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Mapping green innovation with machine learning: Evidence from China

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ABSTRACT

Achieving green innovation to eliminate the environmental impact of economic activities has been an important task for firms across industries. This study uses the resource-based view (RBV) and upper echelons theory (UET) to develop a green innovation determinants model and explore how firm characteristics, chief executive officer (CEO) characteristics, environmental actions, environmental disclosures, and industry characteristics influence corporate green innovation. Using a large-scale dataset of Chinese companies from 2010 to 2019 to identify the determinants of green innovation through machine learning algorithms, our results suggest that the extreme gradient boosting (XGBoost) method is the best model for predicting green innovation. After that, we visualized the effects and importance of the various feature variables through the best prediction model. Our results indicate that the environmental, social, and governance (ESG) rating is the most crucial determinant for green innovation, followed by internationalization, CEO pay, firm sales, industry size, research and development (R&D) intensity, and CEO education. Overall, our findings contribute to a broader understanding of the drivers of green innovation and offer critical implications for managers and policymakers to improve sustainable development.

1. Introduction

As global resources become increasingly scarce and environmental degradation worsens, an industrial revolution based on new energy is emerging, characterized by green innovation, which will create new demand and markets and change the mode of production, people's lifestyles, and the course of human civilization development. Green innovation has emerged as the keyword in today's economic growth and is essential for building a sustainable world (Gao et al., 2023; Irfan et al., 2022; Luo et al., 2023). Human activities have unfavorable environmental repercussions (e.g., climate change and global warming), such as melting ice caps, heavier storms, and hurricanes (Kunapatarawong and Martínez-Ros, 2016; Patz et al., 2005). The resource consumption and emission activities involved in corporate operations are one of the main factors contributing to the current state of the environment. Simultaneously, various stakeholders' tremendous pressure on environmental legitimacy motivates businesses to produce innovations that benefit the environment. Thus, many organizations attempt to be green by establishing a sustainable operations strategy (Barney, 2001; Bansal and Clelland, 2004).

Does green innovation entail an all-round sculpting of the organization, and does this effort matter to the environment? The following example illustrates this point. Procter and Gamble (P&G) is essential in tackling climate change due to its dedication to green innovation and climate protection through structural change. By extensively engaging in green innovation, P&G saved approximately 7 million sheets of paper and 38.5 tons of cardboard annually by introducing paperless product directions.[1] Furthermore, this multinational consumer goods corporation employed environmental protection in its supply chain management design. It created a sustainable green supply chain network with a rapid response and full link coordination. In 2020, P&G reconstructed the network scale, improved the efficiency of long-distance transportation, and reduced the distance between P&G and customers by 35 % through the new logistics network, which reduced CO_2 emissions by approximately 1700 tons annually, equivalent to planting 90,000 trees. In addition, they have set a new vision to achieve net-zero greenhouse gas emissions by 2040 by implementing green innovations in the supply chain, operations, and product lifecycle.

When pursuing green innovation as a corporate strategy, it is essential to understand its drivers and mechanisms to make appropriate

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[1] Detailed information can be found at https://www.pghongkong.com/en-us/environmental-sustainability/.

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adjustments. Although the previous literature has proposed some antecedents of green innovation (Woo et al., 2014; Liao and Long, 2018; Tan and Zhu, 2022; Wen et al., 2023), their findings are subject to ongoing debate and contention (Ziegler and Nogareda, 2009; Li et al., 2019). Based on the resource-based view (RBV) and upper echelons theory (UET), the current research seeks to fill these gaps by developing a model that systematically examines how to determine corporate green innovation using firm characteristics, chief executive officer (CEO) characteristics, environmental actions, environmental disclosures, and industry characteristics.

The RBV emphasizes that a firm's competitiveness comes from tangible and intangible resources that are unique, durable, and inimitable (Mahoney and Pandian, 1992). Following this logic, the competitive advantage in green innovation may arise from firms' resources and capabilities. Therefore, our model considers a firm's resources from the perspectives of firm characteristics, environmental actions, environmental disclosures, and industry characteristics, as they are heterogeneous resources that drive a firm's performance and sustained competitive advantages. First, firm characteristics, environmental actions, and environmental disclosures are significant intrinsic resources that can play a role in corporate green innovation. For instance, firms that are more internationalized and possess larger market shares may have more tangible (e.g., capital, facilities) and intangible (e.g., intellectual capital) resources to enhance green innovation (Du and Zhao, 2023; Jirakraisiri et al., 2021).

In addition, a firm's environmental actions and environmental disclosures are significant resources that lead to better performance as they reflect a firm's commitment to pro-environmental behavior and can bring reputation-building effects to the firm (Benlemlih et al., 2018; Longoni and Cagliano, 2018). Of note, one should not overlook the impact of industry characteristics on green innovation, as RBV argues that firms need to make trade-offs when allocating strategic resources (Mahoney and Pandian, 1992). Since different industries have different resource bases, environmental challenges, and opportunities, they have different needs and pressures for green innovation. Specifically, some industries (e.g., construction and fashion) may urgently need to transition to a greener and more sustainable model (Shurrab et al., 2019; Ikram, 2022), while others (e.g., steel and pulp and paper) may focus more on innovation in the efficient use of resources and energy (Hernandez et al., 2018; Johansson et al., 2021). In this regard, firms in different industrial settings may allocate resources for green innovation differently.

In addition to the resource-centric perspectives, we used UET as a theoretical basis to study the impact of CEO characteristics on corporate green innovation. UET provides an interesting perspective on corporate green innovation, and the CEO characteristics may have a meaningful impact on the decision-making process, resource allocation, and organizational culture, which in turn affects corporate green innovation (Al-Najjar and Salama, 2022; Waldman et al., 2004). For example, CEO education influences CEOs' values and cognitive preferences (Bai et al., 2020), which may affect their value of green innovation (Daellenbach et al., 1999). CEOs who value environmental sustainability and believe green innovation brings business opportunities and competitive advantages may be more inclined to drive green innovation in their companies (Wang et al., 2023). In addition, the sensitivity and awareness of CEOs to environmental issues can also influence their decision-making, which in turn impacts green innovation (Wang et al., 2023).

Thus, this study attempts to develop a green innovation determinants model and investigate whether and how firm characteristics, CEO characteristics, environmental actions, environmental disclosures, and industry characteristics affect corporate green innovation by employing machine learning models on a large-scale dataset of Chinese firms. The machine learning approach can provide valuable insights vis-à-vis innovation studies using various algorithms supported induction. It can also eliminate estimation bias by "learning" patterns from the data instead of assuming patterns (Choudhury et al., 2021; Liu et al., 2023b). Moreover, the results of machine learning models are interpretable based on various novel methods, and the findings are robust, easily traceable, and replicable by other scholars (Shrestha et al., 2021; Liu et al., 2023a).

Our study adds significant value to the innovation management field in two broad ways. First, this study develops a green innovation determinants model and extends our understanding of the drivers of green innovation. Despite green innovation has been found to be driven by institutional and firm characteristics (e.g., Amore and Bennedsen, 2016; Berrone et al., 2013), our research offers extensions to the theoretical foundation by demonstrating that environmental actions and industry characteristics matter in corporate green innovation. Second, our study contributes to the green innovation literature by offering effective predictive analytics empowered by a machine learning approach and holistically demonstrating how firm characteristics, CEO characteristics, environmental actions, environmental disclosures, and industry characteristics influence green innovation. This contribution has significant implications for emerging markets in terms of improving environmental performance and sustainable economic development, and green innovation can be regulated and encouraged in a targeted manner.

We organized the remainder of this paper as follows. Section 2 reviews the related literature on green innovation and its drivers. Section 3 discusses the sample selection, variable definitions, and machine learning approaches. Section 4 compares the performances of the machine learning models and presents the main results. Finally, we offer the discussion, conclusion, and limitations of our research and future research directions in Section 5.

2. Literature review

2.1. Theoretical underpinning

Green innovation can be defined as new or improved products and processes, including technological, managerial, and organizational innovations that serve to sustain the environment (Huang and Li, 2017; Kunapatarawong and Martínez-Ros, 2016; Oduro et al., 2022). More specifically, scholars emphasize the envisaged advantages of "innovation" over its associated alternatives in terms of negative environmental impacts (Oduro et al., 2022). As one of the most critical components in gaining competitive advantage and sustainable development, green innovation offers significant strategic value for the long-term success of business and society (Huang and Li, 2017; Quan et al., 2021; Xie et al., 2015). Prior literature suggests that firm-level green innovation can be affected by several complex factors that include but are not limited to, environmental mindfulness, legitimacy pressure from the market and stakeholders, and regulations (Barney, 2001; Afeltra et al., 2023; Oduro et al., 2022). Drawing on RBV and UET, we propose a theoretical framework built on five research streams of green innovation determinants: firm characteristics, CEO characteristics, environmental actions, environmental disclosures, and industry characteristics.

RBV is a strategic management theory that explains the differentiated competitive advantages of firms. This theory holds that the success of an enterprise depends on its unique, scarce, and difficult-to-imitate resources and capacities (Mahoney and Pandian, 1992; Barney, 2001). Resources refer to various assets owned by an enterprise, including physical resources (such as equipment, technology, capital, etc.) and intangible resources (such as brand reputation, know-how, intellectual property rights, etc.) (Galbreath, 2005). RBV states that the differentiated competitive advantage of a firm comes from its unique resources and capabilities (Galbreath, 2005). In this study, we argue that the critical resources in promoting green innovation include firm characteristics, environmental actions, environmental disclosures, and industry characteristics.

Firm characteristics can provide companies with a basis for gaining a competitive advantage in green innovation (Woo et al., 2014; Yu et al., 2021). Regarding green innovation, firms must adopt positive environmental actions, such as saving energy and lowering the carbon footprint (Lin and Ma, 2022). RBV emphasizes firms' unique, imitable resources and capabilities in achieving competitive advantages (Galbreath, 2005). Proactive environmental actions can help firms develop and utilize innovative, environmentally friendly technologies and approaches to create a green competitive advantage (Kraus et al., 2020; Yuan and Cao, 2022). From the RBV perspective, environmental disclosure, as a tool of legitimacy, can help corporations demonstrate their unique environmental management and innovation capabilities, increase their reputation and credibility, creating invisible resources for firms (Benlemlih et al., 2018; Tilling and Tilt, 2010).

Also, based on RBV, firms' resources and capabilities evolve as the differences in industry (Lien and Klein, 2013; Ye et al., 2023). Industry characteristics can serve as a valuable information resource for firms, as they can reference "what others are doing" concerning clean energy, green production, and innovation. Notably, firms can collaborate with these peers and experts within the industry to drive green innovation (Rauter et al., 2019). Moreover, industry characteristics also shape enterprises' competitive environment and market demand. A high industry demand for green products and services will incentivize companies to innovate green (Xie et al., 2019). Competition within the industry may also drive companies to engage in more aggressive green innovation to gain a competitive advantage (Esty and Winston, 2009).

UET looks at an organization's top management team to understand and explain its impact on organizational decisions, behaviors, and performance (Waldman et al., 2004). UET states that the characteristics, background, and values of a top management team have a profound impact on an organization's strategic choices and performance (Hambrick and Mason, 1984) and emphasizes the importance of corporate leadership, which can explain the role of CEO characteristics in driving green innovation. First, UET focuses on the leader's cognition and level of awareness. CEO awareness of green innovation is an important factor in promoting green innovation. According to this theory, if CEOs are environmentally conscious and actively identify with green innovation, they are likely to advocate and promote the implementation of green innovation. Second, UET emphasizes the leader's competence and leadership style. Green innovation requires CEOs to have strategic thinking, innovation capabilities, and team management capabilities, and CEOs with overseas experience will be more diversified in this regard (Quan et al., 2021). CEOs need to have keen market insight, integrate green innovation into corporate strategy, and be able to motivate employees to participate in green innovation activities. In addition, UET emphasizes the decision-making ability and action of leaders. Green innovation requires CEOs to make positive decisions and translate decisions into practical actions, and good CEO pay is an excellent incentive. Hence, CEOs lead the way to green innovation through decisions and actions.

2.2. Firm characteristics and green innovation

The importance of firm characteristics as a significant role in green innovation is widely acknowledged (Woo et al., 2014; Yu et al., 2021). First, the existing literature highlights that investing in green innovation requires considerable financial and human resources (Baylis et al., 1998; Chen, 2008; Rehfeld et al., 2007; Woo et al., 2014). Larger companies have an edge in green innovation because they have more significant resources for green innovation investment (Lin et al., 2014), while small and medium-sized enterprises (SMEs) fail to have the same level of green core competence or innovation performance as large businesses owing to limited capital and human resources (Woo et al., 2014). Prior literature also argues that higher profitability will facilitate corporate green innovation, as it can obtain more resources to support the research and development (R&D) input of green technology and renewable energy (Barney, 2001). For example, higher profitability would enable a firm to invest in more eco-friendly technologies and management systems (Barney, 2001), and higher financial performance suggests that a company suffers fewer financial constraints, at which point firms are significantly more capable of green innovation (Yu et al., 2021). Furthermore, understanding how R&D activities affect green innovation has been an important research topic for scholars. Several studies have revealed that R&D intensity is critical in promoting corporate green innovation (Horbach, 2008; Sánchez-Sellero and Bataineh, 2021).

2.3. CEO characteristics and green innovation

A firm's pro-environmental behavior results from the external environment and organizational values and the perception and values of the top management team, especially strategic leaders such as CEOs (Liao and Long, 2018). CEOs' different ideas may lead to distinct decision-making outcomes for a given project. For example, CEOs who focus on growth are more "open" to new ideas and values and are more likely to adopt risk-taking strategies (Benischke et al., 2019). In contrast, CEOs prioritizing stability and responsibility are more sensitive and risk-averse, adopting a conservative strategy. In this regard, prevention-conscious CEOs are more likely to adopt a cautious approach when dealing with environmental processes and product innovation. CEOs emphasize the potential increasing costs and resource consumption associated with innovation, leading them to reduce innovation activities to avoid possible losses (Liao and Long, 2018). Recently, scholars have propounded that CEO characteristics are closely related to green innovation (e.g., Liao and Long, 2018; Quan et al., 2021). According to previous research, international experience can strengthen CEOs' competencies, essential in green innovation creation (Leung et al., 2008; Quan et al., 2021).

Moreover, CEO education is an essential aspect of corporate green innovation and contributes to exploring how CEO education fosters corporate green innovation. For example, Zhou et al. (2021) confirm that improved CEO education's positive environmental innovation effect is partly attributable to corporate green R&D investment and environmental responsibility. In addition, He and Jiang (2019) provide a new perspective on green innovation from a CEO gender viewpoint and reveal that a further increase in the representation of women in top management is more likely to promote green product innovation because female CEOs have stronger prosocial preferences and environmental concerns than men. Thus, the CEO facilitates green innovation as a corporate spokesperson representing a firm's image.

2.4. Environmental actions and green innovation

Environmental actions refer to firms' activities to conserve energy and mitigate pollution, as well as initiatives intended to promote environmental protection (Wang et al., 2018), such as environmental, social, and governance (ESG), corporate social responsibility (CSR), and environmental management systems (EMSs), as key indicators of corporate environmental actions. Recent studies have found that ESG and CSR performance positively affect the outcome of corporate green innovation (Tan and Zhu, 2022; Xu et al., 2020). Organizations engage in ESG initiatives to deliver positive messages, transmit green signals to internal employees, and achieve pro-environmental performance. For example, in an investigation of Chinese listed firms, Xu et al. (2020) found that increased ESG ratings may result in higher green innovation performance. This improved performance is because companies seeking ESG development benefit from corporate reputation, investor attractiveness, employee satisfaction, and technological innovation (Xu et al., 2020).

Moreover, firms with a proactive CSR strategy can engender more radical green innovation than those with a reactive CSR strategy (Kraus et al., 2020; Yuan and Cao, 2022). Proactive firms are more concerned about CSR issues and more sensitive to CSR trends than reactive companies, which drives radical green innovation (Kraus et al., 2020; Yuan and Cao, 2022). More importantly, because radical green innovation requires resources such as personnel and equipment, proactive companies devote more resources to green innovation and also stimulate the creativity of researchers to encourage green innovation while at the same time having a high tolerance for failure (Kraus et al., 2020; Yuan and Cao, 2022). In addition, scholars have found that EMSs, such as ISO 14001, significantly and positively promote corporate green innovation (Li et al., 2019). Companies implementing environmental actions to meet different strategies and policies proactively adopt green innovation with potential environmental benefits (Demirel and Kesidou, 2011; Kawai et al., 2018).

2.5. Environmental disclosures and green innovation

As the core of green innovation involves eliminating environmental risks, pollution, and other negative impacts in operations, we argue that firms' environmental disclosures can signal how they develop solutions to pollution and resource depletion and, by extension, green innovation. Voluntary environmental disclosure is a significant driver of corporate green innovation. For example, an empirical study of Chinese companies indicates that environmental disclosures positively impact corporate green innovation in the long term, however, several factors (e.g., stakeholder attention, location, ownership, industry, and financing constraints) generate uncertainty about this link (Luo et al., 2022). Similarly, Yin and Wang (2018) report that heavily polluting firms' environmental disclosures aid their green innovation performance, as voluntary disclosure of information strengthens self-regulation, enhances reputation and creates a good environmental image, and can attract stakeholders concerned about the environment. In addition, an investigation of heavily polluting Chinese listed firms indicates that environmental disclosures contribute to green innovation performance through their diversified financing channels, expanded market sales, and received media attention (Xiang et al., 2020).

2.6. Industry characteristics and green innovation

The driving force of corporate green innovation may depend on industry characteristics. Regulatory pressures can also affect corporate green innovation, especially if the firm is relatively more polluting than other firms in the industry (Berrone et al., 2013; Jaggi et al., 2018). For instance, in heavily polluting industries, chemical companies are responsible for generating substantial. However, these companies are now adopting pro-environmental initiatives for their supply chain partners (Banerjee et al., 2003; Woo et al., 2014). A survey of Korean firms found a considerable difference between pollution-intensive and non-pollution-intensive industries in green technologies; the former are more likely to invest in green innovation than the latter (Woo et al., 2014). Moreover, industry competition affects pro-environmental strategies, forcing companies operating in highly competitive markets to pay attention to green innovation (Keil, 2017). As the stricter the consumer requirements for environmentally friendly products and the more stringent the international environmental protection regulations, the more inevitable it is for pollution-intensive industries to implement green innovation and sustainable management (Xie et al., 2022).

Based on the above discussions, this study developed a green innovation determinants model (see Fig. 1) underlying five driver categories: firm characteristics, CEO characteristics, environmental actions, environmental disclosures, and industry characteristics.

3. Methodology

3.1. Data sources and sample

This study constructed a dataset of firms listed on the Shanghai and Shenzhen Stock Exchanges. There are several reasons for choosing the companies listed in China as a sample. First, there is a dominant stream

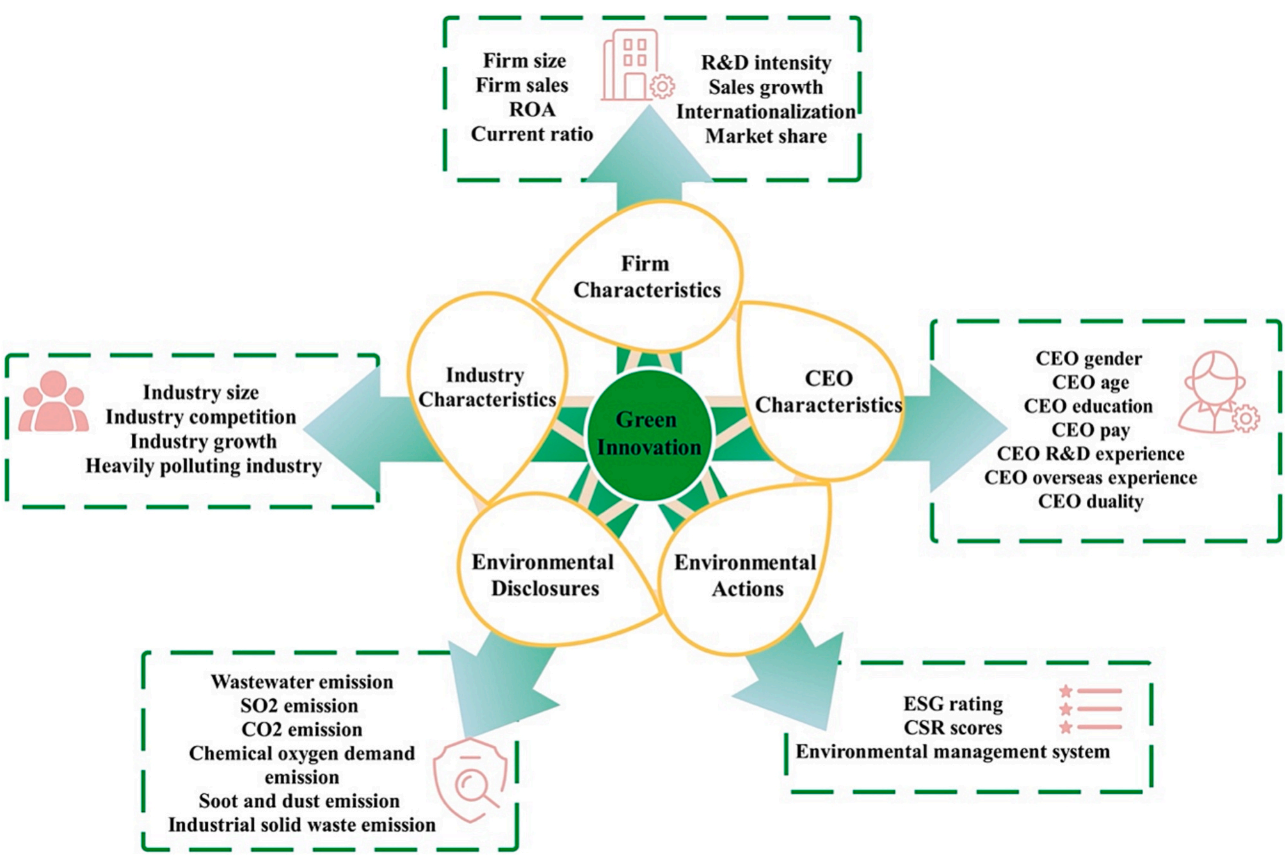

Fig. 1. Green innovation determinants model.

of literature in developed countries, with a limited focus on developing and emerging markets (Rehfeld et al., 2007; Horbach, 2008; Post et al., 2015). As the largest developing country, China has many listed firms and a wide range of industries that can provide rich and diverse data samples, which makes it more feasible for researchers to construct a robust model of the determinants of firms' green innovation (Fang et al., 2023). Moreover, due to long-term rapid economic growth and industrialization, China faces serious environmental pollution and resource constraints (Sun et al., 2021). Therefore, our sample enables a more thorough examination of how firms respond to environmental pressures and suggests innovative solutions. Lastly, China is vital in global industries and environmental protection (Duan et al., 2021). By examining the drivers of green innovation among Chinese firms, firms in other economies can draw guidance from them to promote green innovation.

Our sample is collected from three large databases. First, we collected data on green innovation from China's State Intellectual Property Office (SIPO) for the 2010–2019 period. Notably, SIPO, as the world's third largest patent office, provides detailed information, including applicant name, location, and International Patent Classification (IPC) code, for the patent applications of Chinese companies. To determine whether a patent application should be considered as green innovation, the identification was based on the IPC green inventory of the World Intellectual Property Organization. This tool offers green innovation's IPC codes for seven topics: 1) alternative energy production; 2) transportation; 3) energy conservation; 4) waste management; 5) agriculture/forestry; 6) administrative, regulatory, or design aspects; and 7) nuclear power generation. To ensure the reliability of the collected data, we examined the company's ownership of the patent using a fuzzy-matching technique (i.e., fuzzymatcher in Python). Thereafter, two research assistants independently checked the dataset and compared their results to avoid potential inconsistencies in the screening.

Second, we obtained information on ESG and CSR from the Wind database, a representative data source for investigating the prosocial behaviors of Chinese listed firms. In this data source, the Shanghai Huazheng Index Information Service Limited Corporation developed the ESG data and pooled it into nine categories from C to AAA ratings (AAA represents the highest and C the lowest). Hexun disclosed the CSR data, constructing continuous scores for a firm's annual CSR performance based on its shareholders, employees, supplier–customer rights, environmental protection, and philanthropic donation.

Third, we obtained the other data from the China Stock Market & Accounting Research (CSMAR) database. The CSMAR, one of the largest databases of Chinese listed firms, is a research-oriented database that focuses on China's finance and economy and is extensively used in business and economics research (e.g., Xu et al., 2020). After data processing (e.g., excluding firms with missing data), we analyzed a sample of 1401 firms (10,199 firm-year observations) from 2010 to 2019 using 10 sets of machine learning algorithms.

3.2. Variables and measures

3.2.1. Dependent variable

3.2.1.1. Green innovation. We begin with a company's green patent perspective to focus on corporate green innovation based on the existing literature (Liu and Kong, 2021; Luo et al., 2022; Wang and Jiang, 2021; Yuan et al., 2021). Obtaining eco-labeled product certifications and green R&D is difficult for Chinese companies, so we chose green patents as the most popular and generally recognized green innovation measuring indicator (Brunnermeier and Cohen, 2003; Tan and Zhu, 2022). Following the previous literature (Hu et al., 2021; Yuan et al., 2021), we utilized the number of green patent applications in a given year as a proxy for green innovation.

3.2.2. Independent variables

The independent variables include the firm's characteristics, CEO characteristics, environmental actions, environmental disclosures, and industry characteristics, and each category contains several variables.

3.2.2.1. Firm characteristics. These include firm size, firm sales, return on assets (ROA), current ratio, R&D intensity, sales growth, internationalization, and market share. Among these, we measured firm size and firm sales by the natural logarithm of total assets (Duffie et al., 2007) and the natural logarithm of total sales (Kim and Ahn, 2012), respectively. ROA is the ratio of net income to total assets that measures a firm's profitability (Duan et al., 2012; Zhang et al., 2023). The current ratio, calculated as the ratio of current assets to current liabilities, depicts the liquidity of a company's assets. R&D intensity is the ratio of R&D expenditure to total sales (Tang et al., 2016). Sales growth is the percentage change in total sales from the previous year to the current year (Liu et al., 2021), while internationalization is the ratio of foreign sales to total sales (Kumar et al., 2021). Finally, market share is firm-specific total sales divided by total sales for all companies in the industry (Bai et al., 2021).

3.2.2.2. CEO characteristics. We collected data on the CEO's gender, age, education, pay, R&D experience, overseas experience, and duality. Specifically, CEO gender is a binary variable set to 1 if the CEO is female; otherwise, 0 (Farag and Mallin, 2018). The logarithm of CEO age in years is used to calculate the variable CEO age (Meier and Schier, 2021). We generated a dummy variable that takes the value of 1 if a CEO has a postgraduate degree (e.g., Master's and/or Ph.D.) and 0 otherwise to quantify CEO education (Farag and Mallin, 2018). We measured CEO pay as the natural logarithm of the total salary plus 1 in a given year (Gao and Li, 2015). Furthermore, CEO R&D experience measures whether the CEO has professional experience in R&D, and the variable is set to 1 if the CEO has a career background in R&D and 0 otherwise (Barker and Mueller, 2002; Liu et al., 2023b). CEO overseas experience takes on a dummy variable indicating whether the CEO possesses overseas experience, with a value of 1 if the CEO has overseas experience and 0 otherwise (Tang et al., 2016). We measured CEO duality using a dummy variable with a value of 1 if a firm's CEO and chairman are the same people and 0 otherwise (Farag and Mallin, 2018).

3.2.2.3. Environmental actions. This study divides environmental actions into ESG ratings, CSR scores, and EMSs. We measured ESG rating with nine categories from AAA to C ratings converted into a score of 9 to 1, which means that higher values represent better ESG performances (Tan and Zhu, 2022). CSR scores are a continuous variable and evaluate a firm's annual CSR performance from the Hexun database (Zhu et al., 2021). EMSs determine whether a firm establishes a systematic institution for environmental management, and ISO 14001 is the most popular standard for company environmental protection; thus, this study assigns a value of 1 to companies that have introduced ISO 14001 and 0 to others (Li et al., 2019).

3.2.2.4. Environmental disclosures. The level of environmental disclosure is the degree of detail of corporate environmental information disclosure (Meng et al., 2013). In this study, corporate pollution emissions, that is, 1) wastewater emissions, 2) SO_2 emissions, 3) CO_2 emissions, 4) chemical oxygen demand (COD) emissions, and 5) soot and dust emissions, as well as industrial solid waste emissions, are used as secondary indicators of environmental disclosures, and each indicator is assigned values from 0 to 2—0 represents no disclosure, 1 represents general qualitative description, and 2 represents quantitative description (Wang et al., 2022). In other words, a higher score indicates a higher degree of environmental disclosure.

3.2.2.5. Industry characteristics. This study distinguishes four industry characteristics: industry size, industry competition, industry growth, and heavily polluting industry. We defined industry size as the natural logarithm of the total assets of all firms in the same sector (Lo et al., 2013). The industry competition measure is the total sales of the four largest firms as a proportion of total industry sales using the Herfindahl–Hirschman index (Keil, 2017). Industry growth represents a one-year percentage growth in total sales (Li et al., 2021). We used a dummy variable that equals 1 for firms that are part of heavily polluting industries represented by the List of Environmental Protection Inspection Industry Classified Management of Listed Companies and 0 otherwise (Hu et al., 2021). Moreover, we included dummy variables for each industry in the machine learning analysis to control for unobserved industry characteristics. Table 1 summarizes the descriptive statistics of the independent variables used in the analysis.

3.3. Machine learning approach

This study used machine learning to predict green innovation through five streams: firm characteristics, CEO characteristics, environmental actions, environmental disclosures, and industry characteristics. The core principle of machine learning algorithms is to learn from data and make no assumptions about the features of the variables (Sabahi and Parast, 2020). We believe that using a multiple-machine learning methodology can achieve high prediction accuracy while maintaining interpretability (Liu et al., 2023a, 2023b). Moreover, machine learning methods can help with data theorizing by supplying a vital ingredient: robust data patterns. These patterns serve as the foundation for these algorithms' predictions, but they may also be a robust stylized fact that one can explain by reasoning and then duplicate in new data (Helfat, 2007; Shrestha et al., 2021). Overall, we conduct 10 sets of machine learning algorithms: extreme gradient boosting (XGBoost), random forest (RF), naïve Bayes (NB), logistic regression (LR), adaptive boosting (AdaBoost), decision tree (DT), multi-layer perceptron (MLP), k-nearest neighbor (KNN), linear discriminant analysis (LDA), and quadratic discriminant analysis (QDA).

XGBoost, an optimized distributed gradient-boosted algorithm created by Chen and Guestrin (2016), incorporates the boosting model proposed by Friedman (2001). It is an ensemble model that integrates efficient implementations of DTs to create a combined model with superior prediction performance compared to individual strategies. Applying the second derivative and regular term makes the loss function more accurate and avoids overfitting issues. An efficient, flexible, and portable XGBoost can help us provide superior prediction performance.

RF, an important ensemble method utilizing forecasts from many underlying DTs, relies on a more general technique known as bagging or bootstrap aggregation (Breiman, 2001). For the classification models, the main idea is to build multiple separate trees, and each tree eventually casts a vote for the predicted class. Finally, three hyperparameters for RF (i.e., the depth of trees, the number of trees, and the number of covariates) are tuned to build the prediction model.

NB, a probabilistic classifier, considers every vector feature independent of the others. According to Bayesian theory, "naïve" is derived from the naïve assumption that the features of the sample are independent of each other (Wu et al., 2008). Three standard machine learning methods are based on Bayesian theory: BernoulliNB, GaussianNB, and MultinomialNB. As BernoulliNB is suitable for discrete data, we chose it to predict green innovation.

LR, a type of maximum-entropy (log-linear) classifier, can predict categorical values based on one or more parameters. In this method, we implement probabilities describing the possible outcomes of a single trial using a logistic function (Harrell, 2001). LR can fit model binomial and multinomial variables, and we believe it is a valuable algorithm for green innovation prediction.

AdaBoost, an ensemble classifier of boosting approaches, comprises multiple classifier algorithms, and their prediction is a combination of the outputs of these algorithms (Kuhn and Johnson, 2013). When paired with AdaBoost, a sequence of weak classifiers repeatedly fits the training selection at each iteration (Wu et al., 2008). The final prediction combines through a weighted majority vote of all predictions; thus, it could be improved for accurate prediction.

A DT is an inductively discovered rule series that visually resembles an inverted tree (Dietterich, 2000). We used classification trees and adjusted hyperparameters for tree length, leaf sizes (minimal number of observations allowed on the leaf nodes), tree depth (allowed maximum

Table 1
Descriptive statistics of the dependent variables.

Category	Variable	Mean	SD	25 %	75 %
Firm characteristics	Firm size	6.135	1.160	5.288	6.797
	Firm sales	5.465	1.331	4.498	6.242
	ROA	0.037	0.071	0.016	0.069
	Current ratio	2.770	2.943	1.232	3.071
	R&D intensity	0.047	0.045	0.020	0.055
	Sales growth	0.190	0.384	−0.004	0.293
	Internationalization	0.139	0.210	0.000	0.202
	Market share	0.024	0.067	0.001	0.014
CEO characteristics	CEO gender	0.067	0.250	0.000	0.000
	CEO age	3.890	0.136	3.807	3.989
	CEO education	0.534	0.499	0.000	1.000
	CEO pay	11.138	1.653	10.836	1.772
	CEO R&D experience	0.286	0.452	0.000	1.000
	CEO overseas experience	0.101	0.301	0.000	0.000
	CEO duality	0.303	0.460	0.000	1.000
Environmental actions	ESG rating	6.409	1.110	6.000	7.000
	CSR scores	23.741	16.011	16.010	26.730
	EMS	0.221	0.415	0.000	0.000
Environmental disclosures	Wastewater emission	0.397	0.619	0.000	1.000
	SO_2 emission	0.140	0.489	0.000	0.000
	CO_2 emission	0.069	0.324	0.000	0.000
	COD emission	0.174	0.547	0.000	0.000
	Soot and dust emission	0.200	0.504	0.000	0.000
	Industrial solid waste emission	0.030	0.195	0.000	0.000
Industry characteristics	Industry size	11.458	1.296	10.741	12.244
	Industry competition	0.203	0.177	0.074	0.285
	Industry growth	0.157	0.125	0.076	0.207
	Heavily polluting industry	0.317	0.465	0.000	1.000

depth for the tree), and minimum required parent node size for a split to be allowed. Based on Breiman's (1996) guidelines, DT with bagging (bootstrap aggregation) is used to observe the performance difference based on the framework and provide a more accurate model for predicting green innovation.

MLP is a back-propagation learning algorithm based on an input neural network, hidden layers, and output neural network (Han et al., 2022). In the back-propagation process, the network weights of the MLP are initialized to small random variables and then updated by calculating the derivative of the network's mean square error (MSE). MLP can learn non-linear models in real-time, and its hyperparameters (i.e., the number of hidden layers, the number of nodes per hidden layer, and the learning rate for back-propagation) are tuned by experimenting with the most commonly used set of parameters.

KNN, as a non-parametric supervised learning approach, predicts the label according to the distance between the training samples and new data (Kuhn and Johnson, 2013). Using the relative distances, KNN can find nearer k neighbor instances, thus enabling successful classification even if the decision boundary is highly irregular. In this algorithm, we determine classification by voting on the nearest neighbors of each point, which means that a new point can be assigned the highest appearance frequency among the nearest k neighbors.

LDA and QDA are classification methods based on the theoretical framework of Bayes' theorem. The former predicts the feature variables on a linear decision surface consisting of directions that maximize the distance between the projected means of the classes; the latter assumes that each class has its covariance matrix and predicts classes based on a quadratic decision surface (Kuhn and Johnson, 2013). The two algorithms are robust, user-friendly, and accurate; thus, we applied them in the current research to predict green innovation.

4. Results

4.1. Performance comparison of machine learning models

To effectively evaluate the prediction performance of the machine learning algorithms, this study calculated the proportion of correctly classified observations in classification tasks as the evaluation index for each model. We compared the accuracy of 10 sets of machine learning algorithms to determine which algorithm can effectively predict green innovation (see Table 2). We divided our data into two sets: training and testing. We use the training set to tune the hyperparameters and fit the model and the testing set to evaluate the prediction performance. We considered 20 splitting strategies because there is no consensus regarding the best training size, and there is a view that the ideal splitting configuration may vary between scenarios. The division strategies are in the first column of Table 2. For instance, an 80:20 ratio implies that 80 % of the data is the training data, whereas the remaining 20 % is the test set. Moreover, the values in the last row (average rank) represent the algorithm's ranking in each splitting configuration, where 1 (10) indicates the highest (lowest). As can be seen from Table 2, XGBoost outperforms other algorithms with the highest accuracy (accuracy value of 0.841 with an 80:20 split).

Table 2
Accuracy prediction performance with an average ranking.

Splitting	XGBoost	RF	NB	LR	AdaBoost	DT	MLP	KNN	LDA	QDA
80:20	0.841 (2)	0.841 (2)	0.841 (2)	0.839 (5)	0.840 (4)	0.836 (6.5)	0.825 (8)	0.836 (6.5)	0.800 (9)	0.070 (10)
78:22	0.838 (2)	0.839 (1)	0.837 (3.5)	0.836 (5.5)	0.836 (5.5)	0.834 (7)	0.837 (3.5)	0.833 (8)	0.798 (9)	0.072 (10)
76:24	0.836 (2)	0.838 (1)	0.835 (3.5)	0.834 (5.5)	0.834 (5.5)	0.835 (3.5)	0.827 (8)	0.829 (7)	0.798 (9)	0.074 (10)
74:26	0.837 (1)	0.836 (2)	0.835 (3)	0.834 (4.5)	0.834 (4.5)	0.831 (6.5)	0.826 (8)	0.831 (6.5)	0.798 (9)	0.077 (10)
72:28	0.833 (2)	0.834 (1)	0.832 (3.5)	0.832 (3.5)	0.831 (5)	0.829 (6)	0.826 (8)	0.828 (7)	0.797 (9)	0.078 (10)
70:30	0.831 (2)	0.832 (1)	0.829 (4.5)	0.829 (4.5)	0.829 (4.5)	0.826 (7)	0.829 (4.5)	0.824 (8)	0.795 (9)	0.079 (10)
68:32	0.832 (2)	0.832 (2)	0.831 (4)	0.830 (5.5)	0.830 (5.5)	0.828 (7)	0.832 (2)	0.825 (8)	0.797 (9)	0.079 (10)
66:34	0.832 (1.5)	0.832 (1.5)	0.830 (4.5)	0.830 (4.5)	0.830 (4.5)	0.830 (4.5)	0.827 (7)	0.826 (8)	0.796 (9)	0.080 (10)
64:36	0.830 (2)	0.831 (1)	0.829 (3.5)	0.829 (3.5)	0.828 (6)	0.828 (6)	0.828 (6)	0.824 (8)	0.796 (9)	0.079 (10)
62:38	0.829 (2)	0.830 (1)	0.828 (3.5)	0.828 (3.5)	0.827 (5.5)	0.826 (7)	0.827 (5.5)	0.824 (8)	0.796 (9)	0.080 (10)
60:40	0.830 (2)	0.831 (1)	0.829 (3.5)	0.829 (3.5)	0.828 (5.5)	0.828 (5.5)	0.826 (7)	0.824 (8)	0.796 (9)	0.080 (10)
58:42	0.830 (1.5)	0.830 (1.5)	0.828 (5)	0.828 (5)	0.828 (5)	0.827 (7)	0.829 (3)	0.824 (8)	0.796 (9)	0.078 (10)
56:44	0.831 (1)	0.830 (2)	0.828 (4.5)	0.828 (4.5)	0.828 (4.5)	0.828 (4.5)	0.826 (7)	0.823 (8)	0.797 (9)	0.078 (10)
54:46	0.833 (1)	0.832 (2)	0.831 (3.5)	0.831 (3.5)	0.830 (5.5)	0.830 (5.5)	0.826 (7)	0.825 (8)	0.798 (9)	0.078 (10)
52:48	0.834 (1)	0.832 (2)	0.831 (4.5)	0.831 (4.5)	0.831 (4.5)	0.831 (4.5)	0.822 (8)	0.826 (7)	0.798 (9)	0.078 (10)
50:50	0.831 (1.5)	0.831 (1.5)	0.829 (4.5)	0.829 (4.5)	0.829 (4.5)	0.829 (4.5)	0.826 (7)	0.823 (8)	0.795 (9)	0.078 (10)
48:52	0.830 (1)	0.829 (2)	0.828 (4)	0.828 (4)	0.828 (4)	0.827 (6)	0.825 (7)	0.822 (8)	0.794 (9)	0.078 (10)
46:54	0.830 (1)	0.829 (2)	0.828 (4.5)	0.828 (4.5)	0.828 (4.5)	0.828 (4.5)	0.825 (7)	0.823 (8)	0.793 (9)	0.077 (10)
44:56	0.828 (1)	0.827 (3.5)	0.827 (3.5)	0.827 (3.5)	0.826 (6.5)	0.826 (6.5)	0.827 (3.5)	0.821 (8)	0.792 (9)	0.078 (10)
42:58	0.829 (1)	0.827 (3)	0.827 (3)	0.827 (3)	0.826 (6)	0.826 (6)	0.826 (6)	0.822 (8)	0.792 (9)	0.077 (10)
Average rank	1.525	1.7	3.8	4.3	5.05	5.775	6.15	7.7	9	10

4.2. Statistical test on the performance of machine learning algorithms

Following García et al. (2010), we used the Friedman test to analyze the variations in performance across machine learning algorithms. The null hypothesis of the Friedman test is that there are no significant differences between the MSEs of the machine learning models. The computed Friedman statistic is 164.299, with a p-value less than 0.05, thus rejecting the null hypothesis. Therefore, these findings support the probability of discrepancies between the algorithms.

Based on Demšar (2006), we use the Nemenyi test to determine different performances among machine learning algorithms by performing pairwise tests after obtaining the Friedman test findings (i.e., a substantial difference in algorithm performance). For each pair of 10 algorithms, the Nemenyi test can determine the significance of the differences in rank. We infer a significant difference between their performances at $\alpha = 0.05$ if the difference is larger than or equal to the Nemenyi critical distance. Based on the pairwise comparison, Table 3 shows that XGBoost is superior to the other nine machine learning algorithms; RF is significantly superior to AdaBoost, DT, MLP, KNN, LDA, and QDA; NB and LR are significantly superior to KNN, LDA, and QDA; AdaBoost and DT are significantly superior to LDA and QDA; and MLP is significantly superior to QDA. Accordingly, we confirm that XGBoost is the best machine learning algorithm for predicting green innovation and select it for further analysis.

4.3. Empirical results

SHapley Additive exPlanations (SHAP), a method of class additive characteristic attribution according to the unification of game theory and local interpretation, is used to visualize the prediction results of the best-performing machine learning prediction model XGBoost (Lundberg and Lee, 2017). A SHAP value for a prediction feature represents the extent to which the model prediction changes when that feature is present. As shown in Fig. 2, we plotted the SHAP values for an independent variable on a row in the summary below, and their color shows whether an instance is positive (colored red), negative (colored blue), or in-between (colored purple) for that observation. The results suggest that ESG rating, internationalization, CEO pay, firm sales, industry size, R&D intensity, CEO education, CEO R&D experience, firm size, and industry competition are the 10 most important factors influencing green innovation.

To this end, we calculated the permutation importance of each feature in green innovation. We focused on investigating these features' positive/negative consequences; the results are in Fig. 3. This SHAP diagram shows the importance of each independent variable and the breadth of the impact across the dataset. In the figure, red indicates that an independent variable is positively associated with green innovation, while blue indicates a negative relationship.

As shown in Fig. 3, ESG rating, internationalization, CEO pay, firm sales, industry size, R&D intensity, CEO education, CEO R&D experience, firm size, CO_2 emissions, industry growth, wastewater emissions, CSR scores, ROA, and industrial solid waste emissions are positively related to green innovation. However, the effects of industry competition, market share, current ratio, and CEO age are negative. Specifically, our results indicate that high values for ESG ratings and internationalization lead to higher green innovation; in other words, ESG ratings and internationalization have a positive relationship with green innovation.

We can also observe that CEO pay shows a positive relationship with green innovation, which means that an increase in CEO pay will make them focus on corporate green innovation. In addition, firm sales and firm size positively impact green innovation, as larger firms have more resources available for green innovation investment. Furthermore, an increase in industry size will promote green innovation; however, industry competition and market share negatively affect green innovation, so companies must balance the relationship between green innovation performance and their expanding strategies. Moreover, R&D intensity, CEO education, and CEO R&D experience positively influence green innovation for high investments in environmental technology-related activities. Interestingly, we found that the characteristics of the industry to which the company belongs can drive corporate green innovation. Our results indicate that firms from the electrical machinery and equipment manufacturing industry (_industry_35), automobile manufacturing (_industry_33), and software and information technology service (_industry_59) tend to have better green innovation than those from the pharmaceutical manufacturing industry (_industry_24). Note that some features are not shown in Fig. 3 because of their lesser contribution to the model output (see the Appendix for the detailed SHAP values of all features).

Table 4 shows the importance and effects of firm characteristics, CEO characteristics, environmental actions, environmental disclosures, and industry characteristics on green innovation. First, internationalization, firm sales, and R&D intensity are more important than other firm characteristics and positively affect green innovation. Second, CEO pay is the most important and positive driver among CEO characteristics, followed by CEO education and CEO R&D experience. Third, ESG rating is the most significant predictor of green innovation in a firm's environmental actions, suggesting that a firm with a higher ESG rating may increase its green innovation performance. Fourth, environmental disclosures are relatively less informative in predicting green innovation, though the effects of CO_2 emission, wastewater emission, industrial solid waste emission, and SO_2 emission are positive. Fifth, regarding industry characteristics, industry size is the most important cause of green innovation, indicating that firms in a larger industry would be more willing to carry out green innovation. In addition, we also found higher industry competition is negatively associated with green innovation, and heavily polluting firms tend to exhibit more green innovation performance.

5. Discussion and conclusion

Based on RBV and UET, this study develops a green innovation determinants model and reveals how corporate green innovation can be

Table 3
Results of the Nemenyi test.

Algorithm	XGBoost	RF	NB	LR	AdaBoost	DT	MLP	KNN	LDA	QDA
XGBoost		←	←	←	←●	←●	←●	←●	←●	←●
RF			←	←	←●	←●	←●	←●	←●	←●
NB				←	←	←	←	←●	←●	←●
LR					←	←	←	←●	←●	←●
AdaBoost						←	←	←	←●	←●
DT							←	←	←●	←●
MLP								←	←	←●
KNN									←	←
LDA										←

Notes: ← indicates that an algorithm is better than another, although the difference is not significant; ←● indicates that an algorithm is significantly better than another.

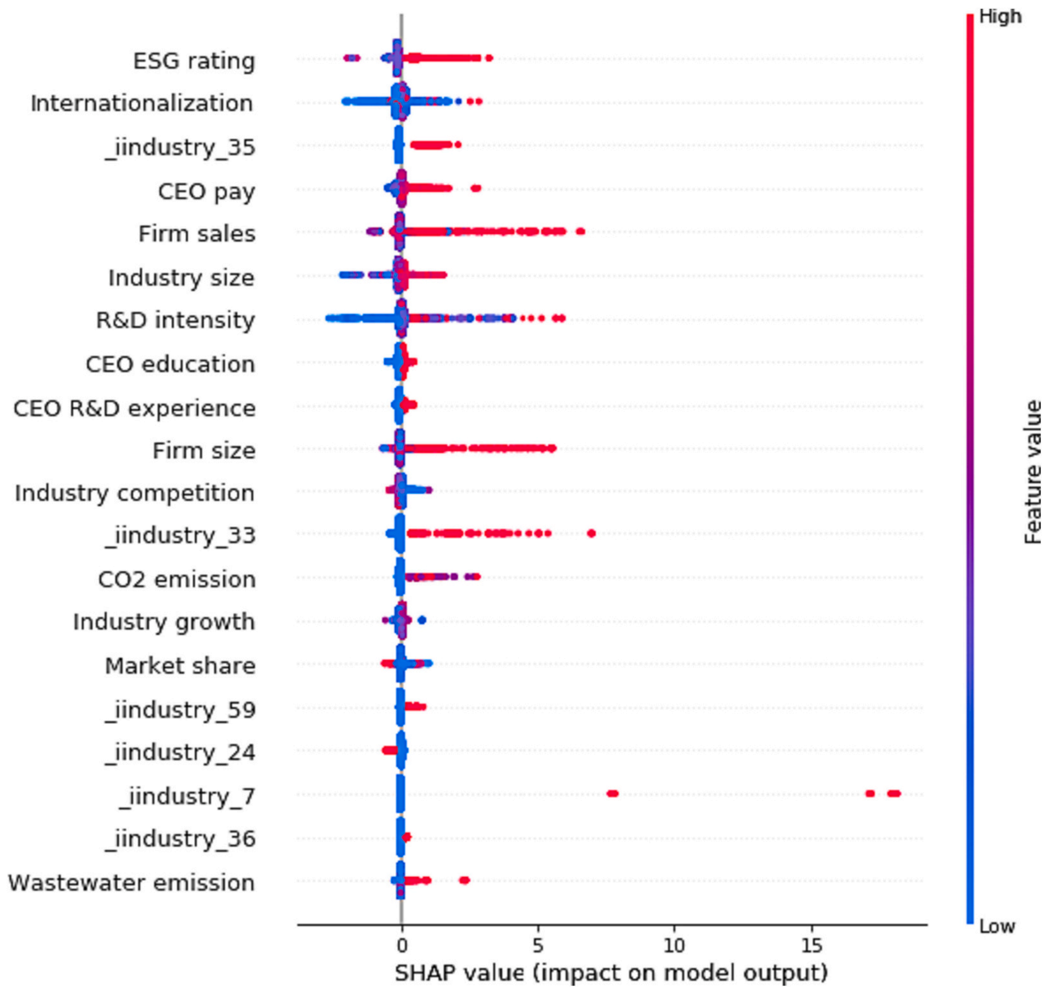

Fig. 2. Summary of SHAP values for green innovation determinants. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

predicted through firm characteristics, CEO characteristics, environmental actions, environmental disclosures, and industry characteristics. By employing various machine learning models on a large-scale sample of Chinese listed firms, this study determines the best-performing algorithm for predicting green innovation and investigates the positive/negative effects of the features. Overall, our study extends a broader understanding of the drivers of green innovation and contributes to the development of the innovation literature on social and institutional changes.

5.1. Theoretical implications

The empirical findings generate several critical theoretical contributions. Our first contribution concerns using a machine learning approach in predicting corporate green innovation. Our research differs from the conventional statistical hypothesis examination of the causality between different factors and green innovation: We used state-of-the-art machine learning algorithms to “learn” from the disordered information rather than assuming patterns. We examined multiple suitable algorithms, such as XGBoost, RF, NB, LR, AdaBoost, DT, MLP, and KNN, to build the model and then conducted model training by adopting 20 different sample splitting methods to ensure a reliable fit because there is no consensus on the perfect size of the training dataset (Sabahi and Parast, 2020). Accordingly, we identified the best-performing green innovation prediction model (i.e., XGBoost). Then, we developed the interpretable model based on XGBoost and SHAP to visualize and explain what drives green innovation.

Second, based on RBV and UET, we scrutinized multiple perspectives of a firm and organized them into our green innovation determinants model, which extends a broader understanding of green innovation drivers and contributes to the innovation literature on social and institutional changes in several ways. To clearly illustrate the green innovation determinants, our findings indicate that, in descending order, ESG rating, internationalization, CEO pay, firm sales, industry size, R&D intensity, CEO education, CEO R&D experience, firm size, and industry competition are the most important factors that significantly influence green innovation. In contrast, industrial solid waste emissions, CEO age, ROA, and current ratio are less critical in predicting green innovation. Overall, our study contributes to the green innovation literature by using machine learning to determine green innovation through firm characteristics, CEO characteristics, environmental actions, environmental disclosures, and industry characteristics.

Third, our study generates multiple interesting findings by taking a closer look at the impacts of the variables in our green innovation determinants model. For firm characteristics, we found that internationalization, firm sales, R&D intensity, firm size, ROA, and sales growth positively impact corporate green innovation. In contrast, we found a negative effect on green innovation for the current ratio and market share. We can explain internationalization’s positive impact on green innovation by market expansion. Prior literature argues that firms tend to improve their environmental policies and perform eco-innovation to gain competitive advantages in the global market and that firms have

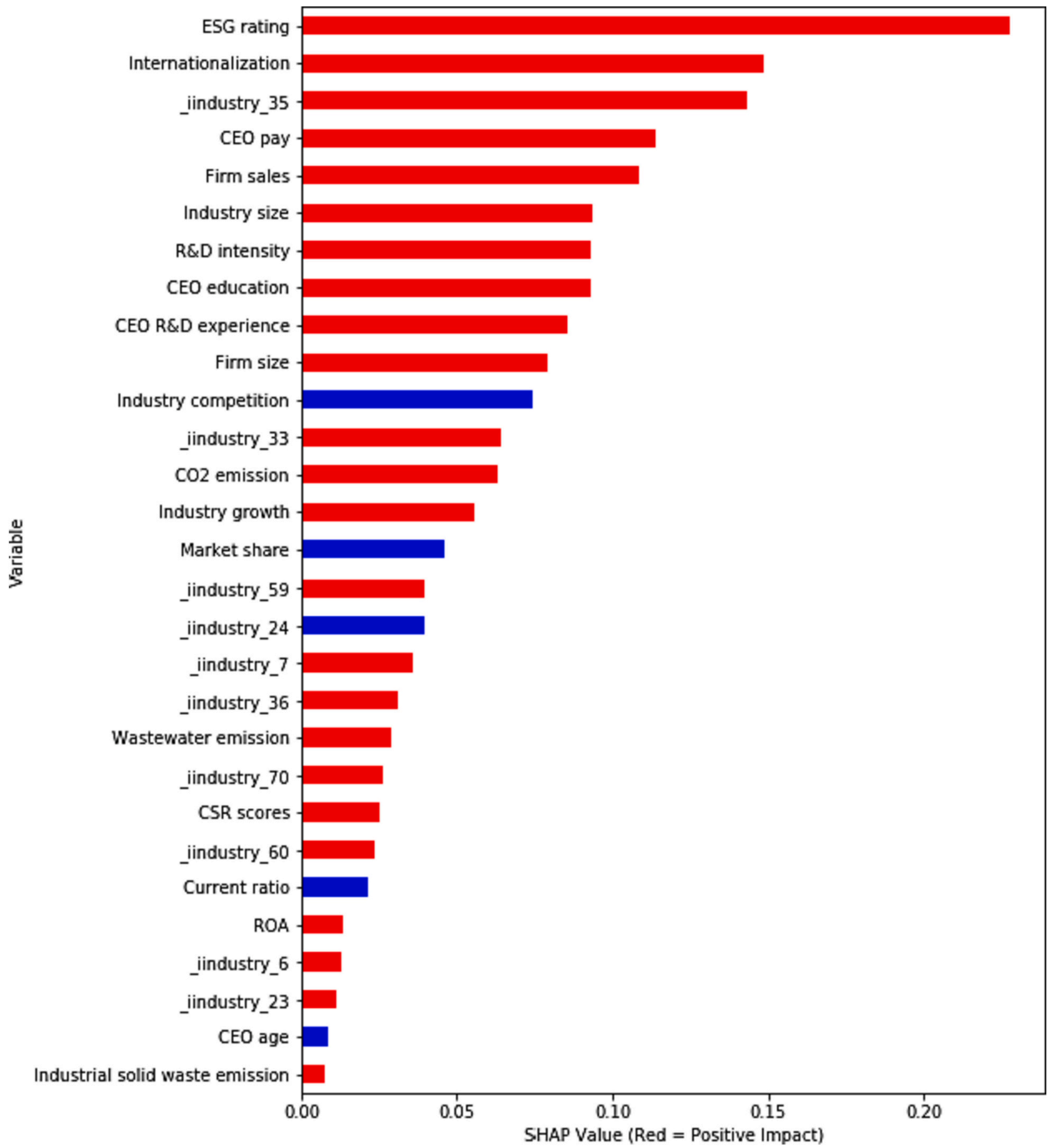

Fig. 3. The results of green innovation determinants effects. (For interpretation of the references to color in this figure, the reader is referred to the web version of this article.)

more incentives to improve product and/or process innovation to avoid personal regulatory and market constraints (Chiarvesio et al., 2015; Usman et al., 2020).

Moreover, as the development of green innovation requires a more efficient use of resources, a firm needs to strengthen its R&D to achieve better product and process designs (Horbach, 2008; Xu et al., 2020). The role of firm sales, firm size, and ROA in improving green innovation is consistent with RBV, as technologies are constantly iterating and investing in green innovation, requiring companies to learn and improve their operations; thus, profitability and sales volume are critical for companies to cope with the uncertainty and risk involved in green innovation (Lin et al., 2014). However, the current ratio and market share findings contradict prior literature (Yu et al., 2021). This difference may be because an excellent current ratio and large market share imply competitive advantages and the ability to respond effectively to market dynamism, thus lacking incentives to improve products/services to develop markets through green innovation.

For CEO characteristics, our findings show that the CEO's pay, education, R&D experience, overseas experience, and duality contribute to improving green innovation performance, while the effects of CEO age and CEO gender are negative. Previous studies have emphasized the role of CEOs in firms' innovation strategies because well-educated CEOs with international visions are more capable of making appropriate strategic decisions (Hambrick and Mason, 1984; Lewis et al., 2014). Our study

Table 4
The SHAP values of the determinants of service satisfaction.

Category	Variable	Absolute SHAP value	Effects	Sign
Firm characteristics	Internationalization	0.149	0.146	Positive
	Firm sales	0.108	0.322	Positive
	R&D intensity	0.093	0.263	Positive
	Firm size	0.079	0.344	Positive
	Industry growth	0.056	0.640	Positive
	Market share	0.046	−0.052	Negative
	Current ratio	0.022	−0.202	Negative
	ROA	0.014	0.146	Positive
	Sales growth	0.003	0.107	Positive
CEO characteristics	CEO pay	0.114	0.481	Positive
	CEO education	0.093	0.902	Positive
	CEO R&D experience	0.085	0.899	Positive
	CEO age	0.008	−0.155	Negative
	CEO overseas experience	0.004	0.862	Positive
	CEO duality	0.002	0.239	Positive
	CEO gender	0.002	−0.209	Negative
Environmental actions	ESG rating	0.228	0.669	Positive
	CSR scores	0.025	0.564	Positive
	EMS	0.003	0.390	Positive
Environmental disclosures	CO_2 emission	0.063	0.834	Positive
	Wastewater emission	0.029	0.495	Positive
	Industrial solid waste emission	0.007	0.529	Positive
	SO_2 emission	0.006	0.862	Positive
Industry characteristics	Industry size	0.093	0.535	Positive
	Industry competition	0.075	−0.594	Negative
	Heavily polluting industry	0.003	0.067	Positive

Note: The independent variables were not presented if their SHAP values less than 0.001.

confirms this view by demonstrating that CEOs with a higher level of education and relevant experiences in R&D can better understand the potential and value of green innovation, and with a pay increase, CEOs may be more motivated to facilitate green management, production, and sustainable development (Barker III and Mueller, 2002; Zhang and Zhu, 2019; Zhou et al., 2021). Moreover, in line with prior literature (Quan et al., 2021), we demonstrate that CEOs with foreign experiences have more knowledge about international markets and better problem-solving abilities, autonomy, and creativity, leading to better leadership effectiveness in pursuing "greenness." Previous studies have argued that the CEO who also serves as the board chair (CEO duality) will seek to enhance the corporate value as the CEO perceives himself/herself as a "good steward" and that dual leadership enables firms to respond to market dynamism effectively (Donaldson and Davis, 1991; Duru et al., 2016). Our study confirms this view by revealing that CEO duality helps to improve performance in terms of green innovation (He and Jiang, 2019). Previous research demonstrates the negative relationship between CEO age and green innovation, arguing that older CEOs are more risk-averse, more concerned about their success, and, therefore, less willing to adopt green innovation (Meier and Schier, 2021; Oh et al., 2019). Nonetheless, our findings on CEO gender contradict He and Jiang (2019) and Huang (2013), who argue that female executives are less power-oriented and care more about green innovation.

Furthermore, we found environmental actions, ESG ratings, CSR scores, and EMSs positively impact green innovation. The promoting effect of ESG ratings on green innovation aligns with Xu et al. (2020), who argue that companies' active engagement in ESG activities can serve as a positive signal to stakeholders and business analysts and thus help firms attract more investments. Similarly, firms with well-established social responsibilities and EMSs can attract high-quality intellectual capital and low-cost external financing and, therefore, have more slack resources to develop green innovation (Kawai et al., 2018; Mbanyele et al., 2022).

Notably, our study confirmed the critical role of environmental disclosures. Specifically, we found that all disclosures positively impact green innovation, including CO_2, wastewater, industrial solid waste, SO_2, soot and dust, and COD emissions. We infer that firms that disclose their environmental information may care more about environmental effectiveness than those that do not. In particular, scholars have argued that environmental disclosures have an anti-driving impact on corporate green innovations; that is, they facilitate firms to overcome the dark side of environmental disclosures by fostering technological innovation to provide better environmentally friendly and high-quality products (Li et al., 2022).

Finally, regarding industry characteristics, we provide empirical evidence that industry size, industry growth, and heavily polluting industries promote corporate green innovation, whereas industry competition hinders green innovation. Firms often cluster together to innovate more effectively (Stanko and Olleros, 2013); when they are in an industry with a considerable market scale effect and expanding, they can access more resources and better information systems to facilitate innovation. Interestingly, firms in heavily polluting industries have better green innovation. A possible reason may be that firms in heavily polluting industries are motivated to seek green solutions when confronted with more stringent environmental regulations. The negative impact of industry competition may be because, as the industry becomes more competitive, firms may be more inclined to spend their money on other forms of investments, such as cost efficiency, to ensure profitability.

5.2. Practical implications

The findings of this study have several practical implications. First, the results suggest that factors such as ESG ratings, internationalization, and R&D intensity can promote corporate green innovation. We recommend that managers actively incorporate ESG practices into their green development strategies and invest more in R&D to foster product and process innovation. In addition, firms should embed green innovation in their market expansion strategies because environmental regulations can differ in diverse international markets. Second, firms should consider the role of the CEO in fostering green innovation. More specifically, when appointing a CEO, a director must consider the level of education, age, and research-related background of the candidates. Firms should also pay attention to establishing relevant development programs to enhance the overall management level of the team and establish reasonable incentives to encourage innovation. Third, policymakers should be aware of the effects of environmental disclosures in promoting green innovation. Governments may develop relevant regulations to facilitate firms' environmental reports on specific issues such as wastewater, SO_2, CO_2, and solid waste emissions. This approach would also help government regulation and law revision.

Moreover, firms' heterogeneous green innovations may result from their industrial characteristics. For example, firms in the electrical machinery and equipment manufacturing, automobile manufacturing, and software and information technology services industries tend to have better green innovation than those in the pharmaceutical manufacturing industry. Therefore, governments should consider ways to encourage firms in the pharmaceutical manufacturing industry to contribute to overall green innovation. Lastly, since the increase in industry competition harms green innovation, governments should carry out their macro-regulatory function, prudently guide market competition, and assist in resource allocation.

5.3. Limitations and recommendations

Our study has a few limitations. First, our sample only contained data from China, which may hinder the generalizability of our findings. Therefore, future studies should address this issue by including more data from other emerging economies and/or developed markets. Second, although we tested numerous factors to predict corporate green innovation, other antecedents, such as government regulations and national policies, can predict green innovation. Consequently, scholars should move one step forward to examine more potential determinants of green innovation.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.techfore.2023.123107.

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