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Dynamics and Effects of Science Technology Translation:
Case of Blockchain Technology

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ABSTRACT

Considering the academic and industrial needs, it is necessary to examine the dynamics and effects of science and technology translation, especially the indirect ones. This study proposes a framework for identifying the levels of translation, called translational generation, and measuring their translational effects. An empirical analysis is carried out in the field of blockchain. The results provide evidence supporting the strength of direct translation and the growth of indirect translation. Firstly, the amount of S&T translation has increased and the amount of indirect translation has grown up to almost three times that of direct ones. Secondly, direct translation has better effects than all levels of indirect groups. However, the advantage of direct translation is not stable. It decreases in the translation intensity dimension and increases in the translation speed dimension. These findings have important implications for S&T innovation and source-allocated policy making.

KEYWORDS

Blockchain, S-T Translation, Technology Innovation, Text Mining

INTRODUCTION

The linkage and interaction between science and technology (S2T) have been of great interest to researchers (Contopoulos et al., 2003; Malva et al., 2015; Ke, 2019; Ke, 2020). Translational knowledge, which bridges the gap between science and technology, has been shown to play a crucial role in driving innovation (Contopoulos et al., 2003; Contopoulos et al., 2008; Weber et al., 2013). For example, translational science in Biomedicine is a key field that translates basic scientific discoveries ("bench") into clinical applications ("bedside") (Ke, 2019). The focus of this study is on the diffusion of knowledge from science to technology within the context of translational research. Technology development absorbs scientific knowledge through various means, including citing scientific articles, direct translation, and indirect translation from other patents. Indirect translation is particularly important for accessing scientific impact and passing on scientific knowledge to future technologies (Jiang & Zhuge, 2019). However, most existing studies focus solely on direct translation

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between science and technology, such as analyzing direct citation between articles and patents (Ke, 2019; Ke, 2020; Marx, 2020; Marx, 2022), while neglecting the indirect citations that account for most of the S2T translation, especially for basic science knowledge (Narin, 1997). Indirect translation involves many nodes and edges from science to technology, similar to "long ties" in social networks. In the past, long ties were widely assumed to be weak in social emotions and information functions. However, recent studies have proposed that long ties bridging different communities play crucial roles in spreading information and integrating relationships in population-scale social networks (Alstyne, 2011; Lyu et al., 2022; Park et al., 2018). Long ties are more persistent and diverse and nearly as strong as ties embedded within a small circle of nodes. Marra et al. (2015) observed direct and indirect citations on patent life and found that indirect citations account for more complex knowledge flows within the innovation network. Inspired by relevant studies, we hypothesize that the long and indirect S2T translational path has surprising power in innovation. The research question of this study is how direct and indirect translation distributes within the innovation system and how well their knowledge flow effects are.

In this study, we aim to extract S2T translation patterns by analyzing patent-article citation networks. Our primary focus is on understanding the patterns of knowledge diffusion and absorption from science to technology, and we believe that citation is a suitable proxy for this purpose (Ke, 2020). Patents absorb knowledge from scientific articles by citing them. Second, patent-article citations are clearer and more accurate in reflecting knowledge absorption than article-article citations. This is because one article may cite dozens of other articles, and it is difficult to claim that the cited article contributed substantively to the research of the citing article due to the complicated motivations and emotions involved (Teplitskiy et al., 2022). However, when a patent application cites a few articles, it is more likely that the knowledge from these articles acts as the key background technology (Li et al., 2017). Thus, we apply citation generations to the patent-article citation network to exert direct and indirect S2T translation (Hu et al., 2011). To precisely measure the translational path length from science to technology, we further define the translation generation (TG) as a simple and powerful indicator. The TG of a translation event is the number of citation generations needed from an article to a patent and the TG of a group of translations is the mean of the individual translation events. Finally, we measure the translational effects from three aspects: translational lag (TL), translational distance (TD), and translational intensity (TI).

To test our hypothesis, an empirical analysis is carried out in blockchain technology. Blockchain is a rapidly evolving technology that holds great promise for various fields of the economy and business (Yang, 2022). For instance, Opensea, the world's largest non-fungible token exchange platform, has a monthly turnover of nearly 5 billion dollars. Given the frequent and close interaction between science and technology in this field, it is an ideal context to explore our research questions. Our study of S2T translation in blockchain has practical significance for addressing the challenges faced by this technology. Specifically, we aim to explore different levels of S2T translation behaviors and their dynamics and effects. First, we will examine a crucial indirect translation perspective that has been overlooked in the literature on S2T innovation. Second, we will provide insights to evaluate basic science, including the argument that public science is not always useful for innovation and social development. Finally, our study aims to accelerate the development of relevant technology and promote the efficiency of S2T translation.

This study contributes to three main research streams. Firstly, we extend the literature on S2T interactions by observing indirect linkages between science and technology. The value of science is potential and profound when considering both direct and indirect impact. Furthermore, we explore how the extent of indirect linkages impacts the performance of translation. Secondly, we contribute to the research of integrated innovation by highlighting the importance of S2T integration in addition to science or technology. By comparing the translational effects of direct and indirect translation, we propose that it is essential to promote scientific knowledge diffusion across borders on breadth, speed, and intensity dimensions. Thirdly, the strength of long ties in social networks has not been investigated in the context of S2T translation. Knowledge diffusion and absorption follow different mechanisms compared to interpersonal social relationships.

Our research is organized as follows: Section 2 provides a literature review of S2T translation and blockchain. In Section 3, we present the dataset construction and methods used to identify S2T translation and measure translational effects. Section 4 presents the empirical results and analysis of these results. In Section 5, we discuss the findings in relation to prior literature, and Section 6 concludes the paper.

2. LITERATURE REVIEW

2.1 Understanding the S2T Translation

The promotion of technology based on scientific knowledge has a long history. In 1997, Narin et al. (1997) observed a growing trend of technology sourcing science from U.S. patents and scientific articles (Carlson & Sullivan, 2010). They discussed the issue of basic science and technological innovation from different theoretical perspectives, including innovation diffusion, knowledge network, and research policy. In this context, two important research questions arise: (1) how to identify the linkages between science and technology; and (2) how to evaluate the impact of scientific knowledge on technology.

In the past, S2T translations have been identified qualitatively using citations from patents to articles (Du et al., 2019). Patents applicants could cite patents academic articles or non-patent literature (NPL) on the front page and within the text of application publications. However, they have various motivations when citing different category references. Specifically, the motivations of patents-patent citation are either granted-patents protection that is bound by patent law, or knowledge ground. However, patents-NPL citations are always the initiative of the patent applicants where knowledge relevance is the main reason (Narin et al., 1997; Carlson & Sullivan, 2010; Li et al., 2017). The citation method facilities S2T translation analysis on the publication level, while deeper micro-level information cannot be observed. Therefore, some scholars have conducted text analysis methods based on machine learning models. They can identify and track the knowledge memes from the patent-article citation networks to observe translation at the micro-level. For example, Ke proposed a series of studies on S2T translation in the Biomedicine field by identifying translational science using word embedding (Ke, 2018; Ke, 2019; Ke, 2020).

Scientific knowledge is a crucial source of information and evidence for technology development and decision-making (Amano, 2023). On one hand, relevant research help to evaluate the role and contribution of basic science to technology innovation. Public science serves as both the knowledge provider and the technological frontier signal (Li et al., 2017). Malva et al. (2015) regarded basic science as the prescription to identify breakthrough inventions. On the other hand, the practical value of a public investment is a long highly controversial issue for scientists and policymakers. Li et al. (2017) examined it by accounting for linkages between public research investment and subsequent patenting using U.S. National of Health (NIH) grants over 27 years. It is worth noting that 10% of NIH grants directly generated a patent, but 30% generated articles that were subsequently cited by patents in their dataset. This suggests that considering only the indirect applied value of basic science investment provides only a partial picture of its impact.

2.2 Blockchain: Development and Challenges

A blockchain is a type of digital ledger technology (DLT) that consists of a growing list of records, called blocks, that are securely linked together using cryptography. Cryptographer David Chaum proposed a protocol similar to the blockchain in 1982 (Sherman et al., 2019), and in 2008, Nakamoto designed the first decentralized blockchain using a Hashcash-like method to timestamp blocks without a sign by other trusted parties (Nakamoto, 2008). A blockchain typically consists of a data layer, networking layer, consensus layer, incentive layer, contract layer, and application layer. Due to its characteristics of decentralization, immutability, security, smart contracts, transparency, and auditability, blockchain is a reliable value-transaction protocol that enables a more trustworthy and confident transaction system (Mehta et al., 2020). For example, Bitcoin, the most successful implementation of blockchain, has been applied and shown high stability and reliability for more than a decade. Blockchain is a rapidly developing information storage form that has been applied in multiple fields, including finance, manufacturing data protection, automotive, information security, digital purchasing, business, supply chain, and more. As of early 2021, the data size of the blockchain had grown to 10EiB.

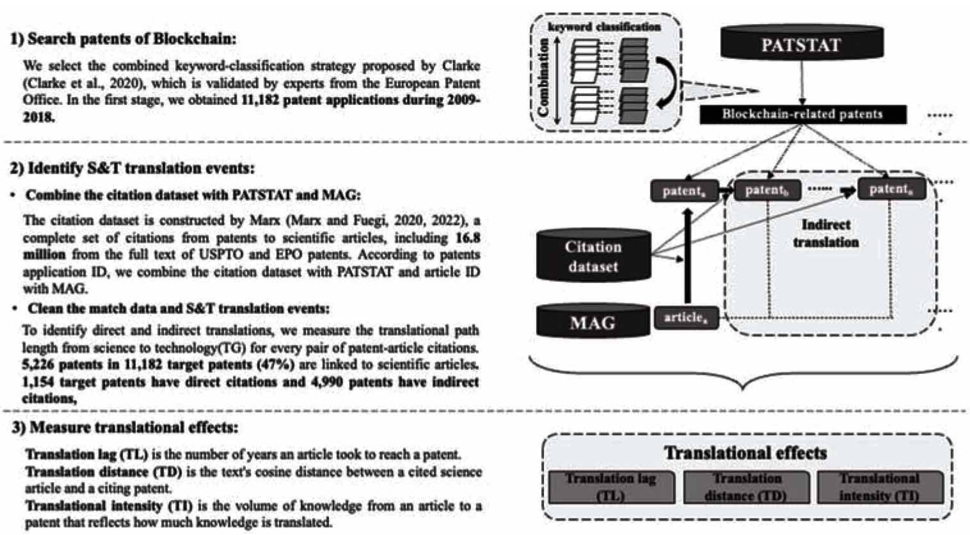
The life cycle of most blockchain technology, such as the encryption, the consensus mechanisms, and the network, is in the emergence stage and there are still many challenges and limitations that need to be addressed (Yang, 2022). For example, Bamakan et al. (2021) proposed two main challenges of blockchain patent analytics and text mining. The first one is security and privacy where various threats (i.e., Liveness Attacks, Double Spending Attacks, 51% Vulnerability Attacks) can attack data contained in the blocks. The second one is energy consumption, including the use of renewable energy and the waste reduction of resources (Bamakan et al., 2021). These challenges require complex knowledge to solve them, while maintaining technical advantages. The rapid development needed by the industry drives the basic science to promote and translate more quickly (Yang, 2022). The exploration of blockchain-related basic theories, especially the security-related theory, was identified to be the main future development trend (Zhang et al., 2021). Researching basic issues and addressing the mentioned challenges is essential to promoting blockchain technology within society.

3. METHODOLOGY

3.1 Data

The overall framework of the research methodology is shown in Figure 1. We intend to obtain the scientific articles and technical patents of blockchain by combining keywords and knowledge categories of the technology from Microsoft Academic Graph (MAG) and PATSTAT, respectively. To identify S2T translation events, we use the dataset constructed by Marx and Fuegi (2020, 2022),

Figure 1. The process flow of the entire research methodology



which is a complete set of citations from patents to scientific articles, including 16.8 million from the full text of USPTO and EPO patents. A blockchain dataset includes all patents of blockchain and all articles cited by these patents.

Searching for all patents of blockchain is the first key step to constructing the dataset. Two main retrieval strategies of blockchain-related patents are the keyword-based search strategy (Bamakan et al., 2021; Denter, 2021; Huang et al., 2020; Zhang et al., 2021) and the combined keyword-classification strategy (Clarke et al., 2020; Filippova, 2019). The former has a lack of effectiveness because the technical vocabulary continues to evolve (Xie & Miyazaki, 2013). Thus, we select the combined keyword-classification strategy proposed by Clarke et al. (2020), which is validated by experts from the European Patent Office. The patents are retreated from the Worldwide Patent Statistical Database (PATSTAT), including bibliographical patent data from more than 80 patent offices worldwide, and are widely used by scholars (De Rassenfosse et al., 2014; Denter, 2021; Pasimeni, 2019).

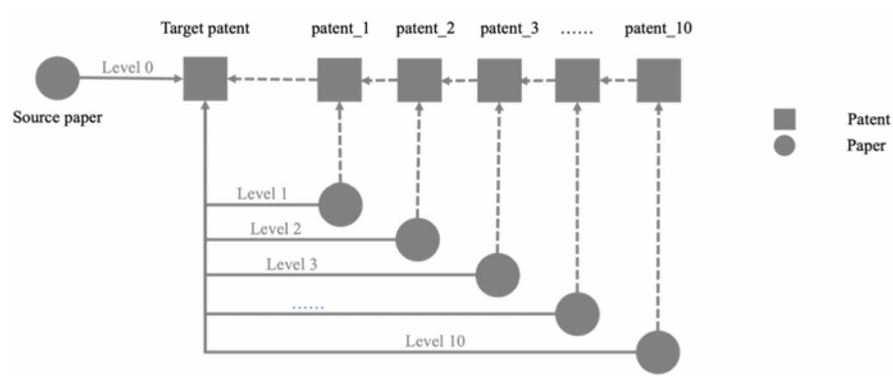
Finally, we receive 11,182 worldwide patent invention applications on blockchain during 2009-2018. Furthermore, we identify 3,519 (31.47%) priority and 7,663 non-priority applications. The priority applications are further characterized by 1,916 (17.13%) PCT priority applications and 9,266 non-PCT priority applications. Additionally, 1,554 (13.90%) of these patents cited scientific articles directly referring to 3,740 articles.

3.2 Identify Direct and Indirect S2T Translations

To identify direct and indirect translation, we measure TG for every pair of patent-article citations. TG represents the translational path length from science to technology. Considering the citation relationship and networks, a publication exerts a direct and indirect influence on other publications by forwarding citations and backward citations (Hu et al., 2011). A stream of literature has proved the value of indirect ties in both article citation networks (Jiang & Zhuge, 2019) and patent citation networks (Marra et al., 2015). It achieves surprisingly good performance in not only recognizing high-impact publications but also identifying under-cited publications. Thus, we compute TG based on the citation.

We search the scientific source for each target patent by the method of iteration. Specifically, the direct ties are defined as level 0 where the target patent cited a scientific article. If the target patent did not cite an article directly, we search for the cited articles of patents that the target patent cited. Considering that the real relationship decreases with the iteration steps increasing, we limit the steps of iteration to 10. As shown in Figure 2, the indirect ties are defined from level 1 to level 10 in terms of the steps of iteration. Finally, 5,226 patents in 11,182 target patents (47%) are linked to scientific articles. And 1,154 target patents translate the scientific knowledge directly, while 4,990 target patents

Figure 2. Definition of S2T TG. The square nodes are the target patent and the circle nodes represent the cited articles. The red lines show the direct translation and the blue ones show the indirect ties.



have indirect S2T translation referring to 189,392 articles. Surprisingly, not every translational level has scientific ties, in fact, only level 1, level 2, level 4, and level 7 do.

3.3 Measure Translational Effects

The concept of TG assumes that for an article to have a knowledge impact, it must reach a patent after several citation generations. However, it cannot guarantee that S2T translation occurs, and that scientific knowledge contributes. From this assumption, we define the following indicators to measure the translational effects. Translation lag and translation distance are proposed by Weber (2013) to measure knowledge translation among different research types in Biomedicine. And translational intensity is modified to measure knowledge contribution from science to technology based on a substantive citation influence intensity (Teplitskiy et al., 2022).

1. Translation lag (TL) is the number of years an article took to reach a patent. The TL of a collection of the TG articles' translations is the mean TL of the individual translational event.
2. Translation distance (TD) is the text's cosine distance between a cited science article and a citing patent. The TD of a collection of a certain number of TG is the mean TD of every event. The text distance is constructed using the title and abstract, succinctly summarizing the most important concept of the articles and the patents. Specifically, we first extract keywords from titles and abstracts using the spaCy (Honnibal, 2017) and then we map these keywords into an independent vector using Doc2Vec (Kim & Koo, 2017):

$$TD_m = 1 - \frac{u * v}{\sqrt{u^2 * v^2}} \tag{1}$$

For a patent-article citation m, u is the vector extracted from the article's title and abstract and v is that from the patent's title and abstract.

3. Translational intensity (TI) is the volume of knowledge from an article to a patent that reflects how much knowledge is translated. The TI of a collection of the TG translations is the mean TI of every event:

$$TI_m = \frac{1}{1+l_m} * \left(\log(w_1 * \sum_{i=n} \beta_i * k_{i\_title} + w_2 * \sum_{i=n} \beta_i * k_{i\_abstract}) + 1 \right) \tag{2}$$

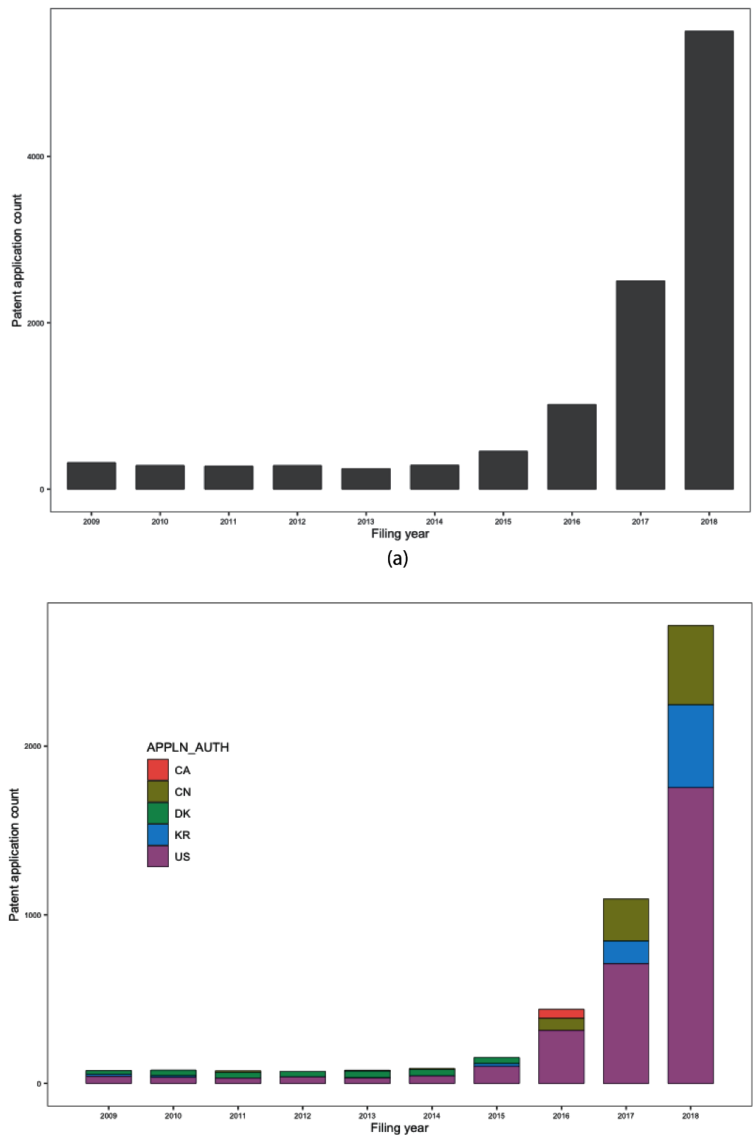
For a patent-article citation m, n is the number of knowledge units. $k_{i_{title}}$ is the number of knowledge units from an article to a patent's title and $k_{i_{abstract}}$ is that to a patent's abstract. β_i is the frequency that a knowledge unit i appears in the article title and abstract, which can present the stock of knowledge. w_1 represents the weight of knowledge citation from an article to the title of the patent and w_2 is the weight from an article to the abstract of the patent. We compute the dynamic weights using relative citation advantage (RCA), which is similar to relative technology advantage (RTA). If most patents cite a knowledge unit in an abstract position, a citation in the title will be given a higher weight. Such a formation takes the knowledge storage of cited articles and the knowledge absorption of citing patents into consideration. If a cited article stores more knowledge utilized in technology innovation, the translation intensity is stronger. $\frac{1}{1+l_m}$ is a translational level decay factor where l_m is the level, TG, of the patent-article citation m. We claim that the total knowledge flow is lower with the generation increasing. It must be noted that the knowledge flow isn't equal to knowledge intensity in our framework. TI is a key indicator to measure knowledge contribution from an article to a patent indicating the S2T translation strength.

4. RESULTS

4.1 Descriptive Statistic and Analysis

Figure 3 shows that the number of patent applications related to blockchain technology has grown rapidly since 2015, with a total of 5,500 applications in 2018. The US office holds the highest number

Figure 3. Dynamics of S2T TG (B) shows the top 5 countries according to the number of patent applications (CN: China; DK: Denmark; JP: Japan. KR: Republic of Korea; US: United States)



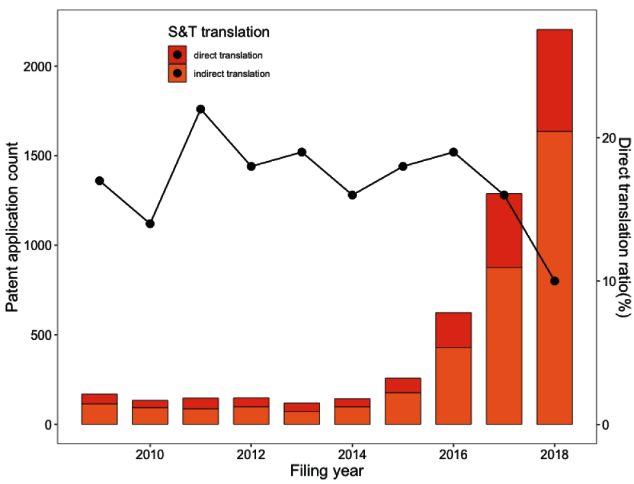
(b)

of patents, accounting for 32.3% of all patents. However, there has been a significant increase in patent applications at the CN (China), DK (Denmark), and KR (Korea) authorities since 2016. For example, the annual average increase rate in China, 8.78%, is almost 250% higher than the United States' 161% from 2016-2018.

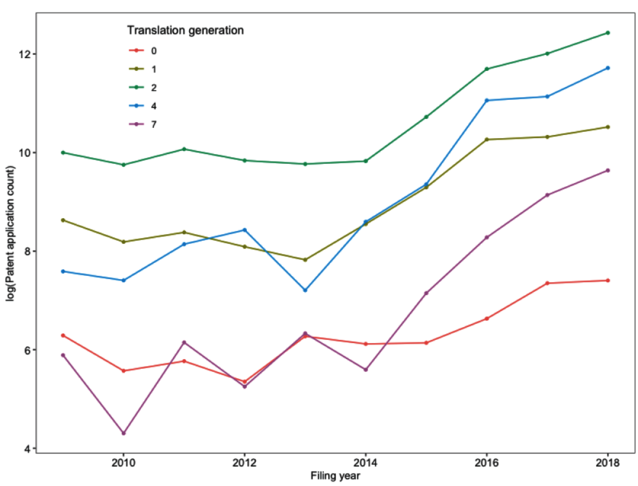
4.1.1 Indirect Translation Trend

We identify the scientific knowledge source and infer TG for each citation in our dataset. Among all indirect S2T translation behaviors, we distinguish their levels for more exploration. Figure 4 shows the dynamic of all translations. Firstly, Figure 4(A) shows that the amount of S2T translation has increased with the development of technology over time, indicating a trend towards S2T integration in innovation. Secondly, in the dynamic development of blockchain technology, the direct S2T translation takes up a smaller amount and a decreasingly lower ratio compared to indirect ties. In 2018, less than 10% of patents utilized scientific knowledge directly compared with 30% of indirect

Figure 4. Dynamics of S2T TG. (B) We take logarithms (log) for the number of patent applications. All translations are classified according to their generations on one year.



(a)



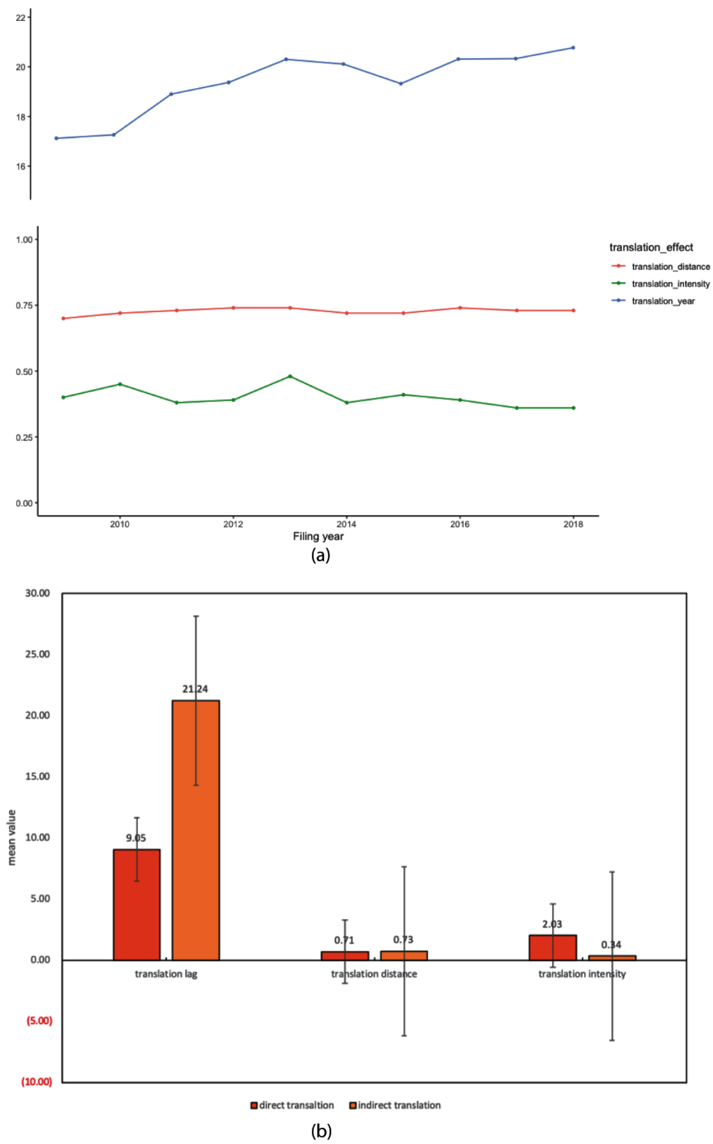
(b)

S2T translation. Among various S2T TG, level-2 indirect translation is consistently in the top place and shows an increasing trend, followed by level-1 and level-4. This data observation may contain a potential finding: although more basic science contributes to technology indirectly, there exists an optimal generation point where the indirect level stands, and S2T translation performs best.

4.1.2 Indirect Translation Power

Figure 5 observes the dynamic of translation effects. For translation lag, we find substantially a longer translation lag, from 17.12 years up to 20.77 years. However, the growth in the overall translation lag could be driven by many factors, including the increase in indirect translation. As shown in Figure 5(B), knowledge flow from an article to a patent requires more bridging patents and a longer time.

Figure 5. Translation effects and difference between indirect and direct groups. (A) Dynamic of translation effects. (B) Difference between two groups. The black line is the standard error and the tag is mean of 3 indicators.



The time lag of indirect translation is about 2.33 times of direct ones and this difference is significant (Kolmogorov-Smirnov, two-sided test, $p < 0.05$).

Put differently, translation distance differs slightly between the two groups (0.71 in direct versus 0.73 in indirect). Importantly, such a slight difference is also significant (Kolmogorov-Smirnov, two-sided test, $p < 0.05$). This phenomenon is driven by the special measurement of knowledge distance, which is between 1-2. We note that translation distance stays at a certain level (almost 0.7) smoothly during the whole period. A possible exploration is that a patent must search for a similar knowledge base to support itself. Meanwhile, to ensure its novelty, it tends to shed light on the innovation and differences with previous knowledge.

According to Figure 5(A), translation intensity remained relatively stable during 2009-2018, decreasing slightly from 0.40 to 0.36. As technology improves, the growth of total articles dilutes the knowledge per article. The mean difference in translation intensity between the two groups is significant (2.03 in direct versus 0.34 in indirect; Kolmogorov-Smirnov, two-sided test, $p < 0.05$). However, due to our strict method of measuring knowledge contribution, almost 50% of translation intensity values are zero. It's important to note that a zero value doesn't necessarily mean no contribution, but rather a smaller contribution relative to other citations.

We observed that the variation in the indirect translational group is larger than the direct group across all indicators. There are likely to be obvious different characters within the internal indirect translation group. To test this hypothesis, we will conduct a more detailed analysis of different translation generations.

4.2 Translation Effects and Translation Generation

4.2.1 Translation Lag

Figure 5(A) shows an overall growth of translation lag from 2009-2018. To analyze patterns of different translations, Figure 6 illustrates the dynamic variation given levels of generation. Translation lag varies among different generations, with the lowest in the direct translation (the overall mean: 8.61 years) and the highest in the 7-level generation (the overall mean: 22.95 years). Previous work found that knowledge iteration will accelerate as technology develops to a certain stage (Ke, 2020). However, our finding in Figure 5(A) seems to contradict this. We can see that growth merely tells part of the story, as overall growth is driven by a drastic fluctuation in the level-7 generation. Excluding this level-7 line, we can observe a stable downward trend across different levels. Level-7 is a long-distance translation group, and its substantial meaning and role in the target patent are still unclear. Additionally, blockchain technology is rapidly developing and expanding into other areas (Bamakan et al., 2021; Denter, 2021). Given this unstable condition, translation lag is also subject to change.

We identified 52,26 patents with translational behavior recording, and Figure 7 analyzes all of them combined with their application authority. The top 5 countries in S2T translations are included in the analysis: US, CN, RU, GB, and DE. Firstly, Japan, Korea, and Denmark are not included in Figure 6, as they grant more patent applications without scientific connections. GB has the lowest mean translation lags, indicating that the overall S2T translation speed in GB is quicker. This advantage also shows in direct translation, with an average of 2.91 years. The United States has the highest direct translation lag, which is more than three times that of GB. Russia translates knowledge from science to technology the slowest, with an average of 19.13 years. Such a disadvantage is due to indirect translation, especially the highest level-7 value abnormally. Secondly, we observed that years decreased with TG increasing, except for level-7, which is an exception. Translation takes more years from science to technology as the level increases from level-0 to level-4 in Figure 6(A).

4.2.2 Translation Distance

Translation distance or similarity, a pair of relative concepts, is a hot indicator most of the time in translational science research. Technology tends to absorb knowledge from relevant and

Figure 6. Dynamic and distribution of translation lag

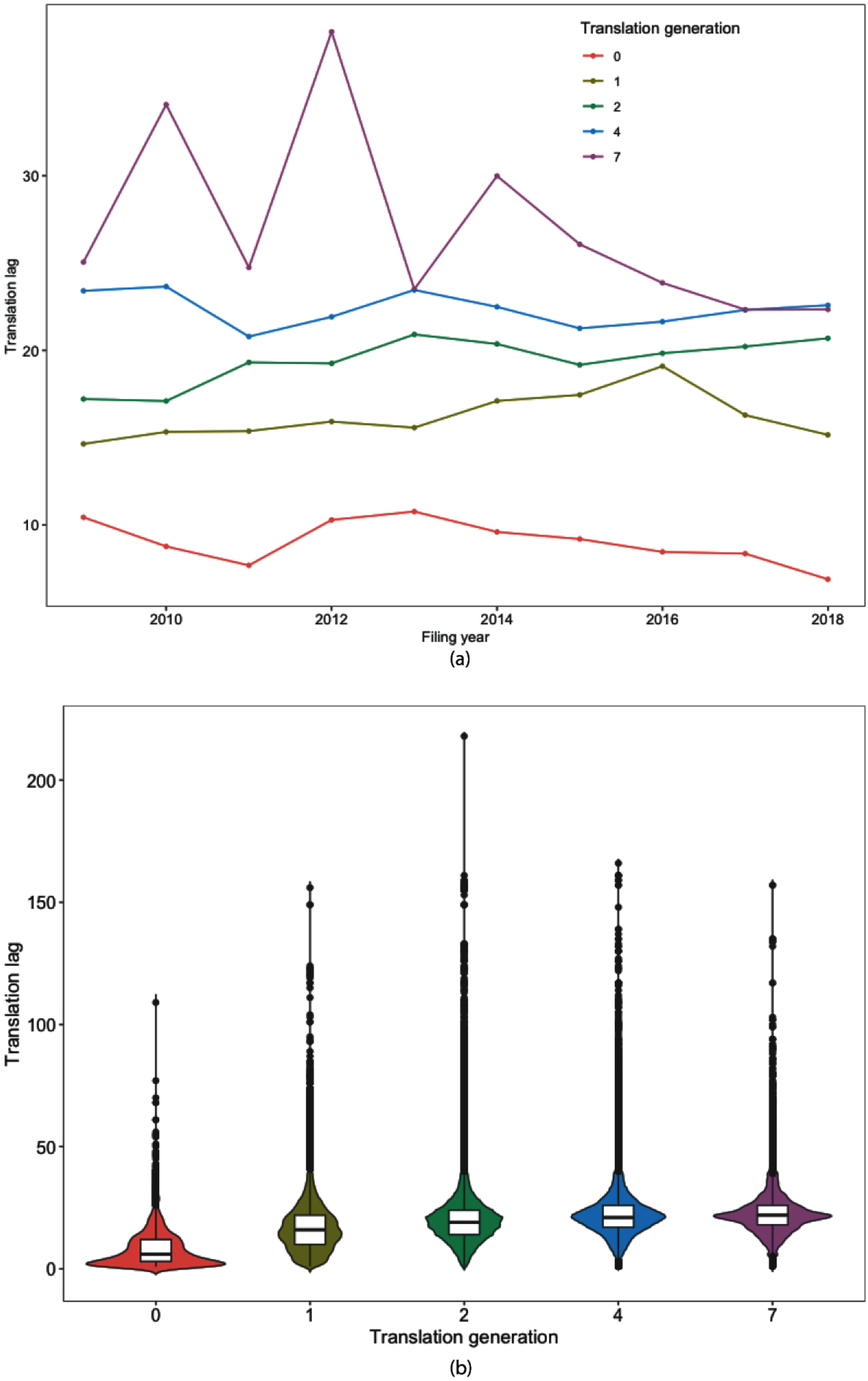
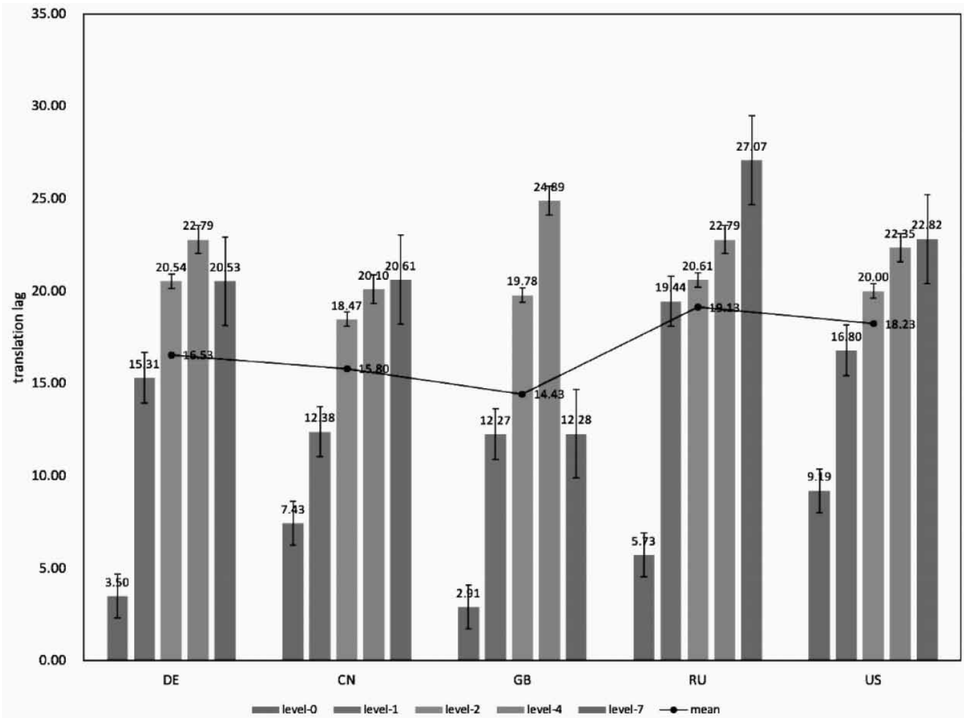


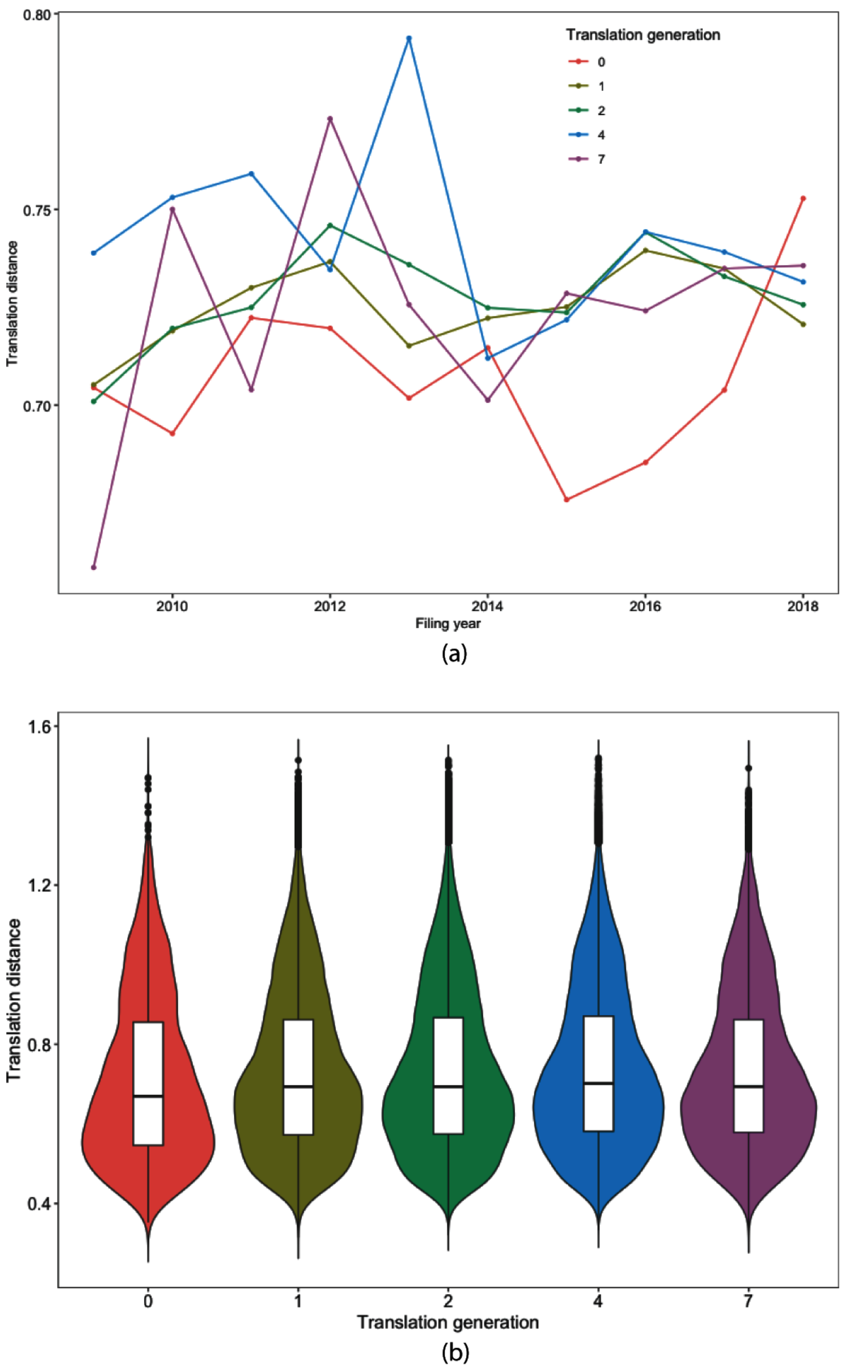
Figure 7. Difference of translation intensity among main countries (DK: Denmark; CN: China; GB: The United Kingdom of Great Britain and Northern Ireland; RU Russia; US: United States)



closer fields. However, with the integration trend among different disciplines, “big science”, the intersection of distant knowledge has become an important way to make breakthroughs. Figure 8(A) shows that there is no obvious hierarchy of knowledge distance among different generations. The level-0 group, direct translation, translates the most similar knowledge from science, while the level-4 group translates the most distant knowledge (0.71 versus 0.74, respectively, Figure 8(B)). No matter how many bridges the translation suffers, the whole knowledge distance is stable. An interesting finding is that the translation distance of indirect translation volatiles violently and then flattens out with time. However, direct translation shows an opposite evolution road. It was small in 2009 (0.70), went down, and went up to 0.75 in 2018, the largest knowledge distance. This growth in the direct group may be the result of interdisciplinary innovation, as researchers seek solutions from other farther fields to break through mature technology. However, distant knowledge absorption is difficult to transmit again and again by other bridging researchers.

We calculate the dynamic of translation distance in the top 5 patent authorities. Compared with translation lag, Figure 9 implies a more obvious distinction among their patterns. GB has the smallest average distance (0.7) while DE has the largest distance (0.85). Patents granted in GB are more likely to apply scientific knowledge from closer fields, which we have also found to result in a faster translation speed in Figure 6. We hypothesize that translation lag and translation distance might associate with each other, shaping a rapid iteration innovation loop within certain fields and reducing the possibility of a breakthrough. This result could be tested using a counterexample from DE, where translation distance is the highest and its translation lag is also higher. It takes patentees more time to absorb scientific knowledge from distant fields.

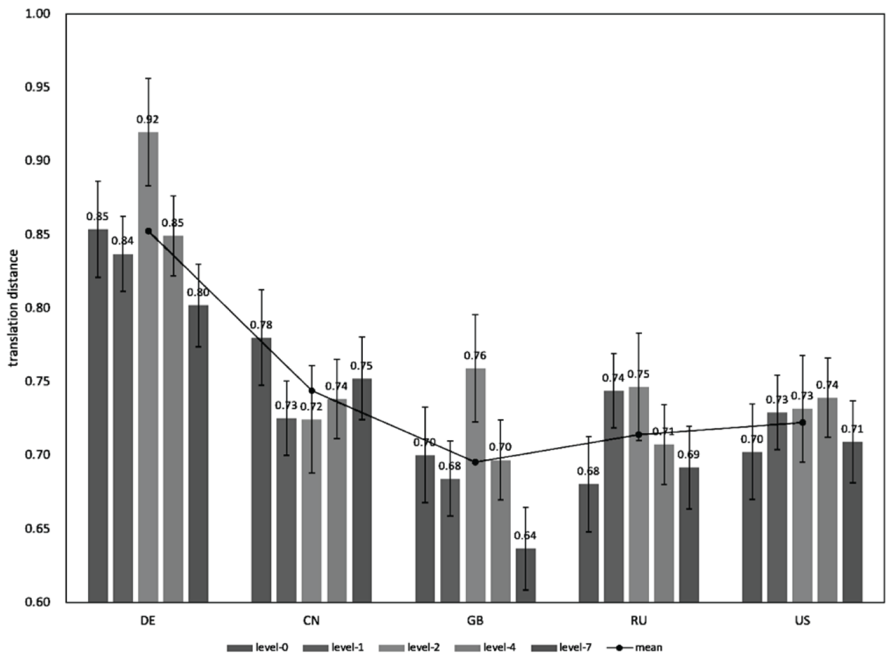
Figure 8. Dynamic and distribution of translation distance



4.2.3 Translation Intensity

To evaluate the substantive knowledge contribution from science to technology, we propose and calculate translation intensity using texting analysis. The data confirms that direct translation has the strongest knowledge contribution, although it has been decreasing since 2015. As the generation

Figure 9. Difference of translation intensity among main countries (DK: Denmark; CN: China; GB: The United Kingdom of Great Britain and Northern Ireland; RU Russia; US: United States)



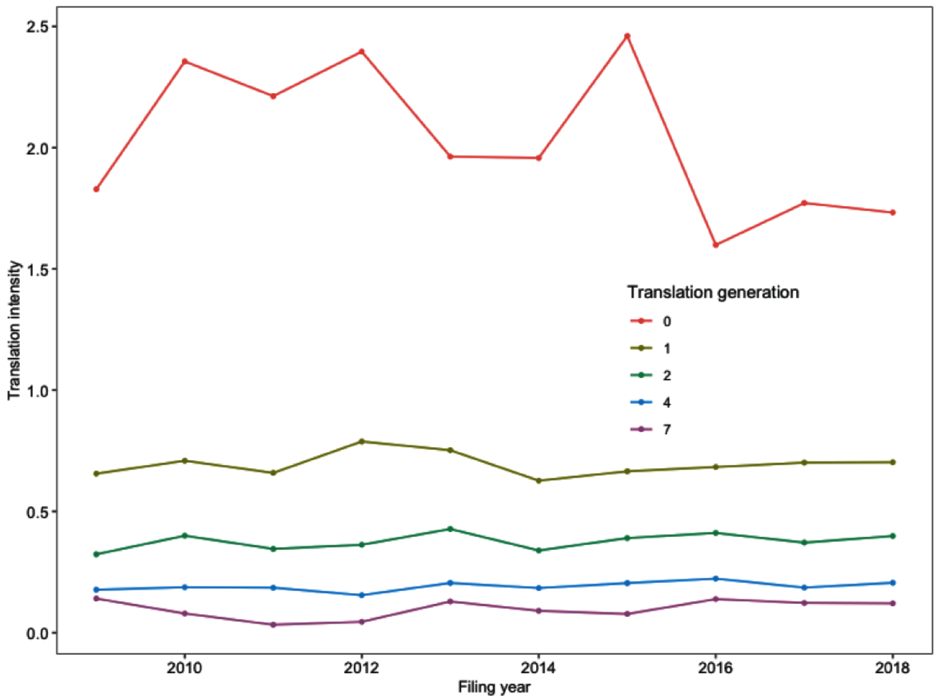
increases, translation intensity decreases and shows different layers. It seems that the long tie's strength in social networks can't be supported in S2T translation. However, we surprisingly find that short ties tend to be weaker with time. Direct translation makes more contributions to technology, but this is not a stable feature. Direct translation varies obviously with a standard error of 3.15, while the standard error of indirect groups is 0.64, on average. About 34% of direct translations contribute, but they tend to translate more knowledge if they do. Indirect translation makes fewer contributions accompanied by a smaller variation.

We compare the knowledge translation intensity patterns of the top 5 countries, as shown in Figure 11. Surprisingly, DE had a weaker average intensity despite having many patents that translate distant knowledge. While we cannot definitively claim that the weak knowledge contribution is solely due to high translation distance, it might be a contributing factor. The other four countries exhibited similar patterns with an overall tendency.

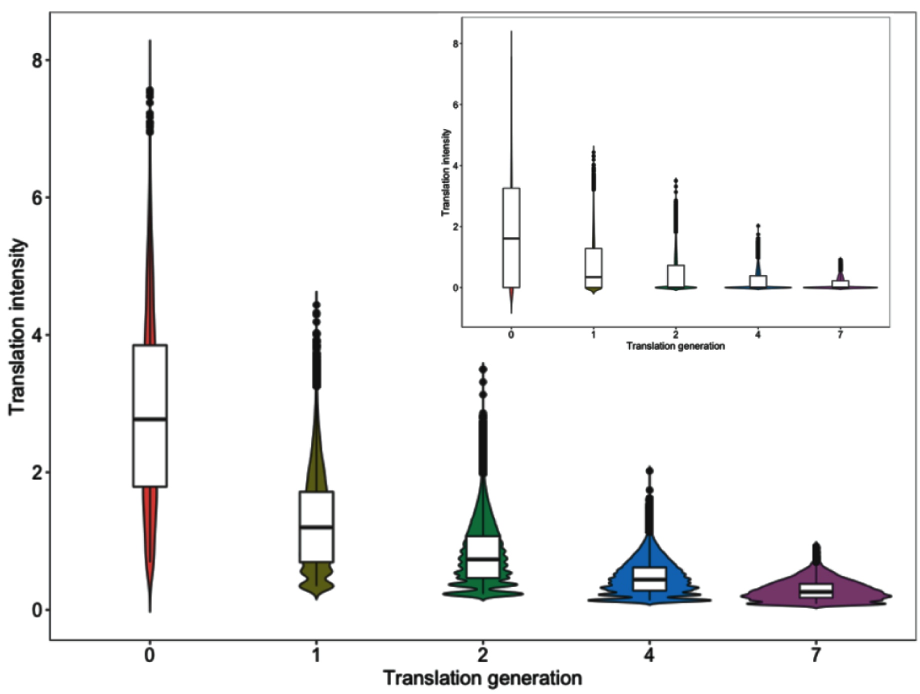
4.2.4 Correlations of Different Translation Effects

To understand the effectiveness of S2T further, we analyzed the correlation among different dimensions of translation effects in Figure 12. Firstly, we found that the direct group has a shorter translation lag and closer translation distance compared to the indirect group. The translation intensity of the indirect group is distributed unevenly with many extreme values. Secondly, we observed a significant negative correlation between any pair of the three dimensions of translation effects. Translation distance and intensity decrease with the increasing translation lag, especially in direct groups. This suggests that patents absorb knowledge from older scientific papers of similar fields, even if these papers couldn't play an important role. This is consistent with the negative correlation between translation distance and intensity. It is more difficult to absorb knowledge from distant fields due to a lack of contextual background and auxiliary information. For example, we find blockchain patents absorb more knowledge from computer science than electronic engineering and social economic topics.

Figure 10. Dynamic and distribution of translation intensity. (B) The main figure non-zero on Translation intensity and the inset is distribution of all data.



(a)



(b)

Figure 11. Difference of translation intensity among main countries (DK: Denmark; CN: China; GB: The United Kingdom of Great Britain and Northern Ireland; RU Russia; US: United States)

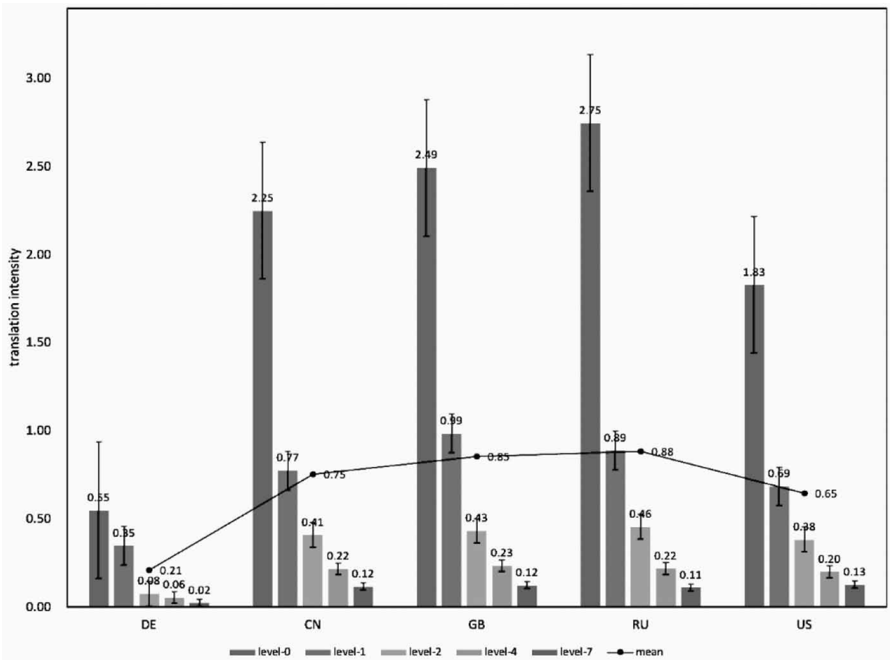
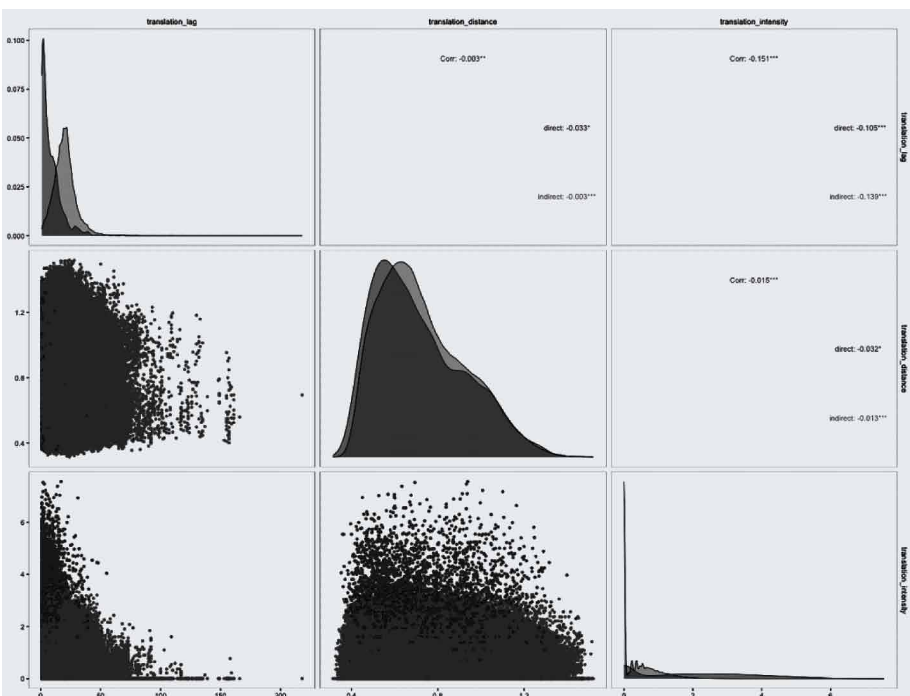


Figure 12. Correlations of translation effects between direct and indirect groups



* $p<0.05$， ** $p<0.01$， *** $p<0.001$

5. DISCUSSION

As a whole, by empirical analysis in blockchain, we have observed an increase in S2T translation with technical development. Previous research in biomedicine found that only 25% of high-impact basic science articles can be applied to technical innovation (Contopoulos-Ioannidis et al., 2003). However, in blockchain, we find the translational ratio is 47%, indicating a strong and frequent interaction between science and technology. The time lag (the research on biomedicine was published in 2003) and field differences may explain this gap. Nevertheless, our analyses of translation suggest an important trend toward integrated innovation. This integration is not limited to the domain of basic research and practical development but extends beyond them. The increasing linkage between public science and technology, proposed by Narin et al. (1997), is accelerating modern science.

Firstly, our study enriches our understanding of S2T translation by distinguishing direct and indirect translation. The results show that indirect translation is the primary way to spread knowledge from science to technology when considering the quantity. In blockchain, the indirect translations are three times as many as direct translations in 2018, and the ratio is increasing. This finding is consistent with previous research in biomedicine. However, direct translation is still the most effective way to make substantive knowledge contributions to technology. Firstly, direct translation translates knowledge more quickly than indirect ones. In general, the amount of time from basic science to technology, called "translation lag" or "translation year," could be many years. Previous research on biomedicine found that it takes an average of 24 years from basic science to clinical application in biomedicine (Contopoulos-Ioannidis et al., 2003; Contopoulos-Ioannidis et al., 2008). Different types of articles have various translation lags. Basic science with less knowledge to human health (i.e., articles only referring to animals or cells) require longer to reach clinical innovation (Weber, 2013). We find that the average time gap for direct translation is 8.61 years, whereas that for indirect translation is 16.56 years. Although these findings have field limitations and time lag, they still provide heuristic insights to observe the overall acceleration of S2T translation.

Secondly, we observed a slight difference in the distance of translation between various generations. Direct translation tends to translate closer knowledge slightly and the distance increases with generation increase. Interestingly, this tendency is changing with the development of technology. Direct translation has shifted towards exploring more distant knowledge, and the average distance has increased since 2014. In 2014, the blockchain industry began the "era of smart contracts" when blockchain 2.0 became synonymous with decentralized blockchain databases. Since then, there has been a focus on the platform's application, and many large organizations have joined, including Citibank, Goldman Sachs, Bank of America, and the Bank of England. This has accelerated technology development but made high-impact innovation more difficult. In this context, the significant improvement in innovation presents a diversity of knowledge sources, yet this trend seems to occur primarily in direct translation. Indirect translation maintains a stable knowledge source.

Thirdly, our analysis suggests that although indirect translation has increased, most of them have worse translation intensity. A recent study on long-range ties in social networks found that long ties were nearly as strong as short ties (Park et al., 2018). And even weak ties among members had strengths in supporting job applications or mobility (Rajkumar et al,. 2022). However, it seems that indirect long-range ties do not maintain their advantage in knowledge innovation activities. There are two interpretive reasons for this. Firstly, innovation is different from other social activities, such as applying for a patent or job. Knowledge absorption and translation require a deep understanding of other people's work, which is always insufficient without direct interaction. Longer ties from knowledge source to recipient (knowledge distance) impede knowledge transfer and decrease translation intensity. This finding is supported by prior literature on knowledge transfer, where knowledge distance is viewed as a contextual character between the source and the recipient (Li et al., 2014). Secondly, we discuss different types of ties: social ties formed based on social relationships, and technical ties based on knowledge transfer. In a social network, long ties are more convenient and have fewer real-world limitations thanks to the improvement of communication technology. In a knowledge network, long ties mean a greater understanding deviation and less knowledge amount resulting from the personal experience of every bridging person. A study on social ties and knowledge transfer activity found that trust among members can improve knowledge transfer, especially nonredundant information access (Daniel et al., 2004). Knowledge ties are out of competence in such a context.

Practically, this study provides suggestions for patent applicants on how to efficiently absorb scientific knowledge. Firstly, direct translation is the preferred way for acquiring knowledge, while indirect translation from other patents could be a supplementary way. Secondly, regardless of the method chosen, translational quality should be considered as much as possible. Furthermore, our findings demonstrate the wide and profound impacts of scientific knowledge, highlighting the need for policymakers to invest in basic science and consider its indirect impact on technology.

Overall, although indirect translation increases rapidly with time and technical development, it does not have the same unexpected effects as long-range ties embedded in social networks. Possible reasons for this difference include the types of relational ties and application purposes.

6. CONCLUSION AND LIMITATIONS

In this paper, we construct an S2T translation dataset in blockchain technology using patents, articles, and their citations. Additionally, we propose a framework to identify TG and measure its effects. Our findings indicate that indirect translation between science and technology has increased with technology development. The level-2 group accounts for the largest amount of translation among different levels of indirect translation, while level-1 has the best translation effects. The rate of S2T translation is increasing rapidly compared to other relevant research on both direct and indirect translation. Furthermore, direct translation has better effects than the entire indirect group. However, the high-effect performance of direct translation is not stable, as some translations are more effective and efficient than indirect translations, while others are even worse.

The main limitation of our study is that we only analyzed blockchain technology, which may limit the generalizability of our findings to other technologies. One reason for choosing blockchain is its close interaction to basic science and technology. Similar findings may be observed in other fast-moving technologies that have a close interaction between basic science and technology. Future research should investigate the tendency and effects of different translations in other technologies. Notably, our finding provides insight into the differences between ties embedded in social networks and technical networks. We infer they have different influences on knowledge diffusion and innovation. This is a potential direction for future research to extend relevant literature.

Our analysis of different generations of S2T translation demonstrates the importance of indirect translation and the ability of basic science to contribute to technology, despite these limitations. These results provide evidence of the long-term value and influence of basic science. Integration between basic science and technology is increasingly important for innovation development in the era of “big science.” Researchers should break domain limitations and utilize multi-source knowledge. Source-allocated policymakers must have confidence in basic science, and incentive policies to promote cross-border cooperation will be helpful.

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