the innovation change. Overall, our study sheds light on the value of AI in fostering the change in innovation directions during uncertain and turbulent times.

Keywords: Artificial intelligence, CEO turnover, innovation, strategic change

Introduction

Innovation is the bedrock of economic growth and a driver of competitive advantages for firms (Coad & Rao, 2008; Kogan et al., 2017; Segerstrom, 1991). Recent years have witnessed significant advances in artificial intelligence (AI) and its wide-spread impacts in spurring innovation (Cockburn et al., 2018). AI, especially its subfield of machine learning, represents computational advancements that can perform better predictions from the data and support decision-making problems (Agrawal et al., 2019; Berente et al., 2021; Jordan & Mitchell, 2015). AI can quickly analyze vast quantities of data and learn about the underlying patterns from data (Babina et al., 2022; Mihet & Philippon, 2019). The associated learning process enables automated predictions, helping a firm effectively identify and develop promising projects previously unexplored, and thus fostering the creation of innovation in uncharted areas. Recognizing the value of using

AI in innovation, many firms actively invest and embed AI into their business and innovation process,[1] especially when it comes to using experimentation to explore new directions in innovation.

Parallel to the quest for innovation is the high turnover rate for chief executive officers (CEO) in U.S. firms.[2] When a new CEO takes office, seeking to change the status quo is commonplace (Cummings & Knott, 2018; Denis & Denis, 1995). In particular, changing established patterns of innovative activities and bringing new ones to the firm are often a key priority for newly appointed CEOs (Bigley & Wiersema, 2002; Tushman & Rosenkopf, 1996). To stay competitive, new CEOs often seek to change existing innovation practices and allocate resources to pursue more promising innovation opportunities. However, making changes in innovation is challenging, and CEOs often seek ways to smooth the change. Despite earlier evidence that AI can enable certain types of innovation (Lou and Wu 2021), it is unclear how AI can facilitate changes in innovation directions during uncertain and turbulent times.

In this paper, we investigate the extent to which a firm's AI investment can affect its innovation directions in uncertain times of leadership change. We examine a) whether firms with higher AI investment are more successful in changing their innovation directions after a CEO turnover event, and b) the channel through which the directional change can be supported by AI. To the best of our knowledge, our paper is one of the first to examine how technologies can be used to accelerate the change in innovation activities after CEO turnover and document the underlying mechanism that explains the change.

We begin by collecting data on public firms in the U.S. that had a CEO turnover event and filed patents. We use job posting data to measure AI investment as reflected in the recruitment of employees with AI skills. Our findings show that following CEO turnover events, firms with greater AI investment create more patents in patent classes that firms had not patented before, suggesting that AI investment is conducive to changing innovation directions during leadership change. These results are robust using various methods (firm-level fixed effects, instrumental variables, Heckman two-stage estimation, and matching estimators) to address potential selection and reverse causality bias issues of our sample. Examining the patent portfolio of firms with a CEO change, we find that AI is especially powerful in enabling a directional change in innovation that is moderately different from the firms' prior art. However, AI has a negligible effect in fostering innovation that differs substantially from the past. Furthermore, we examine the channel through which the directional change can be supported by AI. We find that the effect of AI is likely due to its ability to facilitate the exploration of innovation frontiers.

AI and Change in Firm Innovation

A growing body of literature evaluates the impact of AI on firm innovation (Babina et al., 2022; Lou & Wu, 2021). Thanks to the digitization of various social, economic, and individual behaviors, firms across industries have collected a wealth of data that can serve as necessary inputs for AI to analyze and learn about the underlying patterns of the business practices. In particular, innovation involves a long period of experimentation and uncertain benefits (Braguinsky et al., 2020). Enabled by AI technologies, firms can analyze large-scale data from experimentation or other innovative activities to learn new promising projects and explore new innovation directions (Babina et al., 2022; Mihet & Philippon, 2019). This comes from the ability of AI to greatly improve the process of mining, searching, and aggregating diverse sources of existing knowledge to generate new ones in novel ways (Wu et al., 2019). It helps reduce the uncertainty of experimentation and make the learning process more effective.

With the recent advance of machine learning technologies, AI is able to perform better predictions that allow a firm to learn from the data and create more innovative opportunities at a faster rate and on a larger scale (He et al., 2015; Liu et al., 2023). AI can quickly identify where new projects and innovation opportunities exist (Babina et al., 2022), as it has a remarkable ability to make predictions and generate new insights by discovering hidden patterns from diverse data sources critical for innovation. While human experts are often hampered by information overload and develop innovation within a narrow spectrum of novelty, AI can overcome the limitation by exploring a much larger search space efficiently such that it

[1] See https://www2.deloitte.com/content/dam/insights/us/articles/4780_State-of-AI-in-the-enterprise/DI_State-of-AI-in-the-enterprise-2nd-ed.pdf, accessed on April 14, 2023.

[2] According to a study conducted by Challenger, Gary, & Christmas (see https://www.cnbc.com/2020/01/07/2019-had-the-most-ceo-departures-on-record-with-more-than-1600.html, accessed on April 15, 2023), on average, there are over 1,000 CEO changes in the U.S. every year.

greatly facilitates recombination in innovation (Wu et al., 2019). For example, many firms in the pharmaceutical industry have invested in AI to develop new drug compounds. AI can quickly perform experimentations and identify the most promising compounds with desired pharmacological effects from a combinatoric space of drug candidates (Lou & Wu, 2021).

CEO Turnover and Change in Firm Innovation

Establishing the relationship between a CEO turnover event and a firm' eventual innovation outcomes can be difficult due to the complicated nature of CEO turnover. A CEO turnover event can happen for a variety of reasons, ranging from voluntary departures because of retirement and involuntary terminations due to poor performance (Gentry et al., 2021). Existing studies in the literature have been largely concerned with understanding the relationship between executive turnover and firm performance (Brickley, 2003; Jenter & Kanaan, 2015; Kato & Long, 2006). In particular, a new CEO can affect a firm's innovation outcomes in two ways. First, new CEOs may impede firms' existing innovation trajectories, disrupting the long-term goal of the predecessor, and destabilizing prior organizational routines necessary for developing new innovation strategies (Clayton et al., 2005; Shen & Cannella Jr, 2002). Second, CEO turnover can further promote a change in firm innovation, because new CEOs have not yet established their identity in the firm. They are more risk-tolerant towards engaging in experimentations, and more willing to realign strategic directions and resources with changing environments for innovation (Haveman et al., 2001; Miller & Shamsie, 2001). As the most dominant change agent in a firm, new CEOs seek to guide innovation development teams, influence the quest for new knowledge, and drive the development of innovative projects in a new area (Lavie & Klarner, 2023).[3] Thus, in general, new CEOs aspire to bring changes to their organization (Cummings & Knott, 2018; Denis & Denis, 1995), though the outcomes of the changes are not certain. Furthermore, many CEOs are starting to incorporate AI into their business processes oriented towards innovation development (PwC, 2022). As a CEO turnover event embodies a moment of change in a firm's innovation direction and AI's analytical power is exceptionally suitable to enable some of these changes, new CEOs can adopt AI to facilitate new innovation agenda when they take office.

AI and Innovation Change Following CEO Turnover

Investment in AI can be crucial during the critical but turbulent times of a firm when its new CEO wants to make a change in innovation directions. We argue that during a CEO turnover event, AI can help overcome a new CEO's knowledge inertia, complement the search of new information, and promote a culture of exploring frontiers in innovation. Collectively, they could lead to a strategic change towards new innovation directions.

An important step towards a successful change in innovation is to find a new direction that is feasible and fruitful. A CEO's vision is often backed by her own instinct and past experiences (Sadler-Smith & Shefy, 2004). New CEOs, especially those possessing extensive top management experiences in the same firm, often believe that their experiences are reliable. For such CEOs, known alternatives are more familiar and less risky, and thus they place greater weight on innovation plans that conform to their prior experiences. As a result, they tend to choose innovation areas that are often routinely examined, and disregard unknown directions (Weng & Lin, 2014). Their innovation plans are thus likely to be myopic, leading to knowledge inertia that impedes the exploration in previously untapped areas.

Furthermore, new CEOs need to gather and evaluate new information to determine how to explore new areas of innovation activities (Lavie & Klarner, 2023). However, when searching for information, new CEOs and their innovation development teams often allocate attention to a subset of the environmental factors (Li et al., 2013). This can further reduce the novelty of their ideas and decrease the number of new alternatives for innovation (Weng & Lin, 2014). Accordingly, it's more likely that a new CEO may continue the current innovation direction and not experiment to explore new frontiers.

AI can overcome a new CEO's knowledge inertia and improve the capability of searching and analyzing new information. This can in turn facilitate a firm's strategic change in innovation during a CEO turnover event.

[3] CEOs influence decisions to develop innovation and have the primary responsibility for setting strategic directions and plans for the firms (Calori et al., 1994; Li et al., 2013), even though they may not be directly involved in the execution of innovation process.

First, as known or preferred paths can be wrong, AI can mitigate some of the uncertainty associated with the direction changes by quickly selecting and validating the most feasible paths from a host of ex-ante equally promising directions. For example, with the explosion of granular consumer behaviors data, AI helps firms to better gauge new consumer preferences and design products (Mihet & Philippon, 2019). AI also allows firms to understand new market trends and predict innovation opportunities using external data sources. Informed by AI-enabled predictions, firms can explore more projects with ex-ante unclear prospects, settle on the most promising ones, and efficiently channel limited resources to areas with the highest potentials (Lou & Wu, 2021). AI can thus reduce the costs of experimentation and decrease the needs for repeated trials, both of which can cultivate firms' culture of exploration in innovation.

In practice, shortly after the previous CEO's departure, Nike's current CEO John Donahoe stated that the company would pursue innovation efforts in different directions and unify investment in AI-related technologies to accelerate the company's digital transformation. As a result, AI enables Nike to analyze new consumer behavior and market trend data to develop products tailored to new consumer needs. The products in new areas were produced by customization and recombination of different design elements from an almost unlimited choice set in a short amount of time.[4] It is a feat that is nearly impossible to achieve without AI.

Furthermore, AI helps a firm increase the search scope of new information and improve choices of alternatives for innovation in new areas. This is because AI can operate by performing searches through diverse fields of information space at a larger scale and detecting fresh insights and opportunities unknown to the new CEOs. It can quickly make sense of new information from a changing environment and facilitate a firm's response to external changes. Such power of AI can provide a new CEO with complementary insights and feedback and helps a firm realign strategic directions in changing environments, further promoting a culture of exploring new innovation opportunities in the firm.

Therefore, we propose the following hypothesis: *Compared with firms with less AI investment, firms with greater AI investment are more likely to succeed in changing innovation directions when a new CEO aspires to do so.*

Data and Measurement

To understand how AI can facilitate a directional change in innovation for firms with a CEO turnover, we measure (1) the level of directional change in firm innovation, (2) the AI investment in a firm, (3) CEO turnover, (4) the channel through which AI can facilitate the directional change in firm innovation, and (5) other financial characteristics of a firm that may affect innovation and CEO turnover.

Change in Innovation Direction

We use patent data from the PatentsView database provided by the U.S. Patent and Trademark Office (USPTO) to gauge firms' directional change in innovation, as it has been extensively used in economics and management research to measure innovation and technological progress (Toole et al., 2021). The data provides detailed information through 2021 on patent filling and granted years, assignee, technology class, and citation. We use the filling year of a patent to determine the timing of firms' innovation activities, as it more closely approximates when the firm developed and produced the innovation proposed in the patent application (Wu et al. 2020).

One challenge about using patents to measure innovation direction arises from the difficulty of quantifying the distinctiveness of a patent. One approach widely adopted in the literature is to examine how far technology classes of a firm's patents deviate from those in the firm's prior patent stock (Balsmeier et al., 2017; Wu et al., 2019). A patent's technology class can represent a technological area and proxies the category of a product built upon the patent. Technologically distant patents produced by a firm diverge from its body of existing patents and can capture how the firm undertakes directional change in innovation activities. Therefore, to measure firms' innovation directional change (i.e., to what extent firms enter new

[4] See https://www.digitalsilk.com/nike-artificial-intelligence and https://emerj.com/ai-sector-overviews/artificial-intelligence-at-nike/, accessed on April 14, 2023.

technological areas), we begin by using two measures based on patents' technology classes: technological proximity, and the number of new-class patents.

First, we measure the technological proximity to examine whether a firm stays or deviates from its familiar technological areas (Balsmeier et al., 2017). It is used to quantify the extent of overlap among technological areas between the newly filed patents and the existing patent portfolio. The technological proximity of a firm *i* in year *t* is defined as:

$$Technological\ Proximity_{it} = \frac{\sum_{k=1}^{K} f_{ikt\ to\ t+2} f_{ikt-1}}{\left(\sum_{k=1}^{K} f_{ikt\ to\ t+2}^{2} \cdot \sum_{k=1}^{K} f_{ikt-1}^{2}\right)^{\frac{1}{2}}} \quad (1),$$

where $k = 1,2,\cdots,K$ indexes the four-digit Cooperative Patent Classification (CPC) code of a patent. CPC is a system designed by USPTO to group different technologies based on common grounds. $f_{ikt\ to\ t+2}$ denotes the proportion of firm *i*'s patents that belong to technology class *k* between year *t* and year *t+2*, and f_{ikt-1} is the share of firm *i*'s patent portfolio up to year *t-1* that belongs to class *k*. Technological proximity for a firm in year *t* is computed as the cosine similarity between the firm's patent portfolio between year *t* and year *t+2* and that for all years preceding year *t* (Balsmeier et al., 2017). It provides a continuous measure of whether a firm's innovation stays or deviates from its known innovation areas: if all patents a firm produces in a year are developed in the classes that it never patented before, its technological proximity in the year is zero, implying that innovation direction is changed entirely. On the other hand, a value of one in technological proximity implies that patents filed in a year are distributed across patent classes in the exact same way as the patent portfolio of the same firm in previous years.

Second, we classify a patent as a new-technology-class patent if any of its technology classes appears for the first time for a firm in a year. Thus, at the firm level, we calculate the number of patents filed in technology classes previously unknown to the firm (Balsmeier et al., 2017; Lin et al., 2021). As it takes time for a new CEO to implement innovation strategies, we sum these patents applied by a firm from a given year *t* to year *t+2*.

However, patent class-based measures can be limited when a firm is highly concentrated on certain type of innovation that is less likely to be reflected in the changes in classes of new patents. We address this concern by considering the composition of a firm's patent portfolio and citations. Specifically, for each patent, we calculate the fraction of prior arts it cites that is of existing knowledge to the firm (Brav et al., 2018; Wu et al., 2019). The existing knowledge of a firm is defined as patents that are internally produced by the firm or cited by the firm in the past five years. We classify a patent into five quintiles based on the fraction. A firm's patents in the first quintile only cite 0%-20% of its existing knowledge, and thus represent the most (explorative) effort of a firm to move away from its current knowledge and technology base when more of its citations are built on new knowledge outside the firm. Patents in the fifth quintile, on the other hand, cite 80% -100% of existing knowledge, and thus represent the most effort of a firm to stay with its current knowledge and technology base. We then conduct an aggregation on these patents: for each year, we compute a firm's total numbers of patents in the five quintiles in each year, and then sum the patents applied by a firm in each quintile from a given year *t* to year *t+2*. It also measures varying degree of exploitative vs. exploration in firm innovation.

Overall, these three measures seek to capture different aspects of changes in innovation directions. The use of these measures can be complementary, and thus examining them in tandem allows for a more complete assessment of how AI contributes to directional changes in firm innovation.

AI Investment

We measure a firm's AI investment by using job posting data from a leading analytics company that has collected the near-universe of job postings of U.S. firms from over 40,000 online job boards and company website from 2010 to 2019. A growing body of literature uses labor demand from job postings to infer firms' technology investment and usage (Acemoglu et al., 2020; Babina et al., 2022; Lou & Wu, 2021). In particular, cross-validating job postings with resume dataset of public firms, Babina et al. (2022) find that the two measures of AI investment from the two datasets are highly correlated. From the IS literature, it has been well documented that investment in employees with the requisite technological skills is an important component of technological investment (Tambe & Hitt, 2012; Wu et al., 2020). Thus, using AI-related job postings can capture firms' latent demand for AI skills, intention to engage with AI technologies, and can serve as a good proxy for firm's investment in AI (Acemoglu et al., 2020; Alekseeva et al., 2021; Goldfarb et al., 2023).

Similar to the methods developed in the recent literature on the economic value of AI (Alekseeva et al., 2021; Babina et al., 2022; Lou & Wu, 2021), we examine both the skill requirements and job titles in each posting and search for words commonly related to the knowledge of AI and development of AI technologies. The glossary has words related to the three interrelated technological subfields within AI: robotics, symbolic systems, and machine learning (Cockburn et al., 2018). We also follow a widely accepted computing classification system from the Association of Computing Machinery Computing Classification System that accounts for the computational advancements of AI technologies (WIPO, 2019). This method has been used for over 50 years to organize the classification of concepts and trends of technologies, so it could significantly alleviate the subjective classification of AI.[5] If any of the skills listed under the job title is related to AI, we treat the posting as requiring AI skills. We aggregate the individual-level skill count for each firm-year observation. AI skills are thus estimated by the number of AI-related job postings (*AI*). We also use job-posting data to create a separate skills measure that is only related to machine learning, a subset of the larger AI skills, to reflect recent advances in machine learning (Lou & Wu, 2021). Similarly, we aggregate the number of machine learning-related job postings for each firm in each year and use it to estimate a firm's investment in machine learning to innovate (*AI, machine learning*).

Innovation-oriented Strategic Change

A major approach to measure a firm's level of strategic change in the literature is to trace the change in a firm's pattern of resource allocation decisions over time, using key indicators to profile a firm's strategy (Finkelstein & Hambrick, 1990; Weng & Lin, 2014; Zhang & Rajagopalan, 2010). Thus, innovation-oriented strategic change can be defined as allocations of resources across a set of important strategic areas related to innovation in a firm. Specifically, we begin by using an indicator directly related to firm innovation strategies: research and development intensity, measured by a ratio of R&D expenses to sales (Zhu et al., 2020). We then incorporate another indicator, innovation culture, which entails broader aspects of exploring frontiers in corporate innovation activities than the usual measures of corporate innovation (i.e., R&D expenses and number of patents) (Li et al., 2021). Including a strategic change in cultivating corporate innovation culture can help capture the change in shared values and norms with respect to appropriate attitudes and behaviors for employees in the firm towards innovation. It is manifested beyond R&D expenses and the number of patents, as innovative firms could also have more trade secrets, novel production processes and back-office operations. We leverage corporate innovation culture scores provided by Li et al. (2021). They create a dictionary using the word embedding model on corporate earnings call transcripts to score corporate cultural values of innovation.[6] As CEO is a major speaker in earnings calls, the values extracted from these transcripts can reflect a CEO's intention in exploring new frontiers in innovation. We measure the overall changes oriented towards innovation 2 years after the succession, as it takes time for a new CEO to initiate and implement strategic change (Miller & Shamsie, 2001; Zhu et al., 2020). We calculate the absolute change in each of the two indicators from a given year t to year $t+2$. We then standardize each of these two measures to make them comparable and use the average of the standardized scores to derive a composite measure of innovation-oriented strategic change for each of the CEOs in our sample.[7]

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[5] Using a few variants of the keywords does not lead to significant differences in our measurement.

[6] Li et al. (2021) develop a machine learning approach to measure corporate innovation culture, using earnings call transcripts. They start with using seed words including "creativity" and "innovation" that are established in the literature to be the most representative of innovation culture. Instead of hand-selecting a broader set of words to represent innovation culture, Li et al. (2021) create a *word2vec* embedding model to learn the semantic meanings of words in earnings call transcripts based on their respective contexts. Using this model, each word is represented as a numeric vector and then cosine similarity between any two-word vectors is calculated to determine whether the two words are synonyms. The words that are closest to the seed words are selected to represent the innovation culture. After generating the dictionary about innovation culture, they derive a measure at the firm-year level by calculating the weighted count of the number of words associated with the innovation culture divided by the total number of words in the document.

[7] The literature also measures strategic changes in a firm by examining other five key strategic indicators that appear not directly linked to corporate innovation efforts: advertising intensity (advertising/sales), plant and equipment newness (net P&E/gross P&E), nonproduction overhead in selling, general, and administrative (SGA) expenses (SGA

CEO Turnover and Other Financial Characteristics

To measure CEO turnover, we use two databases that are widely used in the literature to track movements of executives in U.S. firms: BoardEx and Execucomp databases (Bushman et al., 2010; Gentry et al., 2021; Suk et al., 2021) for the 2010-2019 period. The databases extensively track the start and end dates of executives' tenure when they work with their firms, so that we know when a new CEO takes over and an old CEO departs in a firm. We also leverage a CEO turnover dataset provided by Gentry et al. (2021) that identifies different CEO departure reasons. CEO turnover is measured as a binary variable that is equal to one if there is a CEO change in a firm in a given year. As a firm's decision to appoint a CEO is likely an endogenous process that could be influenced by unobservable factors correlated with the firm's innovation performance (Lee et al., 2020), we further identify exogenous CEO turnover events due to CEO death, illness and voluntary retirement.[8]

We collect information about other firm financial characteristics that may affect both firms' innovation activities and CEO turnover from databases including Compustat, Crunchbase, PitchBook and Bureau van Dijk Orbis - these databases are used in prior literature. We include firm age and number of employees to account for firm-level quality and life-cycle considerations in innovation (Lou & Wu, 2021; Loughran & Ritter, 2004; Wu et al., 2019). We also include R&D expense, as it is crucial to facilitate innovation. Our final panel data consists of 1,028 U.S. firms from 2010 to 2019. Table 1 presents summary statistics of variables used in our study.

Empirical Methodology and Identification

To examine the pattern of changes in corporate innovation activities around an CEO turnover event and how a firm's AI investment affects these activities, we extend prior empirical strategies that are used to study the effect of an CEO turnover on firm performance (Kato & Long, 2006) by incorporating AI investment as well as its interaction with the turnover event. In our estimation model, we relate corporate directional changes in innovation (*Innovation*) to a firm's CEO turnover (*CEO turnover*), AI investment (*AI*), controlling for years (y_t) which can address temporal innovation shocks and fluctuations in market movements that may impact CEO turnovers. Firm-fixed effects are used in all models (γ_i) to account for ex-ante differences in innovation and the investment in AI. We control for firm age, number of employees, R&D expenses, and number of patents. Our primary estimating equation is thus:

$$ln(Innovation_{it,\,t+2}) = \beta_0 + \beta_1 CEO\ turnover_{it} + \beta_2 ln(AI)_{it}$$
$$+ \beta_3 CEO\ turnover_{it}\ X\ ln(AI)_{it} + y_t + \gamma_i + Controls_{it} + \varepsilon_{it} \quad (2).$$

The focus of our analysis, β_3, measures the effect of AI on change in innovation direction after a firm has gone through a CEO change. We measure change in innovation direction using a variety of metrics (i.e., technology class-based metrics about technological proximity and new-class patents, as well as the citation-based metrics). We also conduct mediation analyses by adopting similar regression specifications for mechanism tests. Specifically, we first estimate a model by replacing the variable about innovation output in Equation 2 by the mediator, innovation-oriented strategic change. We then estimate another model by including the mediator in Equation 2.

expenses/sales), inventory level (inventory/sales) and financial leverage (debt/equity) (Finkelstein & Hambrick, 1990; Zhu et al., 2020). Data on these strategic indicators are collected from Compustat and updated yearly (Zhang & Rajagopalan, 2010). Similar to how we calculate innovation-oriented strategic change, we calculate the absolute change in each of the five indicators from a given year *t* to year *t+2*. We then standardize each of these five measures to make them comparable and use the average of the standardized scores to derive a composite measure of non-innovation-oriented strategic change for each of the CEOs in our sample.

[8] Gentry et al. (2021) develop a coding scheme that provides detailed categorization of CEO dismissals, as well as voluntary turnover and forms of involuntary turnover not reflecting dismissal (i.e., death and health reasons). They recruit more than 20 coders to identify different CEO departure reasons, and assign a code for each reason. CEO death, illness and voluntary retirement correspond to departure code 1, 2 and 5, respectively, in Gentry et al. (2021).

Variable	Mean	Std dev.
1. Technological proximity, between years t to t+2 and years up to year t-1	0.13	0.22
2. ln(New-class patents, years t to t+2)	0.51	0.73
3. ln(Exploitative 80-100, years t to t+2)	1.40	1.65
4. ln(Exploitative 60-80, years t to t+2)	0.63	1.05
5. ln(Exploitative 40-60, years t to t+2)	0.61	1.04
6. ln(Exploitative 20-40, years t to t+2)	0.60	1.07
7. ln(Exploitative 0-20, years t to t+2)	1.34	1.55
8. CEO turnover	0.13	0.33
9. ln(AI)	0.94	1.37
10. ln(IT)	3.09	2.45
11. ln(AI, machine learning)	0.75	1.22
12. ln(Number of employees)	7.47	1.88
13. ln(Firm age)	3.25	0.64
14. ln(R&D expense)	13.75	7.33
15. ln(Number of patents)	1.41	1.58
Note: we add one to actual values of the variables to avoid the possibilities of taking a natural logarithm of zero.		

Table 1. Summary Statistics

There are several sources of endogeneity associated with Equation 2. While the causal impact of CEO turnover on firm innovation is not the main focus of our study, one may worry that CEO turnover is not exogenous to unobserved firm-year specific factors. Similarly, investment in AI skills is a choice made by firms. A high-performing firms may have more slack resources to invest in advanced technologies (e.g., AI). As a result, estimation on the effects of AI on innovation direction during CEO turnover would be biased.

We employ three methods to address potential endogeneity issues and selection biases with respect to CEO turnover. First, we identify exogenous CEO turnover events due to CEO death, illness and voluntary retirement turnover (Gentry et al., 2021). Second, we use a Heckman two-stage estimation to address the selection biases related to the choice of changing a CEO. The first-stage probit model predicts the probability of firms with a CEO turnover event after controlling for a set of observed firm characteristics including firm age, employee count, R&D expenditure, patent count. We then use the inverse Mills ratio (IMR) calculated from the first stage to correct for selection bias in the second stage regression (Wooldridge, 2010), as recommended in the literature (Certo et al., 2016; Quigley & Hambrick, 2012). Third, we use matching estimators, specifically propensity score matching (PSM), to find a comparable sample of firms without any CEO turnover event that are similar to the firms with a turnover event during the observation period. The matching is conducted on a set of observed firm characteristics as used in the first stage of the Heckman estimation. A matched sample is thus constructed to limit observations in the two groups to those that are as similar to each other as possible.[9] Using PSM in combination with other parametric model estimations can substantially alleviate concerns from selection bias when making causal references (Ho et al., 2007).

Next, we use instrumental variable estimations to address the potential reverse causality of AI investment on firm innovation. Specifically, we create a yearly patent-citation network for each firm in our sample. In the network, each node is a firm, and each link is the aggregate patent citations. For a focal firm's investment in AI skills in a year, we examine AI skills of its neighboring firms whose patents it cites in that year. Our

[9] The matching is conducted on the two group of firms: the treatment group consists of firms with a CEO turnover event and the control group consists of firms without any change in their CEOs in our observation period. Our estimation results on the samples using different matching approaches (e.g., Coarsened Exact Matching) are consistent.

instrument is the total number of neighboring firms with AI skills.[10] The instrumental variable has been similarly used to address endogeneity issues related to firm-level decisions to invest in advanced technologies such as AI (Lou & Wu, 2021; Wu et al., 2020). Having neighbors with AI skills can facilitate knowledge flow across firms, reducing the cost and in turn inducing a focal firm's investment in AI. The associated F-statistic in the first stage is 16.9, passing the threshold for the weak instrument test.

Finally, if it is optimal for firms with a new CEO to invest in AI to facilitate changes in innovation direction, we would expect firms to acquire more AI skills after the CEO turnover. We examine a firm's demand in AI skills around its CEO turnover event, controlling for firm fixed effects (γ_i), year fixed effects (y_t) and other time-varying firm characteristics including firm age, number of employees, R&D expenses, and patent count as used in Equation 2.

$$ln(AI)_{it} = \beta_0 + \beta_1 CEO\ turnover_{it} + y_t + \gamma_i + Controls_{it} + \varepsilon_{it} \quad (3).$$

Overall, we believe that the combination of approaches (fixed effects model, instrumental variables, Heckman two-stage estimation and matching estimators) can reduce the concern that endogeneity issues potentially bias the estimation results. In addition, the use of multiple dependent variables and a specific mechanism test can provide further confidence that our results are likely causal.

Results

We first report estimates of the effects of AI investment using two technology class-based measures of changes in innovation directions: technological proximity (Table 2) and number of new-class patents (Table 3). We find that all else being equal, firms with investment in AI following a CEO turnover event begin to develop patents distinct from those in previous years. Specifically, on average, investment in AI skills is negatively associated with technological proximity of a firm with a CEO turnover (Column 1 in Table 2). We also find that relative to AI skills, a firm's general IT skill has no significant effect on technological proximity when it experiences a CEO change (Columns 2 and 3, $\beta_{ln(IT)\ X\ CEO\ turnover}$ *is insignificant*).[11] While IT is still important to support innovation, it does not provide a competitive edge for firms, possibly because most firms have already invested sufficiently in IT, and earlier best IT practices may have already diffused throughout the firms (Carr, 2003; Chae et al., 2014). However, the main effect of AI (β_2 in equation 2) is insignificant across all specifications in Table 2, indicating that AI investment primarily influences shifts in innovation direction during the CEO turnover period. Because the dependent variable focuses on direction of innovation, this result does not imply that firms cannot benefit from AI investment for innovation outside of the CEO turnover period. Instead, it highlights AI's role in facilitating change, when new CEOs aspire to drive change (Haveman et al., 2001; Miller & Shamsie, 2001). In periods outside CEO turnover, the need and intent for change can be less urgent, and thus, AI's effect on innovation direction change can be limited. AI can be more effective when there is an intent to change.

DV is Technological proximity					
Model: FE	(1)	(2)	(3)	(4)	(5)
CEO turnover	0.0138	0.0131	0.00676	0.00822	0.00719
	(0.00968)	(0.0120)	(0.0120)	(0.00958)	(0.0149)
ln(AI)	-0.00262		0.00106		-0.00256
	(0.00506)		(0.00564)		(0.00591)
ln(AI) X CEO turnover	-0.0174***		-0.0235**		-0.0224**

[10] We also use two variations of the instrument: the average AI skills in the neighboring firms and the average ratio of a firm's AI skills to total skills for these neighbors. We obtain similar results.

[11] We also use job postings to identify IT skills based on skill requirements as well as job titles (Lou & Wu, 2021). For example, IT skills listed in a job posting include software development and hardware support, and IT-related job titles include software engineer and systems analyst (Hitt et al., 2021; Tambe & Hitt, 2012). If a job posting also contains keywords such as computer, website, software, and telecommunication, we identify it as requiring IT skills. We aggregate IT skills in each firm, similar to our construction of AI skills.

	(0.00639)		(0.00992)		(0.0105)
ln(IT)		-0.00426	-0.00481		
		(0.00346)	(0.00387)		
ln(IT) X CEO turnover		-0.00441	0.00395		
		(0.00307)	(0.00473)		
ln(AI, machine learning)				-0.00123	
				(0.00547)	
ln(AI, machine learning) X CEO turnover				-0.0131**	
				(0.00657)	
ln(Firm age)	-0.0506	-0.0540	-0.0511	-0.0505	-0.0300
	(0.0441)	(0.0441)	(0.0439)	(0.0443)	(0.0482)
ln(Number of employees)	-0.00806	-0.00612	-0.00610	-0.00856	-0.00254
	(0.0102)	(0.0105)	(0.0105)	(0.0102)	(0.0121)
ln(R&D expense)	-0.000792	-0.000762	-0.000853	-0.000780	-0.000529
	(0.00220)	(0.00220)	(0.00220)	(0.00220)	(0.00284)
ln(Number of patents)	0.0671***	0.0672***	0.0672***	0.0670***	0.0693***
	(0.00863)	(0.00862)	(0.00860)	(0.00864)	(0.0108)
Observations	5,179	5,179	5,179	5,179	3,766
R^2	0.568	0.568	0.569	0.568	0.557
Notes: (1) Year and firm fixed effects are included in all models. (2) *** p<0.01, ** p<0.05, * p<0.1					

Table 2. AI Skills, CEO Turnover and Directional Innovation Change: Technological Proximity of Patents

We also find that over 70% of the effect of AI comes from recent advances in machine learning (Column 4). To alleviate the potential endogeneity concern of CEO turnover, we identify exogenous CEO turnover events due to CEO death, illness and voluntary retirement turnover (Gentry et al., 2021). We retain firms with an exogenous CEO turnover event and those without any CEO change in our sample, and repeat the estimation again. We obtain consistent results with respect to the effect of AI on technological proximity following a firm's CEO change. In all estimations, standard errors are clustered at the firm level. Similarly, we use the number of new-class patents as a dependent variable in the estimation. We find that all else being equal, on average, a 1% increase in AI skills is associated with 0.05% increase in the number of new patents in technology classes that a firm never had a patent before (Column 1 in Table 3). We also obtain similar results that this effect is not driven by general IT skills (Columns 2 and 3) but driven by machine learning (Column 4), and it is not susceptible to the endogeneity of CEO turnover (Column 5). Overall, our results show that a firm's AI investment is primarily responsible for facilitating directional changes in innovation after a CEO turnover event.

DV is ln(New-class patents)					
Model: FE	(1)	(2)	(3)	(4)	(5)
CEO turnover	-0.0237	-0.0135	0.00730	-0.0126	0.00202
	(0.0276)	(0.0347)	(0.0346)	(0.0266)	(0.0424)
ln(AI)	-0.0110		-0.0165		-0.00384
	(0.0163)		(0.0168)		(0.0195)
ln(AI) X CEO turnover	0.0509**		0.0776***		0.0617*
	(0.0203)		(0.0300)		(0.0330)

ln(IT)		0.000835	0.00634		
		(0.0116)	(0.0121)		
ln(IT) X CEO turnover		0.00982	-0.0175		
		(0.00952)	(0.0140)		
ln(AI, machine learning)				-0.00652	
				(0.0181)	
ln(AI, machine learning) X CEO turnover				0.0456**	
				(0.0229)	
ln(Firm age)	0.0292	0.0398	0.0281	0.0311	-0.0780
	(0.148)	(0.147)	(0.148)	(0.147)	(0.168)
ln(Number of employees)	-0.00990	-0.0129	-0.0119	-0.0112	-0.0445
	(0.0320)	(0.0328)	(0.0329)	(0.0320)	(0.0341)
ln(R&D expense)	-0.00203	-0.00210	-0.00184	-0.00204	-0.00300
	(0.00533)	(0.00528)	(0.00525)	(0.00530)	(0.00668)
ln(Number of patents)	0.279***	0.278***	0.279***	0.279***	0.289***
	(0.0181)	(0.0181)	(0.0182)	(0.0181)	(0.0208)
Observations	5,179	5,179	5,179	5,179	3,766
R^2	0.770	0.769	0.770	0.769	0.777
Notes: (1) Year and firm fixed effects are included in all models. (2) *** p<0.01, ** p<0.05, * p<0.1					

Table 3. AI Skills, CEO Turnover and Directional Innovation Change: New-class Patents

It is possible that our estimation results are driven by selection biases—that firms changing their CEOs were poised to experience directional change in innovation. We follow methods adopted in the literature to address the selection issue around the CEO turnover (Certo et al., 2016). Specifically, we find that Heckman selection methods can help rule out the issue around the decision to change a CEO in the first place and produce consistent results (Columns 1 and 3 in Table 4). We then adopt a 2SLS estimation approach with the Heckman corrections following our regression specification (Equation 2) to address the potential endogeneity arising from a firm's choice to invest in AI skills (Column 2 and 4 in Table 4). The associated F-statistic in the first stage of 2SLS estimation is 16.9, passing the threshold for the weak instrument test. In addition, we adopt PSM method that balances the sample of firms undergoing at least one CEO turnover event and firms without any CEO change, based on the observable characteristics including firm age, number of employees, R&D expenses and patent count. The estimation results on the matched sample generated by PSM are consistent with other estimation results (Table 5). Overall, these results suggest that AI has a positive effect on spurring changes in innovation directions after a firm changes its CEO.

	(1)	(2)	(3)	(4)
Model	FE	FE+IV	FE	FE+IV
DV	Technological proximity	Technological proximity	ln(New-class patents)	ln(New-class patents)
CEO turnover	0.0135	0.0211	-0.0241	-0.137
	(0.00907)	(0.0286)	(0.0202)	(0.0880)
ln(AI)	-0.00243	0.277	-0.0108	-0.125
	(0.00333)	(0.309)	(0.0108)	(0.643)
ln(AI) X CEO turnover	-0.0170***	-0.0510**	0.0514***	0.205**
	(0.00381)	(0.0217)	(0.0130)	(0.103)
ln(Firm age)	-0.0491	0.0376	0.0309	-0.0240
	(0.0346)	(0.222)	(0.0947)	(0.315)
ln(Number of employees)	-0.00821	-0.0822	-0.0101	0.0172

	(0.0111)	(0.0940)	(0.0344)	(0.181)
ln(R&D expense)	-0.000601	0.000975	-0.00183	-0.00216
	(0.00191)	(0.00239)	(0.00664)	(0.00479)
ln(Number of patents)	0.0698***	0.0642**	0.282***	0.290***
	(0.00764)	(0.0272)	(0.0206)	(0.0246)
IMR	-0.457	-0.618	-0.491	-0.799
	(0.641)	(0.602)	(0.896)	(1.207)
Observations	5,179	5,179	5,179	5,179
Notes: (1) Year and firm fixed effects are included in all models. (2) *** p<0.01, ** p<0.05, * p<0.1				

Table 4. AI Skills, CEO Turnover and Directional Innovation Change: Technological Proximity of Patents and New-class Patents (Heckman Corrections)

	(1)	(2)	(3)	(4)
Model	FE	FE+IV	FE	FE+IV
DV	Technological proximity	Technological proximity	ln(New-class patents)	ln(New-class patents)
CEO turnover	0.0126	0.0390*	-0.0237	-0.122*
	(0.00866)	(0.0209)	(0.0248)	(0.0638)
ln(AI)	-0.00289	-0.0497	-0.0130	-0.191
	(0.00481)	(0.125)	(0.0155)	(0.278)
ln(AI) X CEO turnover	-0.0170***	-0.0475*	0.0517***	0.195**
	(0.00602)	(0.0261)	(0.0189)	(0.0837)
ln(Firm age)	-0.0626	-0.0656	0.0391	-0.0342
	(0.0422)	(0.0533)	(0.139)	(0.152)
ln(Number of employees)	-0.00768	0.00547	0.00840	0.0540
	(0.00949)	(0.0353)	(0.0302)	(0.0829)
ln(R&D expense)	-0.00212	-0.00241	-0.00245	-0.00306
	(0.00198)	(0.00210)	(0.00535)	(0.00585)
ln(Number of patents)	0.0684***	0.0702***	0.275***	0.281***
	(0.00805)	(0.00808)	(0.0172)	(0.0196)
Observations	4,851	4,851	4,851	4,851
R^2	0.580		0.769	
Notes: (1) Year and firm fixed effects are included in all models. (2) *** p<0.01, ** p<0.05, * p<0.1				

Table 5. AI Skills, CEO Turnover and Directional Innovation Change: Technological Proximity of Patents and New-class Patents (PSM)

Next, we explore the underlying mechanism of the effect of AI. Specifically, we estimate a model by linking innovation-oriented strategic change to a firm's AI skills, CEO turnover and other observed characteristics. We find that AI can facilitate a strategic change in a firm's R&D resource allocation and innovation culture of exploring new frontiers after a CEO turnover (Column 1 in Table 6). We then estimate another model by including the mediator in Equation 2. We find similar interaction effect of AI investment and CEO turnover, and that the mediator can further change a firm's innovation directions (Columns 2 and 3). We also conduct a falsification test and find that AI cannot significantly facilitate a strategic change in areas that are not directed toward innovation (Column 4).[12] These results suggest that AI capabilities facilitate innovation

[12] Footnote 7 presents more details about how we calculate non-innovation-oriented strategic change.

direction change in the firm by enabling strategic change in innovation culture and R&D investment over time.

Model: FE	(1)	(2)	(3)	(4)
DV	Innovation-oriented strategic change	Technological proximity	ln(New-class patents)	Non-innovation-oriented strategic change
Innovation-oriented strategic change		-0.0105**	0.0320**	
		(0.00525)	(0.0140)	
CEO turnover	-0.0219	0.0136	-0.0230	-0.00328
	(0.0315)	(0.00967)	(0.0276)	(0.0173)
ln(AI)	0.00516	-0.00256	-0.0111	-0.00575
	(0.0122)	(0.00506)	(0.0163)	(0.00771)
ln(AI) X CEO turnover	0.0451**	-0.0170***	0.0494**	0.0190
	(0.0229)	(0.00637)	(0.0202)	(0.0127)
ln(Firm age)	0.0817	-0.0497	0.0266	-0.0376
	(0.143)	(0.0442)	(0.147)	(0.103)
ln(Number of employees)	-0.0178	-0.00825	-0.00933	-0.0820***
	(0.0292)	(0.0103)	(0.0319)	(0.0278)
ln(R&D expense)	-0.00379	-0.000832	-0.00191	-0.00183
	(0.00582)	(0.00221)	(0.00535)	(0.00218)
ln(Number of patents)	-0.00839	0.0670***	0.279***	0.00186
	(0.0126)	(0.00861)	(0.0181)	(0.00578)
Observations	5,179	5,179	5,179	4,501
R^2	0.503	0.569	0.770	0.665
Notes: (1) Year and firm fixed effects are included in all models. (2) *** p<0.01, ** p<0.05, * p<0.1				

Table 6. Mechanism: Innovation-oriented Strategic Change

Furthermore, to explore to what extent a firm's innovation directions can be affected by its AI investment, we repeat our main analyses by counting only innovations that cite a certain fraction of a firm's own prior art (from 0 to 100% in quintiles). We find that the interaction effect of AI and CEO turnover improves as the proportion of external information outside a firm increases, peaking at a citation rate of around 20%-40% of existing knowledge. Thus, AI can be mostly useful in fostering a directional change in innovation that is moderately different from a firm's prior art: a 1% increase in AI investment is associated with about 0.04% and 0.06% increases in numbers of patents that cite 40%-60% and 20%-40% of existing knowledge of the firm, respectively (Columns 3 and 4 in Table 7). This estimate is consistent with that for new-class patents as in Table 3, as they are not drastically different from the prior art (they are only novel to the firm but not to the external market). However, the interaction effect becomes statistically insignificant when prior citations to a firm's patent stock are below 20% (i.e., patents that are drastically different from the prior art) (Columns 5).

Model: FE	(1)	(2)	(3)	(4)	(5)
DV	80-100	60-80	40-60	20-40	0-20
CEO turnover	-0.0428	-0.0265	-0.0208	-0.0176	0.00854
	(0.0267)	(0.0243)	(0.0243)	(0.0263)	(0.0335)
ln(AI)	0.00403	-0.00527	-0.0127	-0.0184	-0.0152
	(0.0128)	(0.0149)	(0.0125)	(0.0121)	(0.0171)
ln(AI) X CEO turnover	0.0158	0.0379	0.0409**	0.0579***	0.0274

	(0.0203)	(0.0232)	(0.0192)	(0.0216)	(0.0239)
ln(Firm age)	0.116	0.245**	0.189*	0.197	0.0532
	(0.140)	(0.113)	(0.109)	(0.130)	(0.162)
ln(Number of employees)	0.0188	-0.000816	0.0461	0.0179	0.0786
	(0.0376)	(0.0318)	(0.0320)	(0.0355)	(0.0532)
ln(R&D expense)	-0.00271	0.00805*	-0.00297	-0.00451	-0.00830
	(0.00591)	(0.00464)	(0.00522)	(0.00701)	(0.00924)
ln(Number of patents)	0.741***	0.391***	0.380***	0.373***	0.656***
	(0.0281)	(0.0331)	(0.0327)	(0.0323)	(0.0294)
Observations	5,179	5,179	5,179	5,179	5,179
R^2	0.956	0.903	0.903	0.901	0.932
Notes: (1) Year and firm fixed effects are included in all models. (2) *** p<0.01, ** p<0.05, * p<0.1					

Table 7. AI Skills, CEO Turnover and Directional Innovation Change: Exploration of Innovation

Lastly, if AI investment is an optimal decision for firms especially when they seek to change innovation directions, we would expect a new CEO should seek to acquire more AI skills. We find that CEO turnover is associated with a 7% increase in investment in AI (Column 1 in Table 8), and the effect is mainly driven by recent advances in machine learning (Column 3). However, we don't observe a significant effect of CEO turnover on IT skills (Columns 2). Overall, these results imply that a new CEO can optimally allocate efforts to acquire employees with AI capabilities to fulfill her plan to undertake change in innovation directions.

Model: FE	(1)	(2)	(3)
DV	ln(AI)	ln(IT)	ln(AI, machine learning)
CEO turnover	0.0688**	0.0288	0.0598**
	(0.0341)	(0.0576)	(0.0300)
ln(Firm age)	-0.285	-0.429	-0.178
	(0.212)	(0.404)	(0.192)
ln(Number of employees)	0.267***	0.639***	0.235***
	(0.0479)	(0.0967)	(0.0405)
ln(R&D expense)	-0.00557	-0.00919	-0.00844
	(0.00782)	(0.0161)	(0.00647)
ln(Number of patents)	0.0314	0.0537	0.0172
	(0.0219)	(0.0373)	(0.0203)
Observations	5,179	5,179	5,179
R^2	0.840	0.875	0.830
Notes: (1) Year and firm fixed effects are included in all models. (2) *** p<0.01, ** p<0.05, * p<0.1			

Table 8. CEO Turnover and Demand for AI Skills

Concluding Remarks

This paper studies the role of a firm's AI investment in shaping its innovation strategies in uncertain times when the new leadership intends to change the status quo. Using a large sample of firms that have gone through a CEO turnover as well as measuring their changes in innovation directions, we find that investment in AI, as measured by skillsets of employees, can induce a directional change in innovating in new areas. The effect of AI is mainly driven by the continued development of innovation in areas that are modestly different from the existing ones. However, we do not find evidence that AI can help firms create innovations that differ substantially from the past. Our results are robust to firm-level fixed effect models, instrumental variables, Heckman selection models and matching estimators. Furthermore, our findings show that AI can enable strategic change in cultivating culture of exploring frontiers in innovation and managing R&D over time. We also find evidence that firms are increasing their investments in AI after CEO turnover events, suggesting that a new CEO can tap into AI to pivot innovation strategies by allocating more resources to the acquisition of employees with greater technological capabilities such as AI skills.

To the best of our knowledge, our study is among the first to highlight the critical role of AI in facilitating strategic change in innovation during the uncertain time of leadership changes. While the IT literature has started to explore technology investments as a key enabler of innovation, our study highlights the importance of examining technology as a critical input factor in innovation during the uncertain time. By showing how AI can accelerate the innovation change after CEO turnovers, our study bridges the IT literature and the innovation literature.

This study informs firms and newly appointed CEOs who seek to overcome the innovation inertia and drive change within their organizations. Our findings highlight the importance of using AI to effectively shift corporate innovation directions. CEOs can allocate more resources toward AI investment, thereby catalyzing a conducive environment for change. Firms can hire individuals with AI skills to realize their envisioned strategic shifts. Meanwhile, we provide boundary conditions that illuminate the nuanced impact of AI in driving change. The effect of AI is most pronounced when orchestrating shifts in directions that exhibit a moderate departure from established precedents. This insight can help leaders target their innovation efforts, ensuring that AI is used optimally to facilitate meaningful transformation.

As existing AI technologies can only facilitate certain types of innovation change, future work could explore how recent advances in AI (e.g., large language models (LLMs)), and potentially other new general-purpose technologies, might further aid innovation (Lou et al., 2023). It is likely that these relationships will continue to evolve during the leadership change as new capabilities in AI are developed.

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