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Leveraging scientific knowledge for technological inventions: insights from knowledge recombination theory

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Abstract

Introduction. Technological inventions are often built on top of previous technological developments and sometimes earlier scientific discoveries. It has been demonstrated that technologies integrating scientific knowledge exhibit superior performance in terms of their technological value compared to non-science-based inventions. However, the factors influencing the utilisation of scientific knowledge components during the technological invention process remain unclear.

Method. By analysing 1,685,970 utility patents granted by the USPTO from 2001 to 2010, this study identifies five characteristics-rooted in the perspectives of knowledge recombination and inventor team-that potentially affect the adoption of scientific knowledge in technological inventions.

Results. Both Logit and Tobit regression analyses reveal that recombination complexity and novelty significantly enhance the propensity and intensity of integrating scientific knowledge into technological inventions, whereas knowledge maturity exhibits an inverse relationship. The most critical determinant identified is the inventor team's experience with science-based inventions, which significantly positively impacts the reliance on scientific knowledge, whereas a broader technical knowledge base within the team tends to reduce the use of scientific components in inventions.

Conclusions. The findings of this study provide insights into the unique recombination processes underlying science-based technologies and offer guidance for optimising organisational and policy designs for innovation activities.

Introduction

Knowledge recombination has been recognized as one of the crucial elements in understanding technological innovation since Joseph Schumpeter's influential work in 1934. Based on knowledge recombination theory, technological innovation can typically be conceptualized as a process of searching and recombining existing technological knowledge elements to develop solutions to technical problems and generate new knowledge (Fleming and Sorenson, 2001; Fleming and Sorenson, 2004; Xiao et al., 2022). However, with the rising complexity of technological issues, the generation and evolution of technological innovation are no longer confined to a single domain of technological knowledge. Instead, they increasingly involve integration and development across multiple scientific and technological fields (Zhao et al., 2023). This trend is clearly reflected in patent citation patterns. Arora et al. (2023) observed a significant increase in the integration of scientific literature within patents, where the proportion citing scientific articles rose from 6% in 1980 to 30% in 2015, and the average number of citations per patent escalated from 0.1 to 4.4. Moreover, science-based innovations exhibit relative advantages in terms of technological impact. Studies by Poege et al. (2019) and Hohberger (2016) have demonstrated that science-based innovations surpass non-science-based ones in both technological value and the rate of technological diffusion.

While the significance of scientific knowledge as a catalyst for technological innovation is increasingly recognized, the transformation of scientific knowledge into tangible innovations remains a complex endeavor. This is attributed to the distinct philosophical logics that underlie science and technology. The essence of science is the accurate discovery of natural phenomena or laws, usually representing more abstract principles touching upon the fundamental relations between causes and effects, but this may not always be the key to solving practical problems (Anckaert et al., 2020; Arora and Gambardella, 1994). Instead, technical knowledge embodies technicality and more contextualized content that stems from simulating real-world situations in experimental settings, making it easier to be incorporated into practical applications (Bozeman, 2000; Marx and Fuegi, 2020; Novelli, 2015). Given the significant disparities between scientific research activities and technological innovation activities, the academic community still lacks a deep understanding and systematic research on how scientific knowledge functions as an effective component in the process of technological invention. Therefore, it is essential to elucidate the mechanisms by which scientific knowledge is utilized in new technological developments. This not only deepens our understanding of its role in driving technological innovation but also equips practitioners with the insights necessary for more effective utilization of this knowledge in technological development.

As highlighted earlier, knowledge recombination is a mature structure that aids in comprehending the origins of technological innovation. Our study aims to explore the mechanisms underlying the use of scientific knowledge in technological inventions by focusing on the process of knowledge recombination during technological invention. The outcomes of technological innovation are contingent upon both the nature of the search scope and the capabilities of the inventors (Hur and Oh, 2021). Accordingly, this study delves into two primary dimensions: the characteristics of knowledge recombination and the traits of the inventor teams involved in technological invention. The research specifically addresses two critical questions:

(1) How do the features of knowledge recombination and the characteristics of the invention team influence the tendency to integrate scientific knowledge into technological inventions?

(2) How do these same factors affect the degree of scientific knowledge integration into technological inventions?

Related work and hypotheses

Knowledge recombination and scientific knowledge

Related studies have demonstrated that the characteristics of both the search space and the knowledge elements significantly impact the process of invention, resulting in variations in the outcomes of inventions (Savino et al., 2017; Fleming and Sorenson, 2001). This study first assesses the impact of three key characteristics associated with the search space—recombination complexity, novelty, and knowledge maturity—on the integration of scientific knowledge into technological invention development.

Recombination complexity

Prior research has shown that the size of the knowledge repository and its interdependencies (i.e., complexity) significantly affect the likelihood of successful knowledge recombination (Kauffman, 1993; Fusillo, 2023; Fleming and Sorenson, 2001). Excessive redundancy in the components of technological knowledge may restrict the range of potential knowledge exploration, inevitably leading to cognitive lock-in (Nooteboom, 2000). In contrast, the diversity of a knowledge base is regarded as a fundamental requirement for long-term technological development (Saviotti, 1996). A series of studies have shown that the expansion of technological knowledge components across different domains within a knowledge base not only broadens the scope of searchable knowledge but also generates more potential technological combinations, thereby increasing the likelihood of successful recombination (Rosenkopf and Nerkar, 2001; Novelli, 2015; Baumann and Siggelkow, 2013). However, greater diversity in the knowledge base also increases the complexity of technological interdependencies. The invention process not only requires managing the substantial noise information resulting from the expanded scope of knowledge search while avoiding the trap of local optima (Dunne and Dougherty, 2016). Choi et al. (2018) observe that scientific knowledge facilitates the comprehension of interdependencies among technologies, the identification of effective technological combinations, and the enhancement of efficiency in complex knowledge recombination. It can be inferred that the more complex the process of knowledge recombination, the greater the likelihood that scientific knowledge being utilized in the invention process. Based on this, we propose the following hypotheses:

H1a: The higher the complexity of knowledge recombination, the greater the likelihood of incorporating scientific knowledge components in the invention process.

H1b: The higher the complexity of knowledge recombination, the more scientific knowledge components are integrated during the invention process.

Recombination novelty

Recombining technological knowledge components from disparate domains results in different levels of novelty. Keijl et al. (2016) highlights that inventions derived exclusively from the recombination of knowledge components within local technological fields typically demonstrate lower levels of novelty. Conversely, technological combinations based on distant technological origins tend to exhibit higher degrees of novelty. Related empirical evidence supports the idea that knowledge recombinations exhibiting higher novelty possess greater potential value for future technological development. For example, Kaplan and Vakili (2015), based on an analysis of 2,826 granted patents in the nanotube sector, found that novel knowledge recombinations are not only more likely to form the basis for subsequent technological advancements but also yield greater economic value. However, high novelty knowledge recombinations often come at the cost of reduced familiarity and recognizability (Keijl et al., 2016; Aldrich and Fiol, 1994). Due to limited familiarity and recognizability of technological knowledge components, elucidating the vast array of potential technological combinations and their potential impacts on technical issues proves challenging during extensive searches (Afuah and Tucci, 2012). Moreover, distant technological knowledge components may not provide readily usable building blocks. Therefore, to mitigate the variability and uncertainty inherent in knowledge recombination due to the pursuit of novelty, the invention process is likely to depend more heavily on scientific knowledge. On one hand, scientific reasoning helps inventors identify invention opportunities that are far removed from local technological fields. On the other hand, the predictive function of scientific knowledge can better ascertain potential technological alternatives, thereby avoiding experiments doomed to fail (Balconi et al., 2010). Based on this, this study formulates the following hypotheses:

H2a: The higher the novelty of knowledge recombination, the greater the likelihood of incorporating scientific knowledge components in the invention process.

H2b: The higher the novelty of knowledge recombination, the more scientific knowledge components are integrated during the invention process.

Knowledge maturity

The foundation of inventive activities may rest upon knowledge bases developed at different times, encompassing both recent and longstanding knowledge. The maturity level of the technological knowledge elements used during the recombination of knowledge can influence the degree of dependence of the invention on established scientific knowledge. Utilizing relatively mature (i.e., older) knowledge enables inventors to gain enhanced insights into the technical attributes and potential uses from industry-specific sources. This facilitates effective evaluation of the merits and demerits of knowledge during the recombination process, thereby reducing the likelihood of technological misapplication and errors (Turner et al., 2013). However, incorporating mature knowledge elements, could result in outdated technological solutions, given that numerous potential combinations of technology might have been previously utilized, thereby leaving less room for valuable technological innovations (Sørensen and Stuart, 2000). In contrast, recent knowledge is well-suited to meet changing requirements, reducing the risk of falling into capability traps and increasing the opportunities for knowledge recombination, which supports the ongoing effectiveness of innovation (Petruzzelli et al., 2018; Levinthal and March, 1993; Ahuja and Morris Lampert, 2001). Nevertheless, compared to well-established knowledge that has been validated over time, the benefits of integrating recent knowledge may be offset by technological uncertainties and higher implementation costs (Heeley and Jacobson, 2008; Petruzzelli and Savino, 2014). Nightingale (1998) notes that scientific knowledge is not merely a tool for generating answers but a means to comprehend how technology functions. This understanding can reduce technological uncertainties and lower the costs of trial and error. Consequently, to maximize the benefits of integrating recent technological knowledge, knowledge recombination may increasingly rely on scientific knowledge. This study proposes the following hypotheses:

H3a: The lower the maturity of the recombined technological knowledge, the greater the likelihood of incorporating scientific knowledge components in the invention process.

H3b: The lower the maturity of the recombined technological knowledge, the more scientific knowledge components are integrated during the invention process.

Inventor team and scientific knowledge

As active contributors to the process of invention, the attributes of inventors, including their knowledge and experience, play a critical role in shaping both the process of knowledge search and the outcomes of knowledge recombination within these inventive activities (Perry-Smith and Shalley, 2014; Ardito et al., 2016). Nevertheless, it is not yet known to what extent and in what ways the attributes of inventor teams impact their inclination or level of utilization of scientific knowledge components during the process of invention. The study primarily investigates two significant characteristics of inventor team: experience in science-based invention and breadth of technical knowledge.

Experience in science-based invention

Inventive experience encompasses the skills, knowledge, and resources that inventors accumulate through prior activities. Existing research suggests that the inertia of past experiences influences the approaches inventors take to seek technical solutions (Liao et al., 2008). In other words, for invention teams with extensive inventive experience, the inertia of past experiences drives them to create new technological combinations based on their existing knowledge base, rather than seeking new knowledge outside their current field (Wang et al., 2017). Consequently, from this perspective, an inventor's past experience with science-based inventions enhances the likelihood of utilizing scientific knowledge to address new technological challenges in the future. Furthermore, while inventors may draw upon the accumulated knowledge produced by technological progress, a thorough and accurate understanding of science enables them to search and recombine information effectively (Ardito et al., 2021). Previous successful experiences in the application of scientific knowledge by inventors have been shown to ease the challenges associated with integrating new scientific and technological insights, thereby reducing the time spent on knowledge exploration (Novelli, 2015). Based on this, the following hypotheses are proposed in this study:

H4a: The richer the science-based invention experience of the inventor team, the higher the likelihood of incorporating scientific knowledge components during the invention process.

H4b: The richer the science-based invention experience of the inventor team, the greater the number of scientific knowledge components they incorporate during the invention process.

Breadth of technological knowledge

The breadth of an inventor's technological knowledge can be defined as all technological knowledge elements they possess, reflecting the diversity of the technological knowledge accumulated (Fleming et al., 2007). Simonton (2003) demonstrated that a rich diversity of cognitive elements available for association enhances the likelihood of identifying unique combinations within these elements. This implies that the broader the scope of technological knowledge, the greater the number of options available to an inventor when addressing new problems. In an investigation targeting inventors in the 3M innovation domain, Boh et al. (2014) employed a mixed-method approach combining qualitative (case study) and quantitative research to investigate how the breadth of inventors' expertise influences their innovative outcomes. Results indicate that extensive professional knowledge indeed plays a crucial role in enhancing inventors' capacity to produce more inventions. Furthermore, during the process of knowledge recombination, inventors may opt to utilize their existing knowledge base or seek out new external information to formulate solutions for distinct technological problems. Wang et al. (2017) pointed out that inventors typically initiate their process by exploring the existing knowledge space, employing iterative trial-and-error methods to test various combinations of existing knowledge until a satisfactory solution is found. Therefore, we argue that the broader the technological knowledge possessed by inventors or invention teams, the less likely they are to seek external scientific knowledge. This study proposes the following hypothesis:

H5a: The broader the range of technical knowledge possessed by an inventor team, the lower the likelihood of incorporating scientific knowledge components during the invention process.

H5b: The broader the range of technical knowledge possessed by an inventor team, the fewer the number of scientific knowledge components they incorporate during the invention process.

Measurement indicators

Knowledge recombination characteristics

Recombination complexity (*Complexity*). Complexity reflects the diversity of the knowledge base and components required in the process of knowledge recombination (Barbieri et al., 2020). This study employs the Originality index proposed by Trajtenberg et al. (1997) as a proxy for recombination complexity. The formula for its calculation is as follows:

$$Originality_p = 1 - \sum_k^{N_p} \left(\frac{Nreferences_{pk}}{Nreferences_p}\right)^2 \quad (1)$$

Where k represents a specific technological field, and N_p denotes the total number of distinct technological fields represented in all patent references cited by patent p. This study uses the first four digits of the IPC classification (hereafter referred to as 'IPC4') to represent technological fields. $Nreferences_p$ indicates the number of patent references cited by patent p, and $Nreferences_{pk}$ represents the number of those references that belong to the technological field k. The Originality index reflects the degree to which the cited references of a patent are distributed across various technological fields, with values ranging from 0 to 1. A higher originality index indicates that the focal patent draws from a wide variety of technological domains, suggesting that it is the result of combining knowledge from multiple fields.

Recombination novelty (*Novelty*). Novelty represents the uniqueness in the process of knowledge recombination, typically reflecting the '*distance*' between new technologies and prior technological knowledge (Barbieri et al., 2020). This study utilizes the improved radicalness index by Squicciarini et al. (2013) to measure novelty. This index not only characterizes the knowledge gap between the technological categories of the focal patent and those of the patents it cites, but also reflects the extent to which the technological invention combines knowledge components in a novel manner. The formula is as follows:

$$Radicalness_p = \sum_j^{n_p} \frac{CT_j}{n_p}; IPC_{pj} \neq IPC_p \quad (2)$$

Where n_p denotes the total number of IPC classification codes in all patent documents cited by the focal patent p. CT_j is the number of IPC4 codes in the cited patent j that differ from those of the focal patent p. This index ranges from 0 to 1, where a higher value signifies greater novelty of the patent.

Knowledge maturity (*Maturity*). Following the approaches of Jiao (2022), we use the average temporal distance between focal patents and backward citations as an indicator of knowledge maturity. The specific formula used is presented below.

$$Maturity = \frac{\sum_{i=1}^{N}(Year_{focal} - Year_i)}{N} \quad (3)$$

Where N is defined as the number of backward citations to the focal patent, $Year_{focal}$ represents the application year of the focal patent, and $Year_i$ refers to the application year of the ith patent cited by the focal patent.

Inventor team characteristics

Experience in science-based invention (*Inventor_Sci_Expe*). This study quantifies the experience in science-based invention of the inventor team by calculating the number of patents citing scientific papers among those previously granted to the inventors. Specifically, for the focal patent p, this study tracks all patents granted to each inventor prior to the applications date of patent p, counts the number of patents that cite scientific literature for each inventor, and uses the maximum value to represent the team's experience in science-based invention for patent p.

Breadth of technological knowledge (*Inventor_Tech_Bread*). To investigate the breadth of technological knowledge utilized by the inventor team, this study calculates the total number of distinct IPC4 codes among the patents granted to the inventor team of focal patent p over the past five years, following the method proposed by Chen et al. (2021).

$$Technical\ Knowledge_p = n_p; n \in \{IPC4_1; \ldots IPC4_i; IPC4_j; \ldots; IPC4_n\} \ \&\ IPC4_i \neq IPC4_j \quad (4)$$

Data, variables, and models

Data collection

To test the hypotheses proposed in this study, we construct a patent-level dataset including U.S. utility patents granted between 2001 and 2010. The dataset consists of two primary datasets:(i) the granted patents research dataset from PatentsView and (ii) the '*reliance on science*' dataset, which provides pairs of citing patents and cited scientific publications by matching U.S. patents to publications in Microsoft Academic Graph with various degrees of confidence (March, 1991). In our study, we match our patent sample to scientific papers cited in patents' front page or in-text with a confidence score of at least 7. After filtering out records with incomplete information, our research sample includes 1,685,970 patents, of which 463,393 cite scientific articles. Overall, the dataset consists of these patents and 1,407,439 scientific publications, yielding a total of 6,473,214 unique citation pairs between patents and papers.

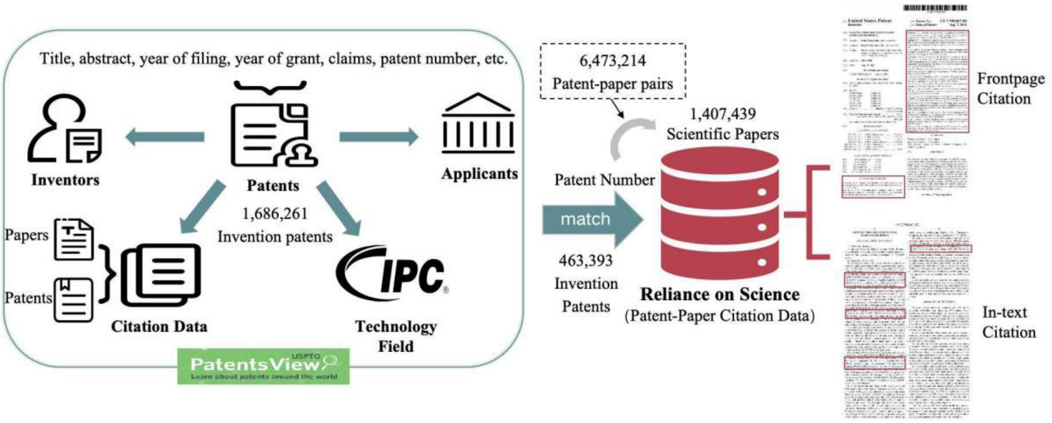

Figure 1. Flowchart of Data process

Variables

Dependent variables

This research delineates two dependent variables in accordance with the posed research questions: ***scientific knowledge integration tendency*** and ***scientific knowledge integration intensity***.

Scientific knowledge integration tendency (*Science*) assesses the tendency to integrate scientific knowledge into the technological development process, as measured by the citation of scientific papers by patents. In our study, a patent that cites at least one scientific paper, defined as a '*science-based invention*', is coded as 1. Conversely, a patent that does not cite any scientific papers, defined as a 'non-science-based invention,' is coded as 0.

Scientific knowledge integration intensity (*science_intensity*) refers to the degree to which scientific knowledge contributes to technological patent, as measured by the number of scientific papers cited by patents, using methodologies established in prior research (Harhoff et al., 2003; Sung et al., 2015).

Control variables

Taking into account potential influencing factors, this study incorporates a set of control variables, including the number of inventors (*Num_Inventors*), the number of applicants (*Num_Applicants*), applicant experience with science-based inventions (*Num_Applicants_Sci*), the number of backward patent citations (*Num_PC*), the speed of technology accumulation (*Tech_Cum_Speed*), and the type of applicant.

The variable $Num\_Applicants\_Sci$ is incorporated because existing studies indicate that the knowledge base of patent applicants influences the trajectory and efficacy of their future technological innovations (Katila adn Ahuja, 2002; Maddala GS, 1987). We measured this by calculating the average number of patents granted that had cited scientific literature prior to the application.

Num_PC represents the count of patent documents that an invention's patent cites. By controlling for the number of backward citations associated with each invention, we aim to mitigate the extent of technological knowledge dependency, as discussed by Gruber et al. (2013).

$Tech\_Cum\_Speed$ represents the speed at which a certain technology develops or evolves along its technological trajectory (Lee and Lim, 2001; Guo et al., 2013). The extent of cumulative development across technologies may affect the propensity of that the knowledge reorganization process relies on scientific knowledge (Grupp and Schmoch, 1992; Meyer, 2000). The formula is as follows:

$$Tech\_Cum\_Speed_p = \sqrt[5]{\frac{n_p}{n_5}} * 100\% \qquad (5)$$

Where n_p represents the cumulative number of the IPC4 classification codes for the focal patent p in its filing year. n_5 indicates the cumulative number of IPC classification codes from five years prior. The greater $Tech\_Cum\_Speed_p$ is, the faster the rate of accumulation in the technical field to which the invention belongs.

Regarding the type of applicant, referring to the applicant categorization algorithm proposed by Du Plessis et al. (2010), we classify patents into five categories: individual, company, government, university, and hospital, and set five dummy variables.

In addition, we include a set of time, country, and technology field dummies to control for potential time-varying effects, geographical and technological heterogeneity. Specifically, $Time$ is a set of dummy variables for the patent's granted year. Geo denotes geographical dummies represented by the country of the first inventor listed on a patent. We also include the technological field dummies, IPC, at the 1-digits IPC level (The IPC is a hierarchical system and is divided into sections, classes, subclasses, main groups, and subgroups. The section of IPC includes A, B, C, D, E, F, G, and H, corresponding to eight broad technical fields).

Table 1 presents the descriptive statistics for each variable. The average Science is 0.275, indicating that 27.5% of patents in this study's sample cited at least one scientific literature. The average scientific_intensity is 3.839, with a maximum value of 3048, representing the highest number of citations to scientific literature by any single patent.

Variables	Obs	Mean	S.D.	Min	Max
Science	1685970	0.275	0.446	0	1
Scientific_Intensity	1685970	3.839	17.620	0	3048
Complexity	1685970	0.477	0.284	0	0.975
Novelty	1632772	0.474	0.341	0	1
Maturity	1660462	3359.372	3232.240	0	638550
Inventor_Sci_Expe	1685970	0.312	0.324	0	1
Inventor_Tech_Bread	1685970	5.734	8.076	0	148
Num_Inventors	1685970	2.510	1.804	0	76
Num_Applicants	1530794	1.034	0.213	1	14
Num_Applicants_Sci	1530794	2188.774	4688.280	0	45899
Num_PC	1685970	22.541	46.978	0	2399
Tech_Cum_Speed	1682142	1.047	0.093	0.574	2.887
Company	1530794	0.942	0.235	0	1
Government	1530794	0.025	0.157	0	1
University	1530794	0.027	0.163	0	1
Hospital	1530794	0.002	0.039	0	1
Individual	1530794	0.004	0.065	0	1

Table 1. Descriptive statistics for the main variables

Regression model

Given that the dependent variable, *science*, is binary, this study employs a Logit regression model for the primary regression analysis. Subsequent analyses utilize the Probit model to further verify the robustness of the results. The baseline Logit model is established as follows:

$$Logit(p) = ln(\frac{p}{1-p}) = \alpha + \beta_i x_i + \gamma_i Controls_i + Time_i + Geo_i + IPC_i + \varepsilon_i \quad (6)$$

Where x_i are the explanatory variables of this study, i.e., *Complexity*, *Novelty*, *Maturity*, *Inventor_Sci_Expe*, and *Inventor_Tech_Bread*. $Controls_i$ are the control variables of this study, $Time_i$, Geo_i, IPC_i denote the time, geography, and technology domain dummy variables, respectively.

The second dependent variable, *science intensity*, exhibits a significant number of zero entries, primarily because the majority of the samples represent '*non-science-based inventions*' that lack any scientific literature citations. To address potential biases that conventional count models might introduce, this research employs a Tobit regression model for analysis. The model is as follows:

$$Science\_Intensity = \alpha + \beta_i x_i + \gamma_i Controls_i + Time_i + Geo_i + IPC_i + \varepsilon_i \quad (7)$$

Results

Logit regression results

This section investigates the impact of five characteristics on the variable 'Science' through logit regression analysis. Prior to the analysis, certain variables were logarithmically transformed to mitigate kurtosis and skewness, and multicollinearity was evaluated. Table 2 presents Spearman's correlation coefficients and the results of the multicollinearity tests, demonstrating low correlations (all below 0.7) and a maximum VIF of 2.05, confirming the absence of multicollinearity.

variables	VIF	1	2	3	4	5	6	7	8	9	10	11	12	13
1.Complexity	2.05	1												
2.Novelty	1.81	0.655	1											
3.Ln (Maturity)	1.20	0.138	0.097	1										
4.Inventor_Sci_Expe	1.19	0.059	0.010	-0.155	1									
5.Ln (Inventor_Tech_Bread)	1.43	0.070	0.050	-0.141	0.481	1								
6.Ln (Num_Inventors)	1.21	0.032	0.007	-0.108	0.218	0.432	1							
7.Ln (Num_Applicants)	1.03	0.007	0.007	-0.009	0.009	0.058	0.102	1						
8.Ln (Num_Applic_Sci)	1.21	-0.097	-0.079	-0.281	0.215	0.291	0.122	0.039	1					
9.Ln (Num_PC)	1.30	0.288	0.091	0.220	0.131	0.066	0.067	-0.026	-0.066	1				
10.Tech_Cum_Speed	1.06	-0.048	-0.010	-0.322	0.048	0.019	0.009	-0.021	0.171	-0.047	1			
11.Government	1.02	0.023	0.022	0.026	-0.012	-0.056	0.012	0.062	-0.050	-0.046	-0.029	1		
12.University	1.03	0.058	0.043	-0.012	0.065	-0.033	0.038	0.056	-0.002	-0.037	-0.043	-0.027	1	
13.Hospital	1.00	0.017	0.012	-0.009	0.027	-0.010	0.001	0.022	-0.008	-0.009	-0.016	-0.006	-0.007	1

Table 2. Spearman's correlation analysis and multicollinearity Test

The results of Logit regression analysis are shown in Table 3. Model (1) incorporates only control variables, while models (2) and (3) build upon model (1) by adding characteristics of knowledge recombination (i.e., *Complexity*, *Novelty and Maturity*) and characteristics of the inventor team (i.e., *Inventor_Sci_Expe*, *Invent_Tech_Bread*), respectively. Model (4) includes all explanatory and control variables. The full model demonstrates good fit with an AUC of 0.8159 and a classification accuracy of 78.52%. The last column of Table 3 details the marginal effects of the five explanatory variables included in Model (4).

Analysis spanning models 2 through 4 demonstrates consistent significance and directionality in the explanatory variables of interest. The findings from model 4 indicate that *Complexity* (β=0.221, p<0.001) and *Novelty* (β=0.120, p<0.001) are positively associated with *science*, confirming hypotheses H1a and H2a. Specifically, for each incremental increase in these recombination characteristics, the probability of incorporating scientific knowledge into the technology development process increases by 3.3% and 1.8%, respectively. In contrast, a significant negative relationship exists between *Maturity* (β=-0.345, p<0.001) and *science*, suggesting that less mature reorganized knowledge in technological inventions is more likely to incorporate scientific components. Moreover, a 1% increase in *Maturity* decreases the likelihood of using scientific knowledge in the invention process by 5.1%, thereby lending support to hypothesis H3a.

Furthermore, the results from Model 4 indicate a significant positive association between *Inventor_Sci_Expe* (β=2.211, p<0.001) and *science*, affirming hypothesis H4a. Each incremental unit of *Inventor_Sci_Expe* enhances the probability of utilizing scientific knowledge components by 32.6%. This finding underscores the role of experiential inertia, where inventors with extensive prior use of scientific knowledge are more inclined to integrate such elements into subsequent technological inventions. In contrast, *Invent_Tech_Bread* (β=-0.183, p<0.001) exhibits a negative correlation with *science*, where a 1% increase in *Invent_Tech_Bread* leads to a 2.7% decrease in the probability of employing scientific knowledge, supporting hypothesis H5a.

Variables	Model（1）	Model（2）	Model（3）	Model（4）	Average marginal effects
Complexity		0.192*** (0.011)		0.221*** (0.011)	0.033*** (0.002)
Novelty		0.109*** (0.008)		0.120*** (0.009)	0.018*** (0.001)
Ln (Maturity)		-0.374*** (0.003)		-0.345*** (0.003)	-0.051*** (0.000)
Inventor_Sci_Expe			2.246*** (0.007)	2.211*** (0.007)	0.326*** (0.001)
Ln (Invent_Tech_Bread)			-0.178*** (0.003)	-0.183*** (0.003)	-0.027*** (0.000)
Control variables					
Ln (Nun_Inventors)	0.348*** (0.003)	0.315*** (0.003)	0.449*** (0.004)	0.421*** (0.004)	-
Ln (Num_Applicants)	0.250*** (0.016)	0.239*** (0.016)	0.295*** (0.017)	0.281*** (0.017)	-
Ln (Applicants_Sci)	0.064*** (0.001)	0.055*** (0.001)	0.035*** (0.001)	0.029*** (0.001)	-
Ln (Num_PC)	0.302*** (0.002)	0.410*** (0.002)	0.238*** (0.002)	0.330*** (0.003)	-
Tech_Cum_Speed	0.837*** (0.021)	0.487*** (0.021)	0.865*** (0.022)	0.545*** (0.022)	-
Government	0.947*** (0.012)	0.972*** (0.012)	0.982*** (0.012)	0.995*** (0.013)	-
University	2.149*** (0.014)	2.166*** (0.014)	2.109*** (0.014)	2.109*** (0.015)	-
Hospital	2.786*** (0.081)	2.712*** (0.083)	2.641*** (0.083)	2.534*** (0.086)	-
Individual	-0.254*** (0.035)	-0.172*** (0.036)	-0.162*** (0.036)	-0.097*** (0.038)	-

Note：Standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001

Table 3. Logit regression results for *science*

Tobit regression results

In this section, the impact of five key explanatory variables on *science_intensity* was examined using Tobit regression, as detailed in Table 4. Model (5) served as the baseline with only control variables. Models (6) and (7) sequentially introduced additional variables pertaining to knowledge recombination and inventor team, based on the foundation established by model (5). Model (8) included all explanatory and control variables. The full model demonstrated an acceptable fit (pseudo R^2 = 0.176, Log likelihood = -1,238,628.6), although the normality assumption of error terms was violated (CM test: $p < 0.001$). We address this limitation through negative binomial regression in our robustness tests. The significance and direction of the five key explanatory variables remained consistent from model (6) to (8), indicating the robustness of the findings.

Firstly, the results from Model (8) showed that *Complexity* (β=0.306, p<0.001) and *Novelty* (β=0.148, p<0.001) were significantly and positively correlated with *science_intensity*. These results supported hypotheses H1b and H2b, suggesting that increased complexity and novelty in an invention's recombination are linked to a greater reliance on scientific knowledge. In contrast, *Maturity* (β=-0.413, p<0.001) has a significant negative effect on *science_intensity*. This indicates that an invention's knowledge maturity is inversely related to its dependence on scientific knowledge. Specifically, inventions developed within newer technological fields tend to incorporate more scientific components. Thus, hypothesis H3b is confirmed.

Secondly, *Inventor_Sci_Expe* (β=2.471, p<0.001) significantly positively influences *science_intensity*, whereas Invent_Tech_Bread (β=-0.211, p<0.001) demonstrates a significant negative effect. This suggests that a team with more experience in scientific invention tends to rely more heavily on scientific knowledge during technological development. Conversely, a broader range of technical knowledge among inventors correlates with less reliance on scientific knowledge components. Therefore, both H4b and H5b are supported.

Variables	**model（5)**	**model（6)**	**model（7)**	**model（8)**
Complexity		0.296*** (0.012)		0.306*** (0.011)
Novelty		0.148*** (0.009)		0.148*** (0.008)
Ln (Maturity)		-0.477*** (0.003)		-0.413*** (0.003)
Inventor_Sci_Expe			2.538*** (0.007)	2.471*** (0.007)
Ln (Invent_Tech_Bread)			-0.206*** (0.003)	-0.211*** (0.003)
Control variables				
Ln (Nun_Inventors)	0.433*** (0.004)	0.383*** (0.004)	0.499*** (0.004)	0.461*** (0.004)
Ln (Num_Applicants)	0.446*** (0.017)	0.427*** (0.017)	0.460*** (0.016)	0.439*** (0.016)
Ln (Applicants_Sci)	0.067*** (0.001)	0.055*** (0.001)	0.027*** (0.001)	0.019*** (0.001)
Ln (Num_PC)	0.374*** (0.002)	0.498*** (0.003)	0.268*** (0.001)	0.369*** (0.002)
Tech_Cum_Speed	0.835*** (0.023)	0.413*** (0.023)	0.800*** (0.023)	0.435*** (0.022)
Government	1.182*** (0.013)	1.181*** (0.013)	1.093*** (0.012)	1.082*** (0.012)
University	2.392*** (0.011)	2.371*** (0.012)	2.122*** (0.011)	2.094*** (0.011)
Hospital	3.036*** (0.046)	2.924*** (0.047)	2.564*** (0.042)	2.451*** (0.044)
Individual	-0.349*** (0.038)	-0.260*** (0.039)	-0.239*** (0.036)	-0.168*** (0.037)
Year	control	control	control	control
Country	control	control	control	control
IPC	control	control	control	control
Constant term	-3.046*** (0.051)	0.762*** (0.058)	-3.174*** (0.047)	0.130*** (0.054)
Pseudo R2	0.127	0.135	0.170	0.176
Observed Values	1,518,530	1,464,685	1,518,530	1,464,685

Table 4. Tobit regression results for *science_intensity*

Robustness test

To ensure the reliability and robustness of the research findings, this study conducted a revalidation of the empirical results by substituting both the model and the dependent variables. The outcomes confirmed that the direction and significance of all variables were consistent with the primary analysis results, thereby affirming the robustness of the findings. Detailed displays of these results are omitted here due to space limitations, but the robustness results are available upon request from the author.

Conclusions

Technological advancement is increasingly reliant on scientific discoveries, yet the mechanisms driving this reliance remain unclear. Grounded in knowledge recombination theory, this study utilizes a dataset of 1,685,970 invention patents granted by the USPTO from 2001 to 2010. Through regression models including Logit and Tobit, this study examines the effects of knowledge recombination and invention team characteristics on the propensity and intensity of scientific knowledge incorporation. This study yields several interesting findings.

Firstly, this study reveals that the complexity and novelty of recombination significantly promote both the tendency and intensity of scientific knowledge integration. Specifically, the higher the complexity and novelty of a technological invention's recombination, the more likely it is to utilize scientific knowledge in the invention process, and the greater the number of scientific knowledge components involved. As previously mentioned, it is evident that more complex inventions engage a wider variety of technological knowledge components throughout the knowledge recombination phase. Fleming and Sorenson (2004) noted that scientific knowledge enables inventors to overcome the inherent difficulties associated with integrating highly coupled technological components. Consequently, the greater the complexity of a technology, the more likely it is that inventors will incorporate scientific knowledge components during the technological development process. Similarly, the higher the novelty of knowledge recombination in a technology, the more it indicates the integration of technologically distant knowledge components during its invention process. This increased distance necessitates a greater input of scientific knowledge to mitigate the uncertainties and identification challenges that such distant recombination might introduce (Balconi et al., 2010).

Secondly, the knowledge maturity exists a significant negative impact on both the tendency and intensity of scientific knowledge integration. This suggests that more mature technologies are less likely to incorporate scientific knowledge. As demonstrated by Chin et al. (2012), in more mature technologies, domain-specific literature increasingly becomes common knowledge. Inventors often internalize this information as part of their foundational skills, consequently reducing their reliance on citing scientific literature during the patent application process. Therefore, as technology matures, its dependency on scientific knowledge diminishes.

Thirdly, the science-based invention experience of invention teams demonstrates a significant positive impact on both the tendency and intensity of scientific knowledge integration. As evidenced by the marginal effects presented in Table 3, the science-based invention experience of the inventor team emerges as the most critical factor influencing the propensity for scientific knowledge input. Specifically, each unit increase in the inventors' science-based invention experience is associated with a 32.6% increase in the probability of leveraging scientific knowledge in technological inventions. This phenomenon may be attributed to the inventors' prior successful experiences with science-based inventions, which potentially enhance their ability to identify connections between past experiences and current challenges, as well as to conceptualize potential solutions. In contrast, the breadth of inventor teams' technological knowledge exhibits a significant negative impact on both the tendency and intensity of scientific knowledge integration. That is, the broader the range of technological knowledge possessed by the invention team, the less likely they are to utilize scientific knowledge in addressing specific technical challenges. The individual knowledge base serves as the fundamental wellspring of innovation (Boh et al., 2014; Castaneda and Cuellar, 2020; Zhu et al., 2023). Inventors typically initiate their problem-solving process by exploring their existing knowledge domains, seeking to identify and synthesize knowledge components that address specific technological challenges. The broader the technological knowledge base of an invention team, the more diverse knowledge combination strategies they can employ, consequently reducing their reliance on scientific knowledge components.

In contrast to many existing studies, our primary focus is the nature of science-based technologies, rather than the subsequent impacts of inventions. Inventive activities involve various interconnected stages, ranging from conceptualization to market development. Knowledge recombination characteristics of inventions can potentially influence the entire innovation chain. Technological complexity, novelty, and maturity have been shown in prior studies to explain their knowledge spill over effect on the value of subsequent inventions to varying degrees (Barbieri at al., 2020; Capaldo et al., 2017). Therefore, re-examining previous empirical research by taking these factors into account can shed new light on the impact of science on technological inventions, which also serves as a direction for our future research.

Our study is not without limitations. We solely rely on the USPTO patent data for the empirical analyses. In fact, there exist disparities in the patent systems of different countries. USPTO has been identified as exhibiting a greater frequency of citations than patents from other patent offices (Svensson, 2022) and US generated about 63% of the world's science-based patents (Gazni and Ghaseminik, 2019). Future research could investigate the robustness of our findings across different patent offices. Likewise, the degree of science dependency within various technological fields should also be considered. Technological inventions with high scientific dependence, such as those in biomedical and chemical fields, may present distinct recombination patterns than patents in other fields. Additionally, while our study examines the individual effects of knowledge recombination characteristics and inventor team attributes, future research could explore their interactive effects to better understand how they jointly shape scientific knowledge integration in invention processes.

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