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How Digital Transformation Enhances Green Innovation Performance: An Empirical Study of Manufacturing Firms

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With China's dual carbon goals and the global sustainability agenda, manufacturing companies are under more and more pressure to go green and digital. This study looks into how digital transformation (DT) helps green innovation (GI) in Chinese manufacturing companies that are listed on the A-share market. Using the Resource-Based View and Dynamic Capabilities Theory, I look at how the intensity and speed of DT affect GI performance, which we measure by the number of green patents issued. The results show that DT intensity, R&D spending, and company size all have positive effects on GI. On the other hand, digital speed has weaker or negative effects. There is a link between general innovation and green innovation output, but it doesn't fully explain it. This study adds to what we know about the connection between digital and green technologies and has implications for sustainable industrial growth.

Keywords: Digital transformation; Green innovation; Manufacturing; Green patents; China; Sustainability; Dynamic capabilities

1. Introduction

One of the most important things to do in the 21st century is to move toward sustainable development. In this context, green innovation (GI) has become very popular among academics, policymakers, and business leaders because it can help the economy grow while also lowering environmental footprints (Rennings 2000). At the same time, the quick spread of digital technologies is changing the way companies compete and do business, especially in the manufacturing sector (Bharadwaj et al. 2013, Vial 2019). Digital transformation (DT) helps businesses become more productive, come up with new ideas quickly, and adapt to changing market and regulatory needs by using advanced technologies like artificial intelligence (AI), the Internet of Things (IoT), big data analytics, and cloud computing (Teece 2007, Li et al. 2021).

China's manufacturing sector, which is a major source of carbon emissions and energy use, is under a big pressure to meet the country's "dual carbon" goals. Digital-green synergy, which is the strategic combination of DT and GI, is a promising way to reach both economic and environmental goals. However, even though more and more people are paying attention, there aren't many real-world studies that look at how DT affects GI, especially in developing countries like China (Del Giudice et al. 2021).

This study tries to fill this gap by looking at how different aspects of digital transformation, especially its speed and intensity, affect the results of green innovation in Chinese manufacturing companies. It also looks into whether general innovation activities can predict how well green patents do, and how things like ownership, size, and productivity at the company level affect green innovation outputs.

This study builds on the Resource-Based View (Barney 1991) and the Dynamic Capabilities Theory (Teece 2007) to suggest that companies with better digital skills are better able to use sustainable practices and come up with new ideas that are good for the environment. The study uses a large dataset from 3,287 Chinese A-share listed manufacturing companies for the year 2022 and a strong methodological framework that includes multiple regression, mediation, moderation, and quantile regression analyses.

Here are the exact research questions:

- What variables influence the number of green patents in the sample?
- Does the number of general patents predict the number of green patents?
- Does digital transformation, particularly its intensity and speed, predict green patenting outcomes?

The structure of this paper is as follows: Section 2 gives a full review of the literature on digital transformation, green innovation, and the two of them together. Section 3 talks about the research design, which includes where the data comes from, how the variables are chosen, and how the research is done. Section 4 shows the empirical results, which are grouped by the three research questions. In Section 5, we talk about the results in detail and connect them to existing studies and theoretical frameworks. Section 6 wraps up the paper by going over the main points, discussing the implications for managers and policymakers, and suggesting areas for future research.

This study adds to the body of knowledge on sustainable industrial development by looking at how digital transformation can help green innovation in the manufacturing sector. It also gives useful information to practitioners and policymakers in emerging markets.

2. Literature Review

This part looks closely at the current research on digital transformation (DT), green innovation (GI), and their overlap. It gives the current study a theoretical and empirical basis. There are four main themes in the review: the role of digital transformation in manufacturing, the theoretical and empirical landscape of green innovation, the link between DT and GI, and important gaps in the literature, especially when it comes to emerging economies.

2.1. Digital Transformation in the Manufacturing Sector

Digital transformation means using digital tools like AI, big data analytics, the Internet of Things (IoT), and cloud computing to completely change and improve how businesses work, their strategies, and how they create value (Bharadwaj et al. 2013, Vial 2019). DT is not just a simple upgrade to technology; it is a complete change in how organizations are structured and what they can do. It also shows that businesses are changing their way of thinking to focus on flexibility, new ideas, and learning all the time.

In manufacturing, DT makes smart production systems possible by combining cyber-physical integration, real-time process control, and end-to-end digital value chains (Li et al. 2021). The widespread use of IoT sensors makes it easier to see what's going on in the supply chain and plan maintenance ahead of time. AI and machine learning tools help companies plan their production schedules, use less energy, and automate quality control.

DT also changes the way value is delivered to customers by making it possible to combine products and services, customize them for each customer, and use digital platforms. Companies that use DT can respond to changes in customer preferences, government rules, and competition more quickly. People are starting to see this kind of strategic flexibility as a way to stay ahead of the competition in manufacturing environments that change quickly (Yoo et al. 2012).

But the size and success of DT implementation are very different from one company to the next. Research shows that digital maturity, which is based on technological capabilities, organizational readiness, and strategic alignment, is not evenly spread out, especially between large companies and small and medium-sized businesses (SMEs) (Li et al. 2021). In addition, institutional factors like policy support, infrastructure, and digital literacy are very important in determining DT outcomes, especially in developing economies.

Dynamic capabilities theory can help us understand DT from a theoretical point of view. Teece (2007) says that businesses need to be able to combine, build, and change their internal and external skills in response to changes in the environment. DT is a transformative ability that lets businesses see opportunities, take advantage of them through innovation, and change how they do business to stay competitive and sustainable.

2.2. Green Innovation: Definitions and Measurement

Green innovation includes new or better products, services, processes, and business models that help the environment by using fewer resources, polluting less, or releasing less carbon (Rennings 2000). Traditional innovation is often driven by the need to save money or make more money. GI, on the other hand, is mostly driven by the need to be socially responsible, follow the law, and be environmentally friendly.

Kemp and Pearson (2007) say that eco-innovation is "the production, assimilation, or exploitation of a product, production process, service, management, or business method that is new to the organization... and which results, throughout its life cycle, in a reduction of environmental risk, pollution, and other negative impacts of resource use." So, GI goes beyond just technological fixes to include changes in how businesses act and how they plan their business.

There are three main types of drivers of GI: regulatory push (environmental policies and enforcement), technology push (the availability of clean technologies), and market pull (consumer demand for sustainable products) (Horbach et al. 2012). Companies react to these stimuli based on their abilities, the pressures they feel from stakeholders, and their strategic goals.

Green patent data is the most common way to measure GI in real-world research. The OECD's ENV-TECH taxonomy is one way to classify green patents. It includes technologies that help with pollution control, energy efficiency, renewable energy, and waste management (Johnstone et al. 2010). Patent data are useful because they give us standardized, comparable, and time-stamped measures of how much innovation is happening. But they might not show enough incremental or process-based innovations that aren't patented.

Another area of study looks at the difference between general innovation and green innovation. They are often related, but they are not the same thing. General innovation is usually based on how well a company can absorb new ideas, how advanced its technology is, and how focused it is on the market. On the other hand, GI is more affected by how aware a company is of the environment, how many rules it has to follow from outside sources, and how involved its stakeholders are (Carrillo-Hermosilla et al. 2010). So, companies that do well in general innovation might not do well in green innovation unless they have the right incentives or skills that help them reach their environmental goals.

Recent research also stresses how important organizational factors like leadership, culture, and employee involvement are in promoting GI. Companies that include environmental goals in their mission statements, reward systems, and performance reviews are more likely to be able to use GI practices.

2.3. Linking Digital Transformation and Green Innovation

There is a growing body of research that looks at how digital transformation can help or speed up green innovation. In theory, DT helps GI in a number of ways, such as by making environmental data more accessible, allowing for real-time monitoring and optimization, improving communication and collaboration, and encouraging organizational agility (Zhang–Walton 2017, Del Giudice et al. 2021).

Advanced digital tools, like big data analytics, help predict how much energy will be used and how much pollution will be released, which makes it possible to manage the environment more effectively. IoT devices built into production systems keep an eye on material flows, find wasteful practices, and help with resource recovery. AI algorithms can help with eco-design by modeling different stages of a product's life and finding alternatives that have less of an impact.

Digital platforms also make it easier for people from different departments and organizations to work together, which is necessary for innovation at the systems level. Cloud-based tools help with open innovation projects with stakeholders, green supply chain coordination, and joint research and development (R&D) projects. This shows a move away from using only technology to solve problems and toward strategies that take the whole ecosystem into account.

From the point of view of dynamic capabilities, DT makes it easier for a company to see environmental risks, take advantage of chances for sustainable innovation, and change how it does business in response to stakeholder needs (Teece 2007). Companies that use DT as part of their innovation strategy are better able to follow environmental rules, set their products apart from others, and build their reputations.

These ideas are backed up by real-world evidence. Chen et al. (2022) show that IT skills make GI better by making it easier to share and absorb green knowledge. Zhang and Yu (2023a) say that Chinese companies with more digital maturity tend to have more green patents. According to Del Giudice et al. (2021), smart technologies make the connection between digital capability and sustainable performance stronger, especially in new markets.

But the link between DT and GI isn't always the same. Research shows that the speed and intensity of DT adoption have different effects. Quick but shallow implementation might lead to short-term gains in efficiency without affecting long-term sustainability. On the other hand, digital skills that are deeply ingrained and in line with environmental goals are more likely to lead to long-lasting GI outcomes.

Things that are happening around you are also important. How DT affects GI depends on the size of the company, how it is owned, what industry it is in, and what the policies are like. For example, state-owned enterprises (SOEs) may have to deal with different rules and lack of resources than private companies. Differences in digital infrastructure and policy enforcement between regions make things even more complicated.

2.4. Research Gaps and Implications for This Study

Even though more and more people are interested in the DT–GI connection, there are still some gaps. First, a lot of the research is about developed economies, especially Europe and North America. Emerging markets like China, which have their own unique institutional settings, industrial structures, and policy frameworks, are not well represented (Del Giudice et al. 2021).

Second, a lot of the time, studies look at digital transformation and innovation separately. Not many look into how they interact, and even fewer look at green innovation as a dependent variable. This makes it harder for us to understand how digitalization affects the environment.

Third, the idea of DT is not very clear and hard to put into practice. A lot of research uses broad or inconsistent measures that don't make a clear distinction between DT speed (how fast it is adopted) and DT intensity (how deeply it is adopted). This makes it harder to test nuanced hypotheses about how different parts of DT affect GI in real life.

Fourth, people often forget about differences between firms. The type of ownership (SOEs vs. non-SOEs), the level of market concentration, the ability to innovate, and the place where the business is located may all affect the DT–GI relationship. To find these interactive effects, a more detailed analysis is needed.

Finally, it is clear that there are some methodological problems. A lot of research uses qualitative case studies or cross-sectional correlations. Few people use strict econometric methods like mediation, moderation, or quantile regression to figure out what causes what. Also, dynamic analyses that follow companies over time are rare, which makes it hard to figure out what DT will do to GI in the long run.

By filling in these gaps, this study helps us better understand how digital transformation affects green innovation in manufacturing companies, especially in China. It uses a multi-method empirical strategy and new ways to measure the intensity and speed of DT to test hypotheses that are based on theory.

3. Research Design

This section elaborates on the research objective, methodology, and data collection procedures used to examine the relationship between digital transformation and green innovation in Chinese manufacturing firms. It combines both theoretical reasoning and empirical design to ensure a robust investigation of the research questions.

3.1. Research Objective and Questions

The central aim of this study is to empirically evaluate how the degree and nature of digital transformation contribute to green innovation performance within China's manufacturing sector. Green innovation is operationalized through patent-based indicators, which offer an observable and measurable output of innovative activity with environmental implications.

To guide the empirical inquiry, the following research questions are proposed:

- What variables influence the number of green patents in the sample?
- Does the number of general patents predict the number of green patents?
- Does digital transformation, particularly its intensity and speed, predict green patenting outcomes?

These questions reflect the theoretical and empirical dimensions of the study and guide model construction and data analysis.

3.2. Methodology and Variable Selection

This study adopts a quantitative methodology, making use of cross-sectional data from Chinese A-share listed manufacturing companies for the year 2022. Multiple regression-based techniques are applied to examine how different sets of firm-level variables predict green patent performance.

The primary analytical tool is Multiple Linear Regression, used to assess the baseline effect of digital transformation and other firm characteristics on green innovation. To further capture the complexity of these relationships, Hierarchical Regression is employed, enabling the analysis to introduce independent variables in structured blocks to evaluate incremental explanatory power. Given the highly skewed nature of several variables, such as patent counts and firm size, Log Transformation is implemented to improve normality and model robustness.

To capture more nuanced relationships, supplementary methods include:

- Mediation Analysis to test whether intermediate variables (e.g., R&D investment) explain the link between digital transformation and green innovation.
- Moderation Analysis to investigate whether the effect of digital transformation varies by firm size or ownership.
- Interaction Term Regression to test conditional effects.
- Quantile Regression to identify heterogeneous effects across different levels of green innovation performance.

This multifaceted methodological approach ensures both statistical rigor and theoretical depth.

3.3. Data Collection Methods

The study's empirical analysis is based on cross-sectional firm-level data from 2022, with a focus on Chinese A-share listed manufacturing companies. The first sample included all businesses that were open that year. Companies that were delisted, put under special treatment (ST), or suspended from trading were systematically left out of the dataset so that it would stay accurate and observations could be compared. After this filtering process, there were more than 3,000 valid firms left in the final sample.

In the first step of building the data, a full dataset of more than 1,500 raw variables was put together. These variables covered a lot of different parts of how a business works, such as finance, innovation, digitalization, and corporate strategy. About 50 variables were kept for empirical modeling after a careful process of variable selection based on their relevance and theoretical grounding. Using natural language processing (NLP) on company disclosures, these included indicators of digital transformation that showed both how fast and how intense it was happening. The number of green patents filed was used to measure innovation performance. Invention patents and utility model patents were separated to show the different types of innovation.

I also added control variables to see how digital transformation affected green innovation on its own. These were things like R&D spending, the size of the company, the structure of its ownership, total factor productivity (TFP), and the Herfindahl–Hirschman Index (HHI) as a measure of how concentrated the market is. Adding these firm-level characteristics was necessary to reduce omitted variable bias and make the statistical models more useful for explaining things.

A lot of data cleaning and changing have been done to get the dataset ready for analysis. To make sure everything was the same, standardized firm codes were used to match firms across datasets. We used logarithmic transformations on variables that were positively skewed, like the number of green patents and the size of the company. This fixed problems with the distribution and met the requirements for linear regression. Also, missing values and extreme outliers were found and taken out so that the model estimation would not be distorted.

The final dataset is one of the most complete sets of digital and innovation metrics for China's manufacturing sector that are currently available. The study is able to create a nuanced empirical framework that captures both quantitative rigor and contextual relevance by combining structured financial indicators with text-mined measures of digital transformation. This strong set of data is what the proposed research hypotheses will be tested against, and it adds to the body of work on digital innovation in developing countries.

4. Empirical Results

This section presents empirical findings structured around the three research questions (RQs) that guide the study. The analysis uses cross-sectional data from 3,287 Chinese A-share listed manufacturing firms in 2022. All dependent variables (green patent counts) were log-transformed to correct for right-skewness and to allow interpretation in terms of percentage change. This transformation improves linearity and mitigates the influence of extreme values, which is common in patent count data.

4.1. RQ1 – Drivers of Green Patents

This section examines how firm characteristics influence green patent output, especially factors related to innovation input, firm scale, and productivity. Table 1 defines the variables used.

Table 1. Overview of Variables Used in RQ1 Analysis

Category	Variable Name	Description	Measurement/Transformation
Dependent Variable	Green Patents (log)	Green innovation output	Log of total green patent applications
Independent Variable	R&D Spending (log)	Innovation input	Log of R&D expenses
Independent Variable	Total Assets (log)	Firm size (balance sheet)	Log of total assets
Independent Variable	Revenue (log)	Firm size (income statement)	Log of total revenue
Independent Variable	TFP (OP)	Innovation efficiency/productivity	TFP via Olley-Pakes method
Independent Variable	Years Listed	Firm maturity	Years since IPO
Independent Variable	SOE Status	Ownership type	Binary: SOE = 1, non-SOE = 0
Independent Variable	Industry Category	Sector classification	Four-digit CSRC industry codes
Independent Variable	Province Location	Geographic region	Province of headquarters
Independent Variable	Herfindahl Hirschman Index (HHI)	Market concentration (competition)	Calculated per industry segment

Source: Own edition based on my own research and database of A-complete list of companies in China's manufacturing industry

To examine their association with green innovation, Pearson correlations were first calculated. The results that are significant are presented in Table 2.

Table 2. Pearson Correlation Between Firm Variables and Log Green Patents

Variable	Correlation (r)	Significance	Sample Size (N)
Log R&D Spending	.470	$p < .001$	3,249
Log Total Assets	.454	$p < .001$	3,287
Log Revenue	.425	$p < .001$	3,285
TFP (OP method)	.351	$p < .001$	2,930
Years Listed	.302	$p < .001$	3,287

Source: own edition based on calculation results of SPSS

These results indicate that innovation input and firm size have the strongest linear associations with green patent activity, followed by productivity and firm age.

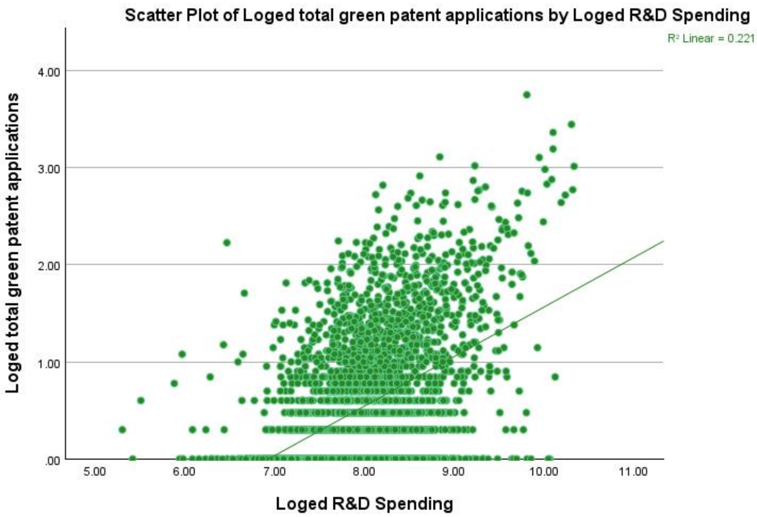
Next, bivariate regressions were conducted to quantify the explanatory power of each variable. The regression results are summarized in Table 3.

Table 3. Simple Linear Regression of Predictors on Log Green Patents

Predictor	Standardized β	R^2	Significance
Log R&D Spending	.470	.221	p < .001
Log Total Assets	.454	.206	p < .001
Log Revenue	.425	.181	p < .001
TFP (OP method)	.351	.123	p < .001
Years Listed	.302	.091	p < .001

Source: Own edition based on calculation results of SPSS

Figure 1. Scatter plot of green patents vs. log R&D spending

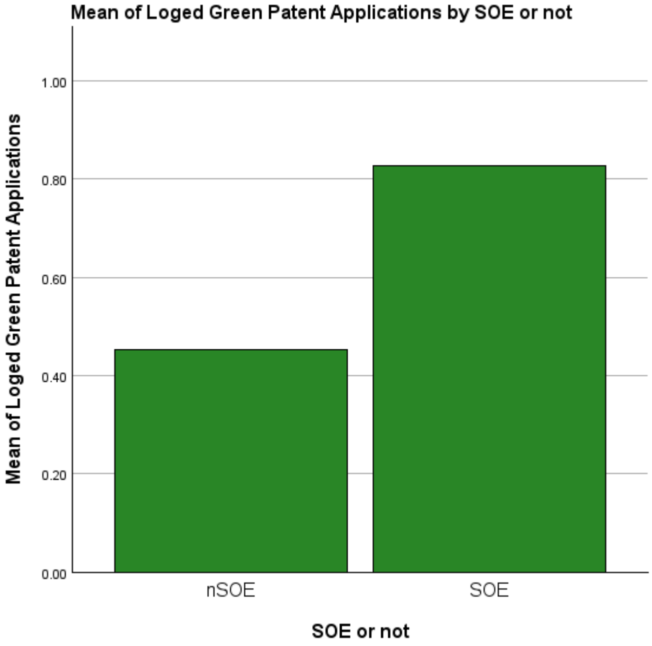


Source: calculation results of SPSS

In addition to these continuous variables, categorical group comparisons provide further insights:

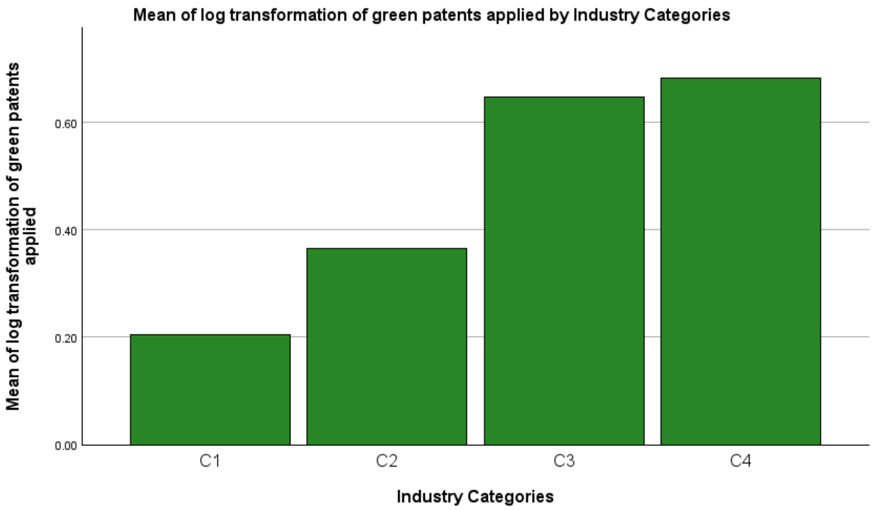
– SOEs demonstrate significantly greater green patent output than non-SOEs (Mean: 49.6 vs. 13.3, $p < .001$).
– Industry type affects green patent activity ($F = 8.413$, $p < .001$), although the effect size is small ($\eta^2 = .008$).
– No statistically significant difference was found by region ($F = .723$, $p = .869$).

Figure 2. Bar charts comparing green patent counts by SOE status



Source: calculation results of SPSS

Figure 3. Bar charts comparing green patent counts by industry group



Source: calculation results of SPSS
Note: C1: High-tech manufacturing; C2: Traditional manufacturing; C3: Energy-intensive manufacturing; C4: Other manufacturing

In summary, internal firm resources, particularly R&D intensity and firm scale, are the dominant drivers of green innovation. Structural conditions such as industry competition and regional location appear less relevant. These findings suggest policy incentives and corporate strategies should focus on bolstering innovation input capacity to enhance green innovation outcomes.

Firm-level factors such as R&D investment and size are the most consistent predictors of green innovation performance. Market structure and geographic effects are relatively weak. This suggests internal resource configurations matter more than external environments in shaping green innovation behavior.

4.2. RQ2 – Green ≠ General Innovation

This section tests whether firms with stronger general patent activity also produce more green patents. Since log-transformation of zero values is undefined, only firms with at least one patent (general and green) were included to ensure regression validity and avoid clustering at the origin.

Adjusted Sample: Firms with at least one patent (Patent count > 0).

Table 4. Correlation Matrix Between General and Green Patent Categories

Variable Pair	Pearson r	Significance
Green Patents ↔ Total General Patents	.486	$p < .001$
Green Invention Patents ↔ General Invention Patents	.414	$p < .001$
Green Utility Patents ↔ General Utility Patents	.426	$p < .001$

Source: own edition based on calculation results of SPSS

These moderate correlations suggest that while green patent activity tends to co-occur with general patenting, it is not perfectly aligned. This implies green innovation may involve distinct strategic priorities beyond general innovation output.

To further explore this relationship, simple linear regressions were performed using logged values of general patent variables as predictors for their green counterparts.

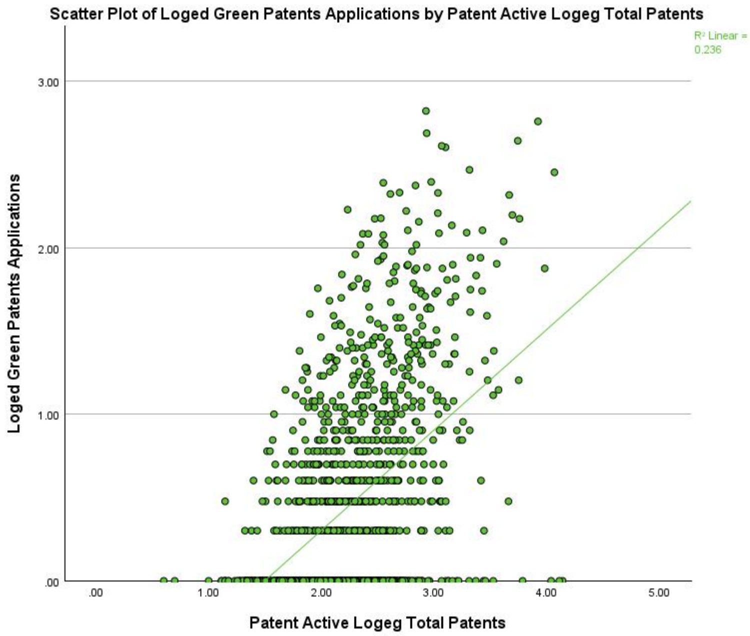
Table 5. Regression Results: General Patent Predictors of Green Patent Output

Predictor	Outcome	Std. β	R^2	Significance
Logged Total Patents	Logged Green Patent Applications	.486	.236	$p < .001$
Logged Invention Patents	Logged Invention Green Patents	.414	.171	$p < .001$
Logged Utility Patents	Logged Utility Green Patents	.426	.182	$p < .001$

Source: own edition based on calculation results of SPSS

The regression analysis shows that total general patenting volume is a strong and significant predictor of green patenting output, explaining nearly one-quarter of its variance. Invention and utility patents each explain 17–18% of their green counterparts. This reinforces the idea that while there is overlap, green innovation may also follow a more intentional, strategic path.

Figure 4. Scatter plot of green patent output vs. total patent volume



Source: calculation results of SPSS

These results confirm that general patenting significantly predicts green patenting, with moderate explanatory power. The strongest predictor was total patenting, accounting for 23.6% of variance in green patents. Invention and utility patent subcategories yielded comparable, though slightly lower, R^2 values.

Although general innovation is positively associated with green patenting, the relationship is not deterministic. Many firms with active general patent portfolios may not prioritize green technologies. Conversely, firms that strategically focus on green domains may not necessarily have high volumes of traditional patenting. This suggests green innovation is not simply a byproduct of total innovation activity, but may reflect deliberate sustainability commitments.

Future analysis could explore how this relationship is moderated by firm type (e.g., SOE vs. non-SOE), industry characteristics, or digital transformation capacity.

4.3. RQ3 – Digital Transformation and Green Innovation

This section evaluates the impact of digital capabilities on green patent performance. Table 6 summarizes the digitalization variables included in the analysis.

Table 6. Definition of Digital Transformation Variables

Variable Type	Variable Name	Description
Intensity	Intensity A	Depth of digital activity scope (e.g., big data, AI)
Intensity	Intensity B	Breadth of transformation scale
Speed	Speed A	Year-over-year change in keyword count (short term)
Speed	Speed B	Smoothed digital speed index
External Digital Environment	Digital Inclusive Finance Index	Regional index of digital financial accessibility

Source: Own edition based on calculation results of SPSS

This table clarifies the three conceptual categories of digital transformation: internal depth (intensity), internal pace (speed), and external environment (digital finance). It provides the foundation for both correlation and regression analysis.

Table 7. Pearson Correlation Between Digital Variables and Green Patents

Digital Variable	Pearson r	Significance
Intensity A	.241	$p < .001$
Intensity B	.233	$p < .001$
Speed A	.037	$p = .075$ (n.s.)
Speed B	-0.079	$p < .001$
Digital Finance Index	-0.036	$p = .039$

Source: Own edition based on calculation results of SPSS

Correlation results indicate that the intensity of digital transformation is significantly and positively associated with green patenting. However, digital speed and digital finance show much weaker, even negative, associations. This highlights that depth, not pace, of digital efforts matters more for sustainability innovation.

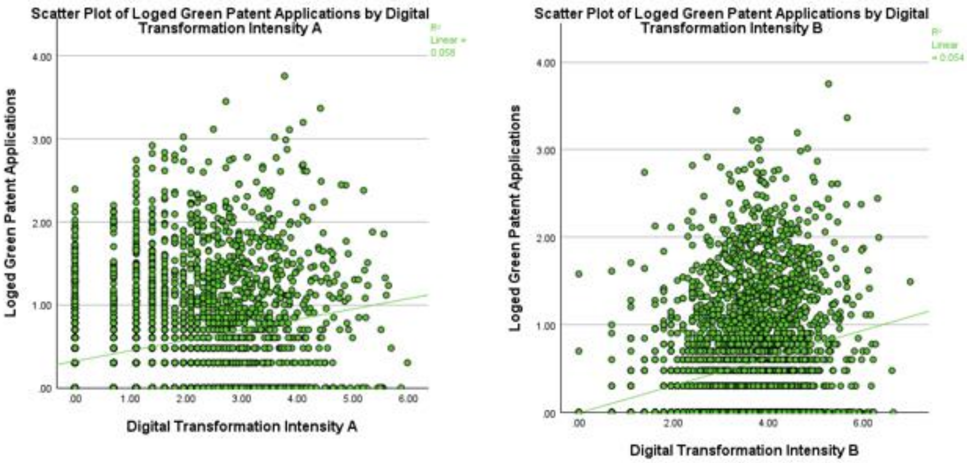
Table 8. Regression Results: Digital Variables Predicting Green Patents

Predictor	Std. β	Sig.	Tolerance	VIF
Digital Transformation Intensity A	.153	<.001	0.471	2.124
Digital Transformation Intensity B	.121	<.001	0.471	2.124

Source: Own edition based on calculation results of SPSS
Note: Total $R^2 = 0.065$

Regression models confirm that both intensity A and B remain significant predictors of green patenting, even when controlling for multicollinearity (VIF < 2.2). Together, they explain about 6.5% of variance in green innovation. This underscores the importance of substantive digital integration rather than simply superficial or fast-paced adoption.

Figure 5. Scatter plot of digital intensity and green patent output



Source: Calculation results of SPSS

Digital intensity significantly predicts green innovation output, but speed and digital finance show weak or contradictory effects. This supports the view that it is the depth, not pace, of digital transformation that matters. Firms with stronger digital integration are more adaptive, capable of environmental data management, and process reconfiguration. Potential moderation with R&D or productivity should be explored in follow-up models.

5. Discussion

This section discusses the main empirical findings presented in Section 4, interpreting them through theoretical lenses and linking them to prior research. The discussion is organized around the three research questions and ends with a synthesis informed by visual insights.

5.1. Analyzing Empirical Results by Research Question

– RQ1: What variables drive the Green Patent number in the sample?

According to the analysis, there is a weak but moderate correlation between general and green patenting. Although there is a positive correlation between the total number of patents and the number of green patents (Pearson r = 0.486), only a portion of the performance of green innovation can be explained by general patenting (R2 = 0.236). This suggests that green innovation is a result of targeted strategies, policy compliance, and potentially stakeholder pressure rather than just a byproduct of overall innovation efforts. The distinction is crucial: regardless of their overall volume of innovation, companies that actively participate in sustainability-focused R&D typically produce more green patents.

– RQ2: Does the number of patents predict the number of green patents?

The findings imply that the performance of green patents is significantly influenced by firm fundamentals. Larger, more productive, and more R&D-invested companies produce more robust green innovation results. It's interesting to note that state-owned businesses exhibit better green performance as well, perhaps as a result of their closer adherence to national environmental regulations. On the other hand, factors such as geographic location and market concentration (as measured by the Herfindahl Index) have little bearing on green outcomes, suggesting that internal capabilities are more important than external structure. This supports the Resource-Based View (Barney 1991), which highlights the significance of distinct internal resources and competencies.

– RQ3: Does digital transformation predict green patents?

According to the study, green patenting is significantly and favorably correlated with digital transformation, particularly in terms of digital intensity. In particular, there are significant positive regression coefficients for Digital Transformation Intensity A and B ($\beta = 0.153$ and 0.121, respectively; both $p < 0.001$). These effects hold true even when firm size and R&D are taken into account, indicating that firms can better develop and implement green technologies through strategic digital investment. However, there are weaker or even negative correlations between digital speed and digital finance, suggesting that the quality and depth of digital engagement are more important than speed or breadth. These results align with the dynamic capabilities framework proposed by Teece (2007).

5.2. Integrated Thematic Reflection

When the three research questions are combined, a number of overarching themes show up that offer a more comprehensive picture of the state of green innovation in Chinese manufacturing companies.

First, while digital transformation is a strategic facilitator of green innovation, its effectiveness varies. According to our findings, digital intensity – which reflects the breadth and depth of digital technology integration – is a more significant driver than digital speed or breadth. This supports the idea that sustained, integrated digital investments promote the growth of internal capabilities (Teece 2007).

Second, green innovation is more than just a subset of innovation in general. Although the two are related, their moderate correlation draws attention to the distinct forces that propel green innovation, including stakeholder pressures, environmental policy, and firm-level sustainability objectives (Horbach et al. 2012). This implies that companies must consciously match innovation activities with green outcomes; innovation strategy alone is insufficient.

Third, the success of green innovation is largely determined by firm-level characteristics. The Resource-Based View is supported by core capabilities such as R&D intensity, scale, and productivity, which have a significant impact on green outcomes (Barney 1991). State-owned businesses in particular seem to have an advantage, most likely as a result of their closer adherence to national environmental policy frameworks.

Finally, thorough data processing is important. We reduced log transformation distortions and increased model reliability by eliminating companies with no patent activity. This emphasizes how crucial methodological rigor is to empirical innovation research.

When combined, these findings support the idea that internal capabilities, intentional digital strategies, and external institutional contexts all influence green innovation in manufacturing. The results have useful ramifications for businesses looking to improve their green performance and for legislators hoping to encourage sustainable innovation.

This comprehensive conversation demonstrates that green innovation is driven by both policy and capability, and that it gains from methodological clarity, resource strength, and targeted digital transformation.

6. Conclusion

The goal of this study was to look into the link between digital transformation and green innovation in China's manufacturing industry. With China's ambitious dual carbon policy and the global push for sustainability in mind, it's important to understand how digital technologies affect the environment. The empirical analysis used a large cross-sectional dataset of 3,287 Chinese A-share listed manufacturing firms in 2022 and used a number of statistical methods, such as multiple regression, correlation analysis, and interaction models.

The results show a number of important things. First, internal factors of the firm, such as the amount of R&D it does and its size, are good predictors of green innovation outcomes. This supports the Resource-Based View, which stresses the strategic importance of firm-specific capabilities (Barney 1991). Companies that have more resources and are more dedicated to research and development are better able to do green innovation work. State-owned companies also do better at green patenting, which suggests that the way a company is owned and how well it fits with national environmental goals can help sustainability efforts.

Second, there is a moderate link between general innovation activities and green innovation. This means that green innovation is not just a part of overall innovation output, but a separate strategic effort that is shaped by regulatory pressures, stakeholder expectations, and a company's own commitments to sustainability. Companies should therefore use targeted green innovation strategies instead of just following the usual paths of innovation.

Third, digital transformation, especially how deeply and broadly digital technology is used, is becoming a major force behind green innovation. The study shows that digital intensity, not speed, has a big effect on green patenting activity. This discovery shows how important it is to include digital skills in key business functions and innovation systems. This is in line with the Dynamic Capabilities framework, which stresses the importance of having integrated, firm-wide skills to deal with complicated environmental problems (Teece 2007).

It was interesting to find that the speed of digital change and the outside digital financial environment had weak or negative links to green innovation. This means that quickly but superficially using digital technologies may not have any real benefits for the environment. Instead, we need to use digital tools in a more planned and strategically integrated way to get long-lasting results.

The study adds a lot to what is already known in the academic world. It shows that there is a real connection between DT and GI, especially in the context of a growing economy. It also introduces more precise measures of digital transformation that take into account the different aspects of digitalization, such as speed and intensity. It also shows how important it is for firms to be different from each other in order to moderate the DT–GI relationship.

The results suggest that practitioners should make sure that their investments in digital infrastructure are in line with their goals for sustainability. Policymakers should think about different ways to help small and medium-sized businesses (SMEs) and non-state-owned businesses adopt digital technology and come up with new ideas for protecting the environment.

However, the study has some problems. It has a cross-sectional design that makes it hard to draw causal conclusions, and the use of patent data, while objective and standardized, may miss new ideas that don't have patents. Longitudinal designs, looking at more industries or regions, and combining qualitative insights could all help future research get a better understanding of how DT and GI are connected.

In conclusion, this study shows that green innovation in the digital age depends on strategic intent, resource configuration, and technological integration. Digital transformation can help manufacturing companies become more environmentally friendly without hurting their bottom line if they do it carefully and thoroughly.

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