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## Research Paper

## The impact of mentorship on the citation-based performance of graduate dissertation: A social capital perspective

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## ABSTRACT

The growing global emphasis on research excellence has heightened academic attention to effective research performance management. Scientific collaboration is a crucial driver for the formation of high-impact research. However, its mechanism of action remains incompletely understood, particularly with respect to the effect of the collaboration among supervisors on the academic impact of dissertations in the context of co-supervision of graduate students. Based on the three-dimensional framework theory of social capital, this paper develops a measurement indicator system for team social capital within dissertations. Using a sample of 16,567 master's and doctoral dissertations in the field of statistics from China during 2000 to 2020, it empirically examines the mechanisms through which social capital influences citation-based performance in the context of co-supervision. The results indicate that the structural, cognitive, and relational dimensions of social capital all significantly affect citation counts. Specifically, cognitive diversity exhibits a positive effect, the strength of co-supervision relationships shows a negative effect, and structural capital demonstrates a U-shaped relationship. Furthermore, the difference in supervisors' seniority significantly moderates the relationship between structural capital and citation-based performance, whereas the moderating effects of supervisor team size and cognitive difference are not supported. This study offers empirical insights for optimizing co-supervision practices, enhancing the citation impact of dissertations, and improving graduate students training.

## 1. Introduction

The growing global emphasis on research excellence has heightened interest in the effective management and monitoring of research performance (Belkhouja, Fattoum, & Yoon, 2021). At the level of individual papers, academic impact is one of the key observable indicators used to measure research excellence. It primarily refers to a paper's contribution to subsequent research and advancement of knowledge within the academic community, as well as the extent to which it proves useful to other researchers (Abbasi & Jaafari, 2013; Guan, Yan, & Zhang, 2017). Using citation data to analyze how frequently an academic paper is referenced in subsequent studies has become the primary way of measuring its academic impact (Bornmann & Daniel, 2008; Tahamtan, Safipour Afshar, & Ahamdzadeh, 2016). This is because citations are regarded as a direct measure of how a paper is recognized, utilized, and

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influential within the academic community. Although not fully equivalent to academic quality, citations provide core evidence for evaluating the academic dissemination and usefulness of academic papers (Donner, 2021). Common citation-based impact metrics include citation count, classification of a paper as highly cited (e.g., an ESI (Essential Science Indicators) Highly Cited Paper), the impact factor of the publishing journal, and indicators derived from citation networks (such as the  $h_i$ -index (Zhai, Yan, & Zhu, 2014)). Among these, the citation count is the most significant and widely employed metric for a paper, defined as the number of times it is formally cited by other papers in subsequent research (Bornmann & Daniel, 2008; Garfield, 1972). Investigating the factors and mechanisms that influence paper citation count has emerged as a significant research topic. This issue needs to be investigated further. Understanding it will provide a crucial foundation for making decisions regarding the accurate identification and management of outstanding research.

As a key form of academic paper, dissertations carry the outcomes of systematic and original research. Often containing in-depth content not fully published elsewhere, they provide a critical window through which to observe disciplinary trajectories and academic heritage (Donner, 2021). Furthermore, they provide empirical evidence with which to assess the quality of graduate education, identify potential areas of innovation, and detect early-career researchers who will have a future impact (Chaparro & Rojas-Galeano, 2021; Donner, 2021; Kousha & Thelwall, 2019). Citation impact of dissertations can be seen as a proxy of the recognition of the utility and relevance of the research results by other researchers. Therefore, for dissertations, the citation count is also an important dimension of their impact. It is frequently utilized as a pivotal metric to assess the impact of dissertations and the quality of graduate student training (Donner, 2021; Kousha & Thelwall, 2019). With the continuous advancement of the open access movement, information technology, and the internet, dissertations have been widely digitized and made publicly available through platforms such as ProQuest and CNKI, as well as through the institutional repositories of universities. This has significantly improved their accessibility. Due to their systematic and comprehensive nature, dissertations have become indispensable reference materials in their respective fields (Donner, 2021). To address the lack of a comprehensive citation index for dissertations, scholars have integrated dissertation databases with citation databases to develop methods for extracting citation information. For example, Kousha and Thelwall (2019) utilized the ProQuest retrieval system to extract citation data from Google Scholar and readership metrics from Mendeley. Donner (2021) combined the German National Library with Scopus and Google Books, demonstrating that citation analysis can serve as an effective supplementary tool for assessing the research performance of early-career researchers at university departments.

The citation count of papers is influenced by a variety of factors related to the paper, author, and journal, and shows heterogeneity and significant differences (Tahamtan, et al., 2016). A substantial body of research has been dedicated to examining the factors influencing the citation count of journal articles. However, there is a notable absence of research on the factors affecting the citation count of dissertations, especially the impact of scientific collaboration. The composition of dissertation authors differs from that of journal articles. In the context of dissertations, authorship comprises supervisors and students, thereby establishing a supervisory relationship that contrasts with the typical equal cooperative relationship observed in journal articles. Consequently, an in-depth analysis of dissertations is imperative, with a focus on the roles of the authors.

There is a broad consensus among scholars that co-authorship plays a significant role in determining the influence of academic papers, with co-authored papers exhibiting higher citation counts (Bai, et al., 2021; Onodera & Yoshikane, 2015). Social capital theory offers a crucial theoretical framework for examining how scientific collaboration shapes the influence of research papers, as it provides a useful and comprehensive conceptual perspective for understanding the benefits and outcomes of individual and collective action (Tsai & Ghoshal, 1998). Social capital is defined as the ability of individuals or organizations to obtain resources from their relationship networks (Casanueva & Gallego, 2010). The core tenet of social capital theory states that the networks of relationships among individuals or groups—such as family, friends, and colleagues—constitute a valuable asset that can be utilized to achieve optimal performance (Woolcock & Narayan, 2000). According to social capital theory, scholars' social interactions within collaboration networks constitute a form of social capital (Abbasi, Wigand, & Hossain, 2014; Fronzetti Colladon, D'Angelo, & Gloor, 2020). Social capital is an integral component of the broader concept of technological human capital, and its effective utilization can enhance research influence (Abbasi, et al., 2014; Li, Liao, & Yen, 2013), promote knowledge creation, sharing, and dissemination (Reagans & Mcevely, 2003), and help establish new academic connections, thereby serving as an effective means of building academic influence (Guan & Pang, 2018; Klofsten, 2012; Liao, 2011).

The three-dimensional framework theory of social capital proposed by Nahapiet and Ghoshal (1998) has been widely recognized in the academic community (Abbasi, et al., 2014; Zuccala, Jensen, Wærn, & Hertzum, 2024). This framework clarifies the meanings of structural, relational and cognitive capital. Although these three dimensions may be separated for analytical purposes, Nahapiet and Ghoshal (1998) emphasize that they are closely related, with their core characteristics being highly interrelated. Specifically, structural capital reflects ties to appropriable organizations, ties with other members in the network, and the overall configuration of the network. The relational capital is characterized by a shared understanding of norms, feelings of interpersonal trust, mutual obligation, and a shared form of identification—elements such as trust and loyalty that emerge from interactions. The cognitive capital, in turn, is defined by shared narratives and shared codes and languages, encompassing common norms, codes of conduct, and convergence of perspectives (Nahapiet & Ghoshal, 1998). In academia, a substantial body of research has examined the impact of co-authors on paper citations from the perspective of social capital. However, most studies have focused on the structural dimension of social capital. Moreover, there is an absence of a unified and recognized measurement indicator system for social capital. A lack of consensus persists among researchers regarding the optimal collaboration pattern, even within the structural capital dimension (Badar, Hite, & Badir, 2013; Jian Cheng Guan, Zuo, Chen, & Yam, 2016).

Graduate dissertations also exemplify scientific collaboration, wherein the collaborators consist of a student and one or more supervisors (Bu, Li, Wei, Liu, & Li, 2022). The literature on scientific collaboration in dissertations predominantly emphasizes the role of mentorship in enhancing student performance, with a specific focus on how supervisors influence students' acquisition of knowledge

and skills, research productivity, academic success, and socialization outcomes (Liénard, Achakulvisut, Acuna, & David, 2018; Nasir Ahmad & Maarten Pieter, 2013). However, there is a notable gap in the literature regarding an in-depth investigation from a scientific collaboration perspective at the dissertation level to explore the impact of supervisors on graduate dissertation citation-based performance.

Concurrently, as scientific research has evolved to become increasingly intricate and interdisciplinary, there has been a marked increase in the number of co-supervisions of graduate students (Pyhälä, Tikkanen, & Anttila, 2024). Numerous countries and universities have established co-supervision or joint training systems for graduates. Two large-scale doctoral surveys conducted in China in 2018 and 2021 showed that 35.8 % and 45.5 % of graduate students, respectively, participated in joint training programs (Xu, Shen, & Zhao, 2024). Co-supervision, also known as team supervision, or group supervision, refers to an academic guidance system involving two or more supervisors. The distinction between co-supervision and solo supervision in terms of training outcomes remains debated. Properly arranged co-supervision can yield superior outcomes by providing students with enhanced resources and support (Almlöv & Grubbström, 2023; Rossi, Damaceno, Freire, Bechara, & Mena-Chalco, 2018).

From the perspective of scientific collaboration, completing a dissertation collaboratively involves not only supervisor-student partnerships but also inter-supervisor collaborations. Exploring the influence of social capital generated through these collaborations on dissertation performance can enhance our understanding of the mechanisms driving dissertation citation impact and elucidate how varying collaboration patterns among supervisors affect dissertation performance – an important yet underexplored area. Therefore, this study empirically examines this issue using a sample of graduate dissertations in statistics from China. Grounded in social capital theory and adopting a scientific collaboration perspective, this study explores how the social capital of a dissertation team in the context of co-supervision affects its citation-based performance, and examines the moderating role of supervisor team diversity. In this study, individual dissertations serve as the analytical units, and the citation count is used as the dependent variable to measure performance.

This study has the following contributions: (1) It explores the author-related factors influencing the citation counts of dissertations. Unlike journal articles and other types of publications, authors are divided into two categories: supervisors and students, who have a supervisory and supervised relationship. Authors are not in an equal cooperative position, and the study enriches the research results on the impact of differences in author roles in scientific collaboration on citation counts. (2) We developed an indicator system for measuring the social capital of supervisors based on co-supervision at the dissertation level. For the first time in this context, we deconstructed the three dimensions of social capital into operational metrics. From the perspective of the author team, we used intra-team and extra-team indicators in social capital measurement, and constructed an indicator of the supervisor team structure of dissertations from the perspective of supervisor team diversity. This will inspire further related research. (3) We clarified the impact mechanism of the three dimensions of social capital on dissertations and the moderating role of supervisor team diversity, which helps enrich existing theories and provides strategic support for team building strategies. (4) We focus on the citation impact of dissertations and the role of co-supervision in influencing the citation impact of dissertations, addressing the gap in quantitative research on co-supervision.

This study found that the structural, cognitive, and relational dimensions of social capital all significantly affect citation counts. Specifically, cognitive diversity exhibits a positive effect, the strength of co-supervision relationships shows a negative effect, and structural capital demonstrates a U-shaped relationship. Furthermore, the difference in supervisors' seniority significantly moderates the relationship between structural capital and citation-based performance, whereas the moderating effects of team supervisor size and cognitive difference are not supported. The research provides valuable insights for enhancing dissertation performance management, supervisor collaboration, and the co-supervision system for graduate students.

This paper is structured as follows: Section 2 reviews the existing literature, and Section 3 introduces the research hypotheses. Section 4 details the data acquisition and preprocessing procedures, the selection and construction of study variables, and empirical methodology. The results are presented in Section 5, followed by the conclusions and discussion in Section 6.

## 2. Relevant literatures

The citation count is an important measure of the influence of academic papers (Bai, et al., 2021; Tian, Xu, & Li, 2021). The factors influencing the citation count of academic papers can be divided into paper-related, journal-related, and author-related dimensions (Tahamtan, et al., 2016). As an author-related factor, scientific collaboration has gained increasing scholarly attention. Existing studies have conducted multidimensional scientific collaboration analyses at the author, institution, and country levels, clarifying the positive impact of appropriate collaboration on the citation count of papers (Bai, et al., 2021; Fronzetti Colladon, et al., 2020; Hsu & Huang, 2011; W. Li, Zhang, Zheng, Cranmer, & Clauset, 2022; Lopaciuk-Goncaryk, 2016).

Social network analysis provides an important tool for studying scientific collaboration. Scientific collaboration networks based on co-authorship represent the most important form of collaboration among scholars. Marked by formally published research results, they are a more direct and meaningful form of knowledge exchange that describes scholars' participation in actual collaborative activities (Liao, 2011). Co-authorship networks are constructed based on the co-authorship relationships between scholars, with scholars as nodes and co-authorship relationships as ties, providing a systematic analytical framework for scientific collaboration and greatly promoting the in-depth development of scientific collaboration. Existing research has explored the position and role of scholars in networks, the structural characteristics of collaboration networks, the laws of evolution, and their impact on scientific research performance (Abbasi, et al., 2014; Zuccala, et al., 2024).

Social capital theory provides theoretical support for understanding scientific collaboration and its impact on research performance. As the ability of individuals or organizations to obtain resources from their network of relationships, social capital can help



individuals or groups obtain information, resources, and opportunities (Casanueva & Gallego, 2010; Fronzetti Colladon, et al., 2020; Rodriguez Miramontes & Gonzalez-Brambila, 2016). Through long-term collaboration, scholars share a wealth of knowledge, establish social norms and trust, and thus co-authorship networks become a pathway for the generation of social capital and an important carrier (Abbasi, et al., 2014). The trust, network ties, and reputation recognition formed by scholars during the collaboration process constitute the social capital of individuals or teams. This social capital accumulated through collaboration can be further converted into research resources, such as reducing the cost of obtaining information, having priority collaboration opportunities or resources, and generating new ideas by combining different professional knowledge. These resource advantages brought about by social capital will improve the efficiency, quality, and influence of research work (Liao, 2011).

Nahapiet and Ghoshal (1998) argue that social capital can typically be divided into three dimensions: structural, cognitive, and relational, which can be referred to as structural capital, relational capital, and cognitive capital (Li, et al., 2013). In academia, these are manifested as structural embeddedness, sustainability of social relationships, and the professional knowledge and understanding (Zhang, Liu, Wang, Zhao, & Zhang, 2022). Similarly, Casanueva and Gallego (2010) point out that an individual's social capital in the academic community can be divided into three components: the individual's position within the network, the quality of the individual's relationships, and the individual's ability to obtain resources through these relationships.

Social capital is complex and difficult to measure, as it has many different components, some of which are intangible (Gonzalez-Brambila, 2014). The three-dimensional framework of social capital—comprising structural capital, cognitive capital, and relational capital—has been widely recognized, but there is still no universally accepted measurement standard and indicator system for social capital of scholars. Scholars have combined bibliometric data and co-authorships to explore the mechanisms of social capital in terms of a single dimension of social capital or a combination of multiple dimensions for its role in academic impact (Abbasi, et al., 2014; Gonzalez-Brambila, 2014; Zuccala, et al., 2024). Among these, structural capital based on collaboration network structure is the most widely noticed and recognized type of social capital, which has been used in a large number of studies.

In these studies, the citation count remains the most widely examined indicator of academic impact, both at the paper and scholar level. Other metrics employed to assess academic impact include the novelty index (Yin, Zhang, Zhao, & Tang, 2024), the journal impact factor (Lopaciuk-Gonzarczyk, 2016), scholar's research awards (Liao, 2011), and the number of publications (Chen, Ding, Zhao, Guo, & Ning, 2025), etc. However, most studies have focused on the level of scholars, with relatively few analyses at the paper level. Nevertheless, analyses at the paper level allow for a more fine-grained examination of how collaboration influences academic impact.

At the paper level, the literature mainly focuses on the research of journal articles, while the research on dissertations is insufficient. Some scholars have explored the influencing factors—such as publication time, discipline, and institution—on the citation counts of dissertations, as well as the reliable data sources for citation data (Donner, 2021; Kousha & Thelwall, 2019). However, no studies have delved into the impact of supervisors' co-supervision and the social capital formed through such co-supervision on the citation counts of dissertations from the perspective of scientific collaboration. At the paper level, authors' social capital is usually aggregated on an average basis to explore the impact of authors' social capital on the impact of their papers. Martín-Alcázar, Ruiz-Martínez, and Sánchez-Gardey (2019) argued that the growing importance of multidisciplinary and scientific collaborations necessitates exploring the configuration and structure of relationships within teams of researchers. Tang, Wang, and Kishore (2014) examined membership within teams noting that, prior co-authorship between author pairs is positively correlated with current citations, and similarity of affiliation between author pairs reduces current citations. Next, based on existing theories and related research, we will propose research hypotheses on the impact of social capital of author team on the citation count of dissertations from the three dimensions of social capital in the context of co-supervision of dissertations.

### 3. Research hypotheses

This study takes dissertations as the research object. We regard the authors of a dissertation as a team, and the social capital within the team refers to the relationships and interactions between team members, such as trust, collaboration, and shared values. The social capital outside the team refers to the connections and interactions between the team and the external environment (Muscio, Lopolito, & Nardone, 2019). Unlike journal articles or conference papers, the social capital of a dissertation team is mainly based on the supervisor, and the supervisor's co-supervision network is an important carrier of the supervisor's social capital. We focus on exploring the mechanism of influence of the structural, cognitive, and relational capital accumulated by supervisors in co-supervision on the citation count of dissertations.

According to social capital theory, cognitive capital measures scholars' professional knowledge and understanding abilities (Zhang, et al., 2022). In co-authorship networks, authors may come from different fields. They can obtain cognitive capital through interaction with interdisciplinary members. Connecting researchers from different disciplines is more likely to yield non-redundant resources, thereby enhancing the impact of their research findings (Li, et al., 2013). Numerous studies have shown that teams with high cognitive diversity can expand their cognitive boundaries by broadening their disciplinary knowledge systems, integrating the professional knowledge and experience of each member, and generating collective wisdom (Chen, Arsenault, & Larivière, 2015). Cognitive diversity plays an important role in creative and innovative work (Zhang, Sun, Jiang, & Huang, 2021). Therefore, we believe that the cognitive diversity of author team of the dissertation has a positive effect on the citation count of the dissertation. From the internal and external perspectives of the team, we propose *Hypothesis 1*.

**Hypothesis 1 (H1).** The cognitive diversity within and outside the team of authors of a dissertation has a positive impact on the citation count of the dissertation.

We measure the cognitive diversity of team members based on cognitive differences. Combining the co-supervision scenario of



dissertations, collaboration within the team involves supervisor-student collaboration and collaboration among supervisors, including two types of cognitive differences: supervisors and student, and supervisors within the team. Meanwhile, we use the co-supervision network of supervisors to summarize their cooperative relationships outside the group, and use the cognitive differences between dissertation supervisors and all their co-supervisors as a measure of cognitive diversity. At the same time, referring to the research of [Li, et al. \(2013\)](#), the number of years that supervisors have guided dissertations in this field is used as an important indicator for measuring cognitive capital, and the difference in the number of years of guidance among supervisors within the team is used as another indicator for measuring cognitive differences. Hypotheses H1a-H1d are then proposed.

**Hypothesis 1a (H1a).** The cognitive differences between supervisors and student of a dissertation have a positive impact on the citation count of the dissertation.

**Hypothesis 1b (H1b).** Cognitive differences among supervisors within a dissertation team have a positive impact on the citation count of the dissertation.

**Hypothesis 1c (H1c).** The cognitive differences between dissertation supervisors and their co-supervisors in co-supervision networks have a positive impact on the citation count of the dissertation.

**Hypothesis 1d (H1d).** Differences in the seniority of supervisors within a dissertation team have a positive impact on the citation count of the dissertation.

Relational capital measures the sustainability, trust, and reciprocity of social relationships. It refers to the assets that people create and utilize through ongoing personal relationships. These assets can change behavior patterns and satisfy social motivations such as gaining social recognition and enhancing reputation ([Nahapiet & Ghoshal, 1998](#); [Zhang, et al., 2022](#)). In academia, relational capital can significantly reduce the transaction costs of academic interaction. A high degree of trust and reciprocity can promote the efficient transfer of tacit knowledge, reduce information concealment or conflict, and make members more willing to invest core resources, thereby improving the quality and innovation of research results. Therefore, we propose hypothesis H2 regarding the co-supervision relationship between supervisors. Furthermore, according to social network theory, relational capital also expands the dissemination of research results through strong cooperative relationships, and collaborating with many closely connected authors can increase the visibility and citation potential of papers ([Fronzetti Colladon, et al., 2020](#)). Furthermore, citation rewards driven by reciprocal relationships (such as citations of the research results by collaborators) can directly enhance the visibility of the results and increase the probability of citation. Therefore, we propose hypotheses H2a and H2b.

**Hypothesis 2 (H2).** The relational capital of dissertation supervisors in co-supervision positively influences the citation count of the dissertation.

**Hypothesis 2a (H2a).** The strength of the co-supervision relationships between the dissertation supervisors and their co-supervisors in co-supervision networks positively affects the citation count of the dissertation.

**Hypothesis 2b (H2b).** The strength of the reciprocal relationship between the dissertation supervisors and their co-supervisors in co-supervision networks positively affects the citation count of the dissertation.

Structural capital manifests as structural embeddedness, which is primarily measured based on social network structures ([Granovetter & Mark, 1985](#)). It is the most commonly used in single-dimensional studies of social capital. Co-authorship analysis has become a standard method for observing research collaboration and quantifying social capital. A supervisor's position within the co-supervision network reflects the magnitude of their social capital. Scholars' positions within these networks significantly positively influence their academic impact and research performance ([Abbasi, Jalili, & Sadeghi-Niaraki, 2018](#); [Chen, et al., 2025](#); [Liao, 2011](#)). The position of knowledge producers within these networks is a key factor influencing creativity, as it provides advantages such as better access to knowledge sources, political factors, and awareness of potential projects ([Guan & Pang, 2018](#); [Hansen, 1999](#); [Reagans & Mcevily, 2003](#)).

However, the value of structural capital does not increase monotonically ([Liao, Lavender, & Zhai, 2024](#); [Zhang, Ding, Yan, He, & Wang, 2022](#)). [Zhang, et al. \(2022\)](#) found that the degree centrality of scholars in the collaboration network has a positive impact on the citation count of papers, while the U-shaped or inverted U-shaped relationship does not hold true. A study on the citation count of papers in cancer research found that there is an inverted U-shaped relationship between the degree centrality of the first author in the collaboration network and the citation count ([Liao, et al., 2024](#)). [Zeng, Han, Zhang, and Zhang \(2022\)](#) found, in their study on the citation impact of journal papers by Chinese scholars in the field of chemistry, that there is a U-shaped relationship between scholars' closeness centrality and betweenness centrality in collaboration networks and the citation count, whereas the degree centrality exhibits an inverted U-shaped relationship.

In this paper, we examine the nonlinear influence relationship of structural capital on citation counts. Take degree centrality as an example, in the early stages of network development, new ties are mostly weak ties or cross-field ties. An increase in degree centrality brings heterogeneous information and resources, which enhances the influence of its outcomes. However, when the number of ties reaches a moderate level, the network may experience information overload and resource homogenization due to redundant interactions. At this point, the marginal benefit of degree centrality decreases or even turns negative. According to the resource dilution theory, the utilization of any resource incurs management costs. When the quantity of resources exceeds scholars' processing capacity,

the resources' value becomes diluted. Once the number of ties reaches a certain scale, the time and effort required for communication and collaborative coordination increases sharply, causing influence to decrease despite increases in degree centrality. When node degree is sufficiently high, the network's heterogeneity is re-enhanced, facilitating the formation of an orderly, cross-field network structure. Scholars can thus access a broader range of academic resources while accelerating the dissemination of research outcomes through diverse channels, thereby promoting the diffusion of research findings to a wider academic community, with marginal benefits increasing rapidly. Therefore, we believe that there is a nonlinear relationship between the structural capital of supervisors, represented by node degree, and the influence of dissertations, which first declines and then rises. We propose the following hypothesis:

**Hypothesis 3 (H3).** The relationship between dissertation supervisors' structural capital in co-supervision and the citation count of the dissertation follows a U-shaped pattern.

At the same time, we examine the impact of supervisor team diversity on the above relationship. Team members often exhibit diversity in terms of discipline, age, background, and other aspects, which essentially brings about knowledge heterogeneity. According to information processing theory, highly diverse teams have a broader knowledge base, cognitive perspectives, and methodological tools, which amplify the resource integration capabilities and conversion efficiency of structural capital. Team diversity also necessitates higher coordination costs and may present both higher risks and rewards (D'Este, Llopis, Rentocchini, & Yegros, 2019; Zhang, et al., 2021). Therefore, we further hypothesize that team diversity has a moderating effect on the relationship between the degree centrality of supervisors in co-supervision networks and the number of citations of dissertations. Thus, we propose hypothesis H4. Specifically, we explore the moderating effects of three different types of supervisor team diversity: supervisor team size, supervisor team seniority differences, and field differences. To this end, we propose hypotheses H4a-H4c.

**Hypothesis 4 (H4).** The supervisor team diversity moderates the relationship between supervisors' structural capital in co-supervision and the citation count of the dissertation.

**Hypothesis 4a (H4a).** The supervisor team size moderates the relationship between supervisors' structural capital in co-supervision and the citation count of the dissertation.

**Hypothesis 4b (H4b).** The supervisor team seniority differences moderate the relationship between supervisors' structural capital in co-supervision and the citation count of the dissertation.

**Hypothesis 4c (H4c).** The supervisor team field differences moderate the relationship between supervisors' structural capital in co-supervision and the citation count of the dissertation.

## 4. Methods

### 4.1. Data acquisition and preprocessing

The specialties of *Statistics*, *Probability Theory and Mathematical Statistics* are two core components of the first-level discipline of statistics in China. Generally, they focus on applied research and theoretical research, respectively. We will conduct empirical analysis using dissertation data from these two specialties spanning the years 2000 to 2020. The data were sourced from the China National Knowledge Infrastructure (CNKI) Dissertations Database, which includes the China Doctoral Dissertations Full Text Database and the China Excellent Master's Thesis Full Text Database. It is currently the most comprehensive and authoritative repository of Chinese doctoral and master's dissertations. The program is distinguished by its continuous, dynamic updates (Bu, et al., 2022).

Data other than citation counts was retrieved on January 17, 2021. The data comprises detailed information for each dissertation, including the title, student name, year of degree conferring, degree-granting institution, supervisor name, degree level (master's or doctoral), and citation count, et al. Following preprocessing steps, such as data consolidation, matching, and deduplication, a total of 16,632 dissertations were retained. Specifically, there are 9450 dissertations in *Statistics* and 7182 dissertations in *Probability Theory and Mathematical Statistics*. The citation data was collected on June 25, 2025, ensuring that the citation period for all dissertations was no less than five years, thereby allowing sufficient time for the accumulation of citations. Following a thorough review and proof-reading process aimed at ensuring data completeness and consistency, 65 dissertations (0.39 %) were excluded from the analysis due to the absence of key variables such as the year of degree conferral. After comprehensive data processing, this dataset has no missing value and contains a total of 16,567 dissertations, involving 2697 supervisors and 195 institutions.

CNKI classifies dissertations into two major categories, natural sciences and humanities and social sciences, and 10 different albums based on their research topics. We consolidated low-frequency categories with similar ones, ultimately dividing dissertations into four areas. Among them, Science and Technology and Basic Sciences belong to the natural sciences category, accounting for 46.1 %; Social Sciences & Humanities and Economics & Management belong to the humanities and social sciences category, accounting for 53.9 %. We standardize institution names using the first-level institution nomenclature. For institutions that have undergone mergers or renaming, we update their names to reflect the most recent designations. At the same time, we marked the institutions to which the dissertations belonged based on the list of universities included in the "985 Project" or "211 Project" published by the Chinese Ministry of Education as an institutional-level indicator. The "985 Project" encompasses top-tier universities known for excelling in elite talent cultivation and leading-edge scientific research and technological innovation. The "211 Project" aims to accelerate the development of Chinese higher education by fostering key disciplines in leading universities, thereby narrowing the gap with world-class institutions

and achieving international standards. Both projects collectively include over 100 prestigious universities.

## 4.2. Variables

### 4.2.1. Dependent variable

The performance of scientific research achievements can be demonstrated through various dimensions, with citation impact, derived from citation behavior, serving as a key indicator of recognition by academic peers. Citation counts provide a straightforward quantification of citation impact and serve as the most direct metric reflecting the influence of scientific research outcomes (Egghe & Rousseau, 1990). This is also applicable to measuring the impact of dissertations (Bangani, 2018). Scholars generally agree that although the evaluation of the influence of theses is more complex and there is no unified evaluation standard, citation counts remain an important indicator in evaluating the impact of dissertations and the quality of graduate student training (Chaparro & Rojas-Galeano, 2021; Kousha & Thelwall, 2019). In addition, dissertations are frequently cited in China due to their systematic and comprehensive coverage of topics, as well as the accessibility afforded by national dissertation databases like CNKI and Wanfang,

**Table 1**  
Variable Descriptions.

|                    | Variable            | Description                                                                                                                                                                                                                                                                                                                                                                             | Type                | Moderator |
|--------------------|---------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------------|-----------|
| Cognitive Capital  | SupStuMatch         | The match between the supervisor's field and the dissertation (student) field is defined as the Bhattacharyya coefficient of the distribution vector of the supervisor and dissertation fields.                                                                                                                                                                                         | continuous          |           |
|                    | InterSupDiv         | Cognitive difference among supervisors within the team. Defined as the opposite of the average Bhattacharyya coefficient of the field distribution vector among dissertation supervisors, plus 1. For dissertations that were not co-supervised, the value is set to 0.                                                                                                                 | continuous          | Yes       |
|                    | AvgCoSupSim         | Average field similarity between supervisors and co-supervisors. Defined as the average Bhattacharyya coefficient of the field distribution vectors of supervisors and all co-supervisors. Aggregated at the dissertation level based on the average of all supervisors.                                                                                                                | continuous          |           |
|                    | SDSupSeniority      | Differences in seniority of the supervisor team is defined as the standard deviation of the supervisors' seniority. Here the supervisors' seniority is calculated by subtracting the minimum value from the maximum value of the years of the dissertations they have supervised, and then adding 1.                                                                                    | continuous          | Yes       |
| Relational Capital | AvgTieStrengthSup   | Defined as the mean of the average tie weights of supervisors in the co-supervision network.                                                                                                                                                                                                                                                                                            | continuous          |           |
|                    | ReciprocityRatioSup | Defined as the average proportion of reciprocal relationships in co-supervision network among all supervisors of a dissertation, while the reciprocal relationships are determined by whether there has been a reversal of author order in different co-supervision relationships.                                                                                                      | continuous          |           |
| Structural Capital | DegreeCentralitySup | The average of degree centrality of supervisors in co-supervision networks. In the empirical analysis, it was standardized using the Z-score method: $z = \frac{x - \mu}{\sigma}$ , where $\mu$ and $\sigma$ are the sample mean and sample standard deviation of the original values, respectively. After standardization, the variable has a mean of 0 and a standard deviation of 1. | continuous          |           |
| Control Variables  | DegreeLevel         | The degree level of a dissertation. 1=doctoral, 0=master's.                                                                                                                                                                                                                                                                                                                             | Binary              |           |
|                    | Specialty           | The specialty to which the dissertation belongs. 1=Statistics, 0=Probability theory and mathematical statistics.                                                                                                                                                                                                                                                                        | Binary              |           |
|                    | DissertationAge     | Dissertation age, calculated as (2025-Y)+1 and Y is the year of degree conferring.                                                                                                                                                                                                                                                                                                      | Count               |           |
|                    | InstitutionLevel    | An institution's prestige level. 2=985 Project, 1=211 Project (non-985), 0=Other.                                                                                                                                                                                                                                                                                                       | ordered categorical |           |
|                    | AlbumField          | Dissertations are classified into four Album categories: Science and Technology, Basic Sciences, Social Sciences & Humanities, Economics & Management.                                                                                                                                                                                                                                  | Nominal             |           |
|                    | TopicPopularity     | The topic popularity of a dissertation, defined as the sum of the heat of the dissertation's keywords, where heat is calculated as the keyword's word frequency across all dissertations. A natural logarithmic transformation was applied to this metric due to its extreme right skewness.                                                                                            | Continuous          |           |
|                    | Interdisciplinarity | Indicator of interdisciplinarity, defined as whether the dissertation is labeled with more than one different four-level CLC codes.<br>Binary: 1 = labeled with more than one; 0 = labeled with only one.                                                                                                                                                                               | Binary              |           |
|                    | CoSupervision       | Whether or not the dissertation is co-supervised reflects the size of the team's supervisor.<br>Binary: 1=co-supervision, 0=sole supervision.                                                                                                                                                                                                                                           | Binary              | Yes       |
|                    | AvgStudents         | Mean of the number of students supervised by supervisors of a dissertation, reflecting experience or prestige.                                                                                                                                                                                                                                                                          | Count               |           |
|                    | AvgSupHindex        | Mean of the supervisor's h-index, where the h-index is calculated based on the dissertations supervised by the supervisor and their citations, and is an indicator of the supervisor's prestige.                                                                                                                                                                                        | Count               |           |

Note: The sample unit is the dissertation.



which provide convenient full-text access (Bu, et al., 2022).

#### 4.2.2. Measurement of social capital

Currently, there is no universally accepted standard for measuring scholars' social capital. Existing studies are inconsistent in terms of measurement dimensions and indicator selection due to differences in research subjects, scenarios, and focus (Gonzalez-Brambila, 2014; Li, et al., 2013; Liao, 2011; Yin, et al., 2024). Combining the context of dissertations with data from dissertation literature and co-supervision by supervisors, this paper systematically deconstructs the three-dimensional theory of social capital (Nahapiet & Ghoshal, 1998) and establishes a measurement indicator system of social capital for dissertation author teams. The indicator system is shown in Table 1 and includes three dimensions and seven indicators. Fig. 1 provides a schematic diagram of the measurement plan.

The dissertation team comprises the student and supervisor(s). Social capital is calculated separately within and outside the team. Within the team, the relationship between supervisors and students and between supervisors is considered. Outside the team, the social capital accumulated by supervisors in the co-supervision network is measured. At the dissertation level, the average value is used to calculate the social capital of supervisors in order to eliminate the impact of supervisor size (Fronzetti Colladon, et al., 2020; Guan, et al., 2017; Tian, et al., 2021).

The structural dimensions of social capital involve general connectivity and density within network structures. The node centrality is one of the most crucial types of indicators for measuring scholars' structural capital (Miramontes & Gonzalez-Brambila, 2016). Among various centrality measures, degree centrality quantifies the size of a node's local network by counting the number of nodes to which it is connected, thereby reflecting the node's position and influence within the network. Due to its straightforward interpretation and relevance to connectivity, degree centrality is commonly used in the literature as an indicator of the structural dimension of social capital (Li, et al., 2013; Tian, et al., 2021; Yin, et al., 2024; Zhang & Wang, 2017). We employ node degree centrality in the co-supervision network to characterize the structural characteristics of a supervisor's social capital. In the co-supervision network, each supervisor is represented as a node, and a tie between two supervisors signifies a co-supervision relationship. The weight of each tie is determined by the number of shared students. The degree centrality quantifies the number of direct ties a node has with other nodes, reflecting the number of supervisors collaborating with a given supervisor.

In terms of relational capital, an effective way to measure relationship sustainability and trust among scholars is to see if they have collaborated multiple times. When scholars have collaborated twice or more, it can be inferred that they have a sustainable and trustworthy relationship and are willing to share resources. Commonly used measures in the literature include the average tie weight (Zhang & Wang, 2017) and the number of collaborators engaging in more than three repeated collaborations within a 15-year period (Casanueva & Gallego, 2010). In this study, we adopt the supervisor's average tie weight in the co-supervision network to capture relational strength—specifically, the average number of collaborations between the supervisor and his/her co-supervisors. A higher value indicates more stable and frequent collaborative relationships. Second, reciprocity is an important component of relational capital. We define the proportion of reciprocal relationships in co-supervision as one of the metrics for relational capital, where a reciprocal relationship means that two supervisors have opposite signing orders in co-supervision. In a directed co-supervision network, where the supervisor with the later signing order points to the supervisor with the earlier signing order, the reciprocal relationship is manifested as two supervisors having bi-directional ties.

In terms of cognitive capital, research seniority and academic field are the basis for measurement. Chen, et al. (2025) measures the cognitive proximity of scholars by calculating the cosine similarity between the distributions of scholars across 27 academic fields, using this as an indicator of cognitive capital. Li, et al. (2013) assesses cognitive capital based on the number of years a scholar has been published within a specific field, referring to this as publication seniority. Scholars with greater seniority typically develop a deeper understanding of the relationship between their expertise and the field knowledge, accumulate more cognitive capital, and are

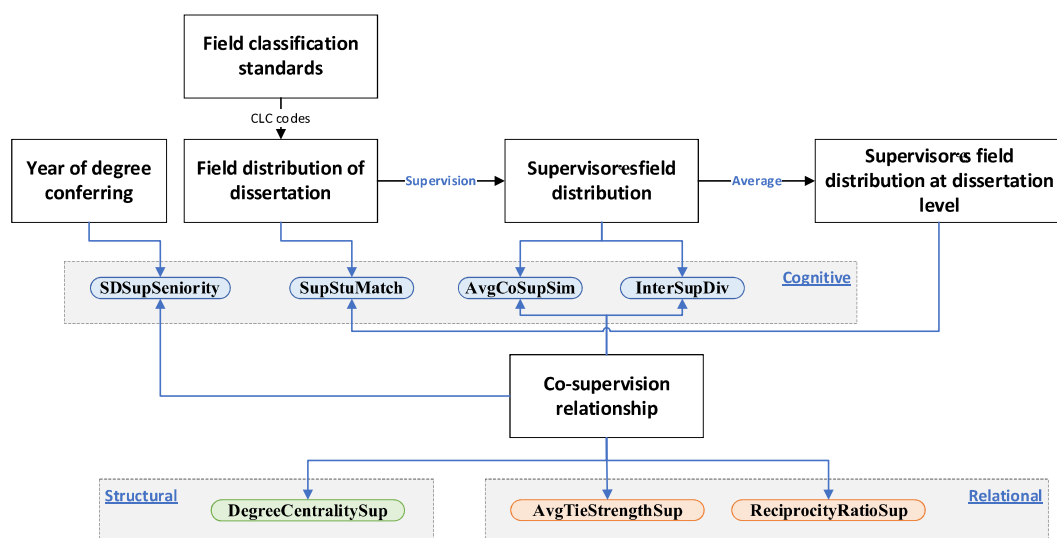


Fig. 1. Illustration of the Measurement of Social Capital.

therefore more effective in applying this knowledge. Building on these studies, this paper examines the cognitive differences within and outside research teams and proposes four corresponding indicators. Within the team, we measure the similarity in the fields between supervisors and dissertations (also known as the matching between supervisors and students), as well as the field and seniority differences among supervisors. Outside the team, we measure the similarity in the fields of supervisors and their collaborators in the context of co-supervision.

For seniority differences among supervisors, we define the supervision age of a supervisor as the difference between the maximum and minimum years of degree conferral among the dissertations they have supervised, plus one. Furthermore, calculate the standard deviation of the supervision age within the team as the difference in supervisor seniority. For dissertations without co-supervision, set this value to 0, representing no difference in seniority.

For the specific calculation process of the three cognitive dimension indicators based on the research field, it was done in the following steps (see Fig. 1).

Step 1: Determine the division of fields. Use the 22 major categories in the first level of the Chinese Library Classification (CLC) as the standard for dividing fields (<https://www.clcindex.com/>). Select the 22 major categories to describe the field distribution of dissertations and supervisors. This is a moderate number of categories that allows for detailed division of fields without making the distribution of supervisors too sparse.

Step 2: Determine the field distribution of dissertations. Simplify the CLC codes of dissertations to the first level and remove duplicates. Based on this, the field distribution vector of the dissertation is constructed, which consists of 22 components, each representing the probability of belonging to one of 22 fields. Mark 1 at the corresponding position of the vector according to the first-level CLC codes marked on the dissertation, and mark 0 at other positions. If a dissertation has multiple first-level CLC codes, normalize vectors to meet the requirements of probability distribution norms.

Step 3: Determine the field distribution of supervisors. For each supervisor, sum the field distribution vectors of the dissertations they have supervised, normalize them, and use them as the field distribution vector for that supervisor.

Step 4: Aggregate the supervisor's field distribution vector at the dissertation level. For a dissertation, use the average value of all supervisors' field distribution vector as the supervisor's field distribution vector for that dissertation.

Step 5: Calculation of the field match between the supervisor and student (SupStuMatch). The Bhattacharyya coefficient (BC) is a measure of field distribution similarity that should be utilized. This statistical method is employed to assess the degree of overlap or similarity between two probability distributions. Its value range is from 0 to 1. The closer the value is to 1, the more similar the two distributions are. For two discrete probability distributions  $P = (p_1, p_2, \dots, p_k)$  and  $Q = (q_1, q_2, \dots, q_k)$ , define  $BC(P, Q) = \sum_{i=1}^k \sqrt{p_i q_i}$ . In this study,  $k=22$ . For each dissertation, calculate the BC of the field distributions of the dissertation and its supervisor. The larger the BC, the more the dissertation's research field matches the supervisor's research field, which is the supervisor's area of expertise.

Step 6: Use the Bhattacharyya Coefficient to calculate the similarity between all pairs of supervisors.

Step 7: Calculation for field differences between co-supervisors at the dissertation level (InterSupDiv). For a dissertation, the similarity between the fields of the supervisors within the team is measured by the average similarity between all pairs of supervisors. The opposite of this value plus 1 is defined as the difference between the fields of the supervisors of a dissertation. The larger the value, the greater the cognitive difference between the co-supervisors and the more obvious the cross-disciplinary collaboration. If the dissertation is not co-supervised, the value is defined as 0, indicating that there is no cognitive difference.

Step 8: Calculate the average field similarity between supervisors and their collaborators in co-supervision (AvgCoSupSim). For each supervisor, calculate the average field similarity between them and their collaborators, which represents the average cognitive similarity between the supervisor and the co-supervisor. The larger the value, the more consistent they are. If a supervisor has never participated in co-supervision, define this value as 0. Subsequently, at the dissertation level, this metric is aggregated by averaging the values of all supervisors.

In summary, we constructed a full-dimensional social capital measurement indicator system as shown in Table 1, consisting of seven continuous indicators. It is calculated based on information of the field to which the dissertation belongs, the supervisor's co-supervision relationship and the supervisor's supervision age (seniority). It should be noted that SupStuMatch and AvgCoSupSim measure cognitive similarity or consistency, which are negative indicators of diversity, whereas InterSupDiv and SDSupSeniority measure diversity and are positive indicators.

#### 4.2.3. Moderating variable

We use three moderator variables to measure the supervisor team diversity. First, co-supervision increases the size of team, resulting in greater diversity from more collaborators. Therefore, we selected the size of the supervisor team as a moderator variable. However, since 97.5 % of co-supervised dissertations have two supervisors, while the remaining 2.5 % have three supervisors, this proportion is too low. Thus, we changed the moderating variable for supervisor size to whether the dissertation was co-supervised. The variable description is shown in Table 1. Second, we examined the difference in seniority (SDSupSeniority) and cognitive difference (InterSupDiv) within supervisor teams. We used the standard deviation of supervisor team seniority and field differences to measure these diversities. Detailed definitions are provided in Section 4.2.2.

#### 4.2.4. Control variables

To enhance the estimation of the coefficients of the core independent variables in the model, we need to control for the influence of

potential confounding variables on dissertation citations. After reviewing studies on the influencing factors of papers (Tahamtan, et al., 2016), we identified the main variables to be controlled based on factors related to the dissertation and the author. For the dissertation, we controlled for the degree level, the publication age, the specialty of degree conferred, the dissertation field, the research topic popularity, and the interdisciplinarity. Regarding the author, we controlled for institutional prestige, the size of supervisor team (Guan, et al., 2017) and supervisor prestige. The supervisor prestige of a dissertation was measured by two indicators: the average size of the supervisor's supervised students (Gonzalez-Brambila, 2014; Liénard, et al., 2018) and the average h-index of supervisors (Yu, Yu, Li, & Wang, 2014). We controlled for supervisor prestige to distinguish between the influence of the supervisor's social capital and their capabilities and characteristics. Table 1 details all variables used in this study and their descriptions.

### 4.3. Models

The dependent variable, citation count, is a discrete count variable. As shown in Table 2, the variance (which is the square of the standard deviation) is significantly larger than the mean. Consequently, the data demonstrates characteristics of over-dispersion. Therefore, we used a negative binomial regression model with a log link function for the empirical analysis. This model is widely adopted by researchers to investigate citation counts (Chen, Wu, Li, & Sun, 2023; Lopaciuk-Gonczaryk, 2016; Onodera & Yoshikane, 2015; Tian, et al., 2021). In contrast to Poisson regression, the negative binomial regression model is designed to accommodate overdispersion in the dependent variable. This makes it more appropriate for data with dispersion levels that exceed Poisson distribution's handling capacity.

In light of the cumulative effect of the citation count of dissertations over time, a negative binomial regression model with publication age as the exposure variable was incorporated for the purpose of robustness analysis. Concurrently, given that 4365 (26.4 %) of the dissertations in the dataset had zero citations, constituting a relatively high proportion, a zero-inflated negative binomial regression model was employed as a supplementary analytical method. In the empirical analysis, robust estimates were employed for standard errors. The models were compared and diagnosed using statistical criteria and methods such as AIC, BIC, and pseudo- $R^2$ . All empirical analyses were conducted using the statistical software STATA 17.0.

## 5. Results and analysis

### 5.1. Descriptive statistics

Table 2 presents the descriptive statistics and Spearman correlations for the variables. The distribution of citation counts is characterized by a mean value of 4.506 and a standard deviation of 10.664, with a range between 0 and 673. Additionally, the maximum variance inflation factor (VIF) in these variables is 3.74, which is well below the commonly accepted threshold of 10. This finding indicates that multicollinearity is not a substantial concern in the context of this analysis.

### 5.2. Empirical analysis

In Table 3, we display the results of negative binomial regression models incorporating robust estimators. The values and significance of  $\ln\alpha$  in Table 3 indicate that the negative binomial regression model is appropriate, in comparison to the Poisson regression model. The results of the control variables are not listed. For detailed results, please refer to the online supplementary materials.

Model 2, Model 3, and Model 4 analyze the cognitive, relational, and structural dimensions of supervisors' social capital, respectively. In the cognitive dimension, the results for cognitive diversities were consistent with the hypotheses. At the 0.01 level of significance, the field match between supervisor and student and the cognitive similarity of supervisors in the co-supervision network have a significant negative effect on the citation counts to the dissertation, and Hypotheses H1a and H1b are supported. Both intra-team supervisor cognitive and seniority differences in the supervisor team showed a positive effect, but the significance was insufficient, suggesting that the available evidence is insufficient to support hypotheses H1c and H1d. In the relational capital dimension, the average tie strength showed a significant negative effect ( $p < 0.01$ ), Hypothesis H2a does not hold. Reciprocity share has a positive effect at 0.1 level of significance and hypothesis H2b is supported. For structural capital, degree centrality has a significant positive coefficient of quadratic term and negative coefficient of linear term ( $p < 0.01$ ), and a nonlinear relationship holds.

Model 5 synthesizes the three dimensions of social capital, and the effects of supervisor and dissertation field match and average tie strength remain unchanged, further supporting hypotheses H1a holds and H2a does not hold at the 0.05 level. It is important to note that the average tie strength exhibits the opposite of what was hypothesized, a negative effect on citation count. In co-supervision, excessive intensity of the supervisor's ties (e.g., frequent collaboration or strong reliance on a small number of partners) may limit scholars' exposure to heterogeneous information and resources in new fields, leading to a convergence of research perspectives and a lack of innovation. At the same time, strong ties require higher maintenance costs, which crowd out efforts to explore new collaborations or deepen research, and ultimately reduce the academic impact and citation likelihood of the results.

The quadratic coefficient for degree centrality is significantly positive in Model 5 ( $P < 0.01$ ). To further investigate the non-linear relationship between degree centrality and the number of citations, we present the results of the U-shaped test in Table 4 and Fig. 2, based on Model 5 in Table 3. In this analysis, all other variables are set to zero, and the constant term is excluded. This configuration does not alter the shape of the non-linear relationship. The structural capital of supervisors has a U-shaped impact on the citation count of dissertations, and the U-shaped relationship proposed in H3 is valid. The curve attains its minimum value at a standardized degree



**Table 2**  
Correlation matrix and descriptive statistics.

|                        | Mean   | SD     | Min    | Max    | VIF  | 1       | 2       | 3       | 4       | 5       | 6       | 7       | 8       | 9      | 10      | 11      | 12      | 13      | 14      | 15     | 16     | 17     | 18     | 19     | 20 |
|------------------------|--------|--------|--------|--------|------|---------|---------|---------|---------|---------|---------|---------|---------|--------|---------|---------|---------|---------|---------|--------|--------|--------|--------|--------|----|
| 1 CitationCount        | 4.506  | 10.664 | 0      | 673    | -    | 1       |         |         |         |         |         |         |         |        |         |         |         |         |         |        |        |        |        |        |    |
| 2 DegreeLevel          | 0.087  | 0.282  | 0      | 1      | 1.10 | 0.127*  | 1       |         |         |         |         |         |         |        |         |         |         |         |         |        |        |        |        |        |    |
| 3 Specialty            | 0.567  | 0.496  | 0      | 1      | 1.66 | 0.223*  | -0.079* | 1       |         |         |         |         |         |        |         |         |         |         |         |        |        |        |        |        |    |
| 4 DissertationAge      | 11.654 | 4.549  | 5      | 25     | 1.37 | 0.138*  | 0.061*  | -0.265* | 1       |         |         |         |         |        |         |         |         |         |         |        |        |        |        |        |    |
| 5 InstitutionLevel     | 0.822  | 0.847  | 0      | 2      | 1.04 | 0.189*  | 0.045*  | 0.066*  | 0.120*  | 1       |         |         |         |        |         |         |         |         |         |        |        |        |        |        |    |
| 6 SocialScience        | 0.105  | 0.307  | 0      | 1      | 1.96 | 0.101*  | -0.004  | 0.238*  | 0.006   | 0.018*  | 1       |         |         |        |         |         |         |         |         |        |        |        |        |        |    |
| 7 BasicScience         | 0.359  | 0.480  | 0      | 1      | 3.47 | -0.252* | 0.133*  | -0.487* | 0.003   | -0.116* | -0.256* | 1       |         |        |         |         |         |         |         |        |        |        |        |        |    |
| 8 EconManagement       | 0.434  | 0.496  | 0      | 1      | 3.59 | 0.148*  | -0.105* | 0.311*  | 0.093*  | 0.104*  | -0.300* | -0.655* | 1       |        |         |         |         |         |         |        |        |        |        |        |    |
| 9 TopicPopularity      | 4.138  | 1.315  | 0      | 6.895  | 1.03 | 0.090*  | 0.016*  | 0.0004  | 0.071*  | 0.036*  | -0.045* | -0.023* | 0.107*  | 1      |         |         |         |         |         |        |        |        |        |        |    |
| 10 Interdisciplinarity | 0.405  | 0.491  | 0      | 1      | 1.29 | 0.072*  | -0.097* | 0.131*  | -0.046* | 0.052*  | -0.155* | -0.330* | 0.436*  | 0.098* | 1       |         |         |         |         |        |        |        |        |        |    |
| 11 CoSupervision       | 0.048  | 0.214  | 0      | 1      | 3.28 | 0.003   | 0.145*  | -0.026* | 0.012   | 0.007   | 0.001   | 0.026*  | -0.035* | -0.006 | -0.027* | 1       |         |         |         |        |        |        |        |        |    |
| 12 AvgStudents         | 19.552 | 17.287 | 1      | 106    | 2.45 | 0.039*  | 0.078*  | -0.139* | 0.327*  | 0.041*  | -0.009  | 0.017*  | 0.047*  | 0.086* | 0.010   | -0.049* | 1       |         |         |        |        |        |        |        |    |
| 13 AvgSupHindex        | 4.345  | 2.936  | 0      | 16     | 2.42 | 0.360*  | 0.088*  | 0.120*  | 0.345*  | 0.136*  | 0.077*  | -0.206* | 0.176*  | 0.100* | 0.071*  | -0.053* | 0.758*  | 1       |         |        |        |        |        |        |    |
| 14 SupStuMatch         | 0.802  | 0.205  | 0.097  | 1      | 1.36 | -0.036* | 0.005   | 0.044*  | 0.051*  | 0.009   | -0.225* | 0.045*  | 0.228*  | -0.001 | 0.114*  | 0.013   | -0.269* | -0.247* | 1       |        |        |        |        |        |    |
| 15 InterSupDiv         | 0.008  | 0.054  | 0      | 0.875  | 2.08 | 0.006   | 0.144*  | -0.025* | 0.018*  | 0.007   | 0.003   | 0.025*  | -0.037* | -0.001 | -0.028* | 0.946*  | -0.019* | -0.027* | -0.021* | 1      |        |        |        |        |    |
| 16 SDSupSeniority      | 0.211  | 1.186  | 0      | 13.435 | 3.02 | 0.001   | 0.147*  | -0.021* | 0.016*  | 0.009   | 0.005   | 0.024*  | -0.035* | -0.006 | -0.030* | 0.949*  | -0.030* | -0.040* | 0.004   | 0.934* | 1      |        |        |        |    |
| 17 AvgCoSupSimilarity  | 0.261  | 0.380  | 0      | 1      | 2.75 | -0.004  | 0.180*  | -0.120* | 0.140*  | 0.013   | -0.025* | 0.107*  | -0.062* | 0.035* | -0.053* | 0.288*  | 0.341*  | 0.246*  | -0.101* | 0.256* | 0.265* | 1      |        |        |    |
| 18 AvgTieStrengthSup   | 0.533  | 0.900  | 0      | 9      | 3.74 | -0.004  | 0.189*  | -0.150* | 0.140*  | 0.010   | -0.028* | 0.113*  | -0.071* | 0.041* | -0.053* | 0.336*  | 0.370*  | 0.272*  | -0.165* | 0.323* | 0.320* | 0.943* | 1      |        |    |
| 19 ReciprocityRatioSup | 0.025  | 0.129  | 0      | 1      | 1.48 | 0.028*  | 0.108*  | -0.111* | 0.085*  | 0.016*  | -0.029* | 0.054*  | -0.012  | 0.044* | -0.003  | 0.226*  | 0.246*  | 0.227*  | -0.106* | 0.233* | 0.222* | 0.292* | 0.446* | 1      |    |
| 20 DegreeCentralitySup | 0      | 1      | -0.474 | 5.940  | 1.80 | 0.002   | 0.216*  | -0.168* | 0.141*  | 0.013   | -0.029* | 0.126*  | -0.084* | 0.044* | -0.056* | 0.339*  | 0.390*  | 0.292*  | -0.170* | 0.328* | 0.325* | 0.918* | 0.964* | 0.426* | 1  |

N=16,567.

\*p&lt;0.05.

**Table 3**  
Results of negative binomial regression models (NB2 with Robust SE).

| Models                             | (1)                 | (2)                  | (3)                   | (4)                  | (5)                  | (6)                  | (7)                                    | (8)                                 |
|------------------------------------|---------------------|----------------------|-----------------------|----------------------|----------------------|----------------------|----------------------------------------|-------------------------------------|
| Moderator (M)                      |                     |                      |                       |                      |                      |                      |                                        |                                     |
| SupStunMatch                       |                     | -0.228***<br>(0.076) |                       |                      | -0.267***<br>(0.075) | -0.266***<br>(0.074) | SDSupSeniority<br>-0.263***<br>(0.074) | InterSupDiv<br>-0.267***<br>(0.075) |
| InterSupDiv                        |                     | 0.240<br>(0.517)     |                       |                      | 0.421<br>(0.502)     | 0.359<br>(0.457)     | 0.730*<br>(0.440)                      | 1.130**<br>(0.525)                  |
| AvgCoSupSimilarity                 |                     | -0.143***<br>(0.040) |                       |                      | 0.0220<br>(0.065)    | 0.00377<br>(0.063)   | 0.0283<br>(0.062)                      | 0.000431<br>(0.064)                 |
| SDSupSeniority                     |                     | 0.00963<br>(0.033)   |                       |                      | 0.00802<br>(0.030)   | 0.0169<br>(0.025)    | 0.0407<br>(0.033)                      | 0.0204<br>(0.029)                   |
| AvgTieStrengthSup                  |                     |                      | -0.0700***<br>(0.020) |                      | -0.0589**<br>(0.029) | -0.0587**<br>(0.029) | -0.0590**<br>(0.029)                   | -0.0591**<br>(0.029)                |
| ReciprocityRatioSup                |                     |                      | 0.299*<br>(0.170)     |                      | 0.244<br>(0.161)     | 0.244<br>(0.158)     | 0.218<br>(0.151)                       | 0.244<br>(0.161)                    |
| DegreeCentralitySup                |                     |                      |                       | -0.105***<br>(0.032) | -0.0785*<br>(0.042)  | -0.0622<br>(0.042)   | -0.0766*<br>(0.042)                    | -0.0587<br>(0.042)                  |
| DegreeCentralitySup <sup>2</sup>   |                     |                      |                       | 0.043***<br>(0.009)  | 0.0394***<br>(0.011) | 0.0365***<br>(0.011) | 0.0377***<br>(0.011)                   | 0.0363***<br>(0.011)                |
| M × DegreeCentralitySup            |                     |                      |                       |                      |                      | -0.261<br>(0.213)    | -0.126***<br>(0.043)                   | -1.223<br>(0.996)                   |
| MXDegreeCentralitySup <sup>2</sup> |                     |                      |                       |                      |                      | 0.0618<br>(0.065)    | 0.0432***<br>(0.015)                   | 0.146<br>(0.361)                    |
| Control Variables                  | Yes                 | Yes                  | Yes                   | Yes                  | Yes                  | Yes                  | Yes                                    | Yes                                 |
| Constant                           | 0.107<br>(0.069)    | 0.249***<br>(0.086)  | 0.110<br>(0.068)      | 0.0659<br>(0.070)    | 0.238***<br>(0.087)  | 0.244***<br>(0.086)  | 0.239***<br>(0.085)                    | 0.244***<br>(0.087)                 |
| Inalpha                            | 0.228***<br>(0.023) | 0.224***<br>(0.023)  | 0.225***<br>(0.023)   | 0.223***<br>(0.023)  | 0.219***<br>(0.022)  | 0.219***<br>(0.023)  | 0.217***<br>(0.022)                    | 0.218***<br>(0.023)                 |
| N                                  | 16,567              | 16,567               | 16,567                | 16,567               | 16,567               | 16,567               | 16,567                                 | 16,567                              |
| Log Likelihood                     | -39,742.48          | -39,720.26           | -39,729.73            | -39,700.29           | -39,680.14           | -39,678.55           | -39,666.40                             | -39,674.18                          |
| AIC                                | 79,513.0            | 79,476.5             | 79,491.5              | 79,432.6             | 79,404.3             | 79,405.1             | 79,380.8                               | 79,396.4                            |
| BIC                                | 79,621.0            | 79,615.4             | 79,614.9              | 79,556.0             | 79,574.0             | 79,590.3             | 79,566.0                               | 79,581.5                            |
| Pseudo R <sup>2</sup>              | 0.0562              | 0.0567               | 0.0565                | 0.0572               | 0.0576               | 0.0577               | 0.0580                                 | 0.0578                              |

Standard errors in parentheses

\*\*\* p<0.01,

\*\* p<0.05,

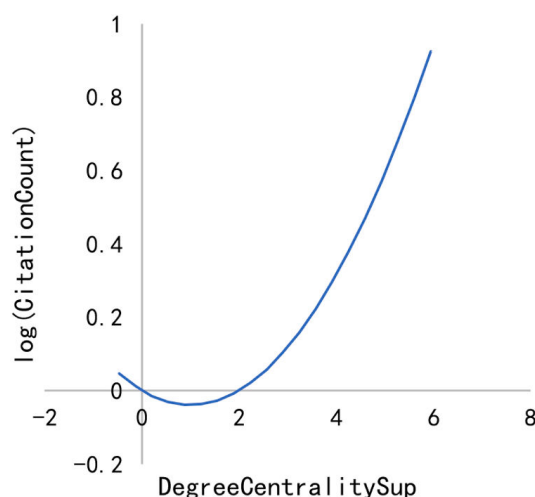
\* p<0.1

**Table 4**

U-test for degree centrality.

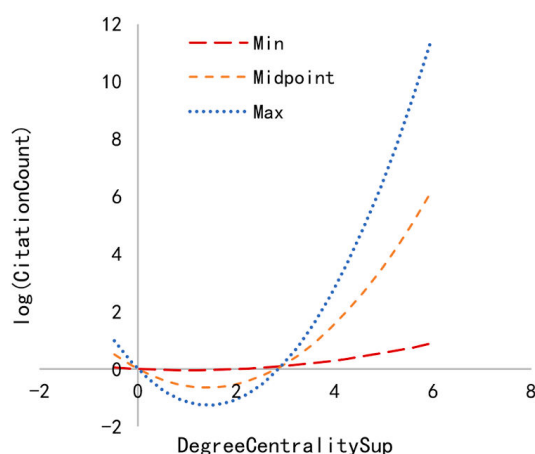
|                         | Extreme point | Slope       |             | U-test  | Model   |
|-------------------------|---------------|-------------|-------------|---------|---------|
|                         |               | Lower bound | Upper bound |         |         |
| No moderator            | 0.9962        | -0.1159     | 0.3896      | U shape | Model 5 |
| SDSupSeniority = 0      | 1.0159        | -0.1124     | 0.3713      | U shape | Model 7 |
| SDSupSeniority = 6.718  | 1.4075        | -1.2342     | 2.9724      | U shape | Model 7 |
| SDSupSeniority = 13.435 | 1.4314        | -2.3559     | 5.5732      | U shape | Model 7 |

Note: Based on the results in Table 3.

**Fig. 2.** Impact of degree centrality on citation counts (based on Model 5 in Table 3).

centrality of 0.9962 (corresponding to an original node degree of 2.5225), with the extreme point falling within the range of -0.474 to 5.940. The inhibitory phase of node degree is shorter than the promotional phase, and the results primarily reflect the promotional effect of structural capital on citation counts.

The moderating role of supervisor team diversity on the relationship between supervisors' degree centrality and citation count, as shown in Models 6 to 8 in Table 3. The result of the interaction term indicates that the size and cognitive differences of the supervisor team do not significantly moderate the relationship between degree centrality and citation count, thus Hypothesis H4a and H4c were not supported. However, the interaction term between the seniority difference of the supervisor team and the square of the degree centrality is significantly positive at the 0.01 level. In Fig. 3, we illustrate the relationship between degree centrality and citation count while controlling the other variables constant at 0 in Model 7, across three distinct levels of supervisor team diversity: 0 (Minimum), 6.718 (Midpoint), and 13.435 (Maximum). Combining the U-tests in Table 4 and Fig. 3, we can see that supervisor team seniority differences significantly moderated the relationship between degree centrality and citation count, and Hypothesis H4b was supported. The greater the difference in seniority among the supervisors, the steeper the U-shaped relationship, the minimum value shifts to the

**Fig. 3.** The moderating effect of supervisor team difference in seniority on the relationship between degree centrality and citation count (based on Model 7 in Table 3).



right, and the minimum value decreases, indicating that increased diversity may introduce both risks and rewards to dissertation citation count, particularly at high levels of social capital.

Therefore, differences in supervisor seniority are an effective source of diversity within dissertation teams. According to knowledge complementarity theory and resource dependence theory, in teams with high differences in seniority, the academic networks of senior members and the cutting-edge perspectives of junior members complement each other's knowledge. This makes the positive effects of structural capital more pronounced and the negative effects more negative. The conflicting differences between the established academic paradigms and resource networks of senior members and the cutting-edge perspectives and innovation demands of junior members manifest as a strong rejection of ineffective resources during the resource redundancy phase, amplifying negative effects and deepening the minimum value. However, this also drives the team to quickly break through the inefficient equilibrium, shift the inflection point to the right, and achieve stronger long-term returns. Differences in seniority inherently have a hereditary nature, with seasoned professionals sharing their experience and newcomers contributing fresh insights. This gives rise to implicit collaborative rules, thereby reducing communication costs. Meanwhile, younger individuals prioritize short-term innovation, while older individuals emphasize long-term accumulation. This creates a natural balance when leveraging social capital, thereby preventing resource misallocation. Therefore, differences in seniority constitute an embedded resource integration mechanism with collaborative resilience, enabling it to steadily moderate the nonlinear relationship between social capital and citation count of dissertation.

### 5.3. Robustness evaluation

To ensure the robustness of our findings, we conducted additional analyses using alternative modeling approaches. Since the

**Table 5**

Results of negative binomial regression models with publication age as the exposure variable.

| Models                               | (1)                  | (2)                   | (3)                  | (4)                   | (5)                   | (6)                   | (7)                   |
|--------------------------------------|----------------------|-----------------------|----------------------|-----------------------|-----------------------|-----------------------|-----------------------|
| Moderator (M)                        |                      |                       |                      |                       | CoSupervision         | SDSupSeniority        | InterSupDiv           |
| SupStuMatch                          | -0.353***<br>(0.076) |                       |                      | -0.382***<br>(0.075)  | -0.382***<br>(0.075)  | -0.381***<br>(0.074)  | -0.382***<br>(0.075)  |
| InterSupDiv                          | 0.163<br>(0.494)     |                       |                      | 0.363<br>(0.469)      | 0.239<br>(0.425)      | 0.622<br>(0.402)      | 1.046**<br>(0.522)    |
| AvgCoSupSimilarity                   | -0.149***<br>(0.039) |                       |                      | -0.0103<br>(0.064)    | -0.0360<br>(0.062)    | -0.00732<br>(0.062)   | -0.0323<br>(0.064)    |
| SDSupSeniority                       | 0.00524<br>(0.033)   |                       |                      | -0.00177<br>(0.029)   | 0.0119<br>(0.025)     | 0.0318<br>(0.032)     | 0.0117<br>(0.029)     |
| AvgTieStrengthSup                    |                      | -0.0748***<br>(0.019) |                      | -0.0779***<br>(0.029) | -0.0779***<br>(0.029) | -0.0778***<br>(0.029) | -0.0781***<br>(0.029) |
| ReciprocityRatioSup                  |                      | 0.386**<br>(0.163)    |                      | 0.327**<br>(0.150)    | 0.330**<br>(0.148)    | 0.305**<br>(0.140)    | 0.327**<br>(0.150)    |
| DegreeCentralitySup                  |                      |                       | -0.0723**<br>(0.032) | -0.0210<br>(0.043)    | 0.000839<br>(0.043)   | -0.0175<br>(0.043)    | -0.00114<br>(0.043)   |
| DegreeCentralitySup <sup>2</sup>     |                      |                       | 0.0414***<br>(0.008) | 0.0327***<br>(0.011)  | 0.0291***<br>(0.011)  | 0.0309***<br>(0.011)  | 0.0296***<br>(0.011)  |
| M × DegreeCentralitySup              |                      |                       |                      |                       | -0.275<br>(0.206)     | -0.116***<br>(0.042)  | -1.150<br>(1.000)     |
| M × DegreeCentralitySup <sup>2</sup> |                      |                       |                      |                       | 0.0542<br>(0.062)     | 0.0390***<br>(0.015)  | 0.112<br>(0.358)      |
| Control Variables                    | Yes                  | Yes                   | Yes                  | Yes                   | Yes                   | Yes                   | Yes                   |
| Constant                             | -1.448***<br>(0.084) | -1.690***<br>(0.064)  | -1.719***<br>(0.065) | -1.425***<br>(0.085)  | -1.417***<br>(0.084)  | -1.424***<br>(0.084)  | -1.419***<br>(0.085)  |
| lnalpha                              | 0.254***<br>(0.021)  | 0.257***<br>(0.021)   | 0.255***<br>(0.021)  | 0.249***<br>(0.021)   | 0.248***<br>(0.021)   | 0.247***<br>(0.021)   | 0.248***<br>(0.021)   |
| N                                    | 16,567               | 16,567                | 16,567               | 16,567                | 16,567                | 16,567                | 16,567                |
| Log Likelihood                       | -39,913.49           | -39,930.76            | -39,898.64           | -39,861.74            | -39,859.25            | -39,851.32            | -39,855.70            |
| AIC                                  | 79,861.0             | 79,891.5              | 79,827.3             | 79,765.5              | 79,764.5              | 79,748.6              | 79,757.4              |
| BIC                                  | 79,992.1             | 80,007.2              | 79,943.0             | 79,927.5              | 79,942.0              | 79,926.1              | 79,934.9              |
| Pseudo R <sup>2</sup>                | 0.0457               | 0.0452                | 0.0460               | 0.0469                | 0.0470                | 0.0471                | 0.0470                |

Standard errors in parentheses

\*\*\* p<0.01,

\*\* p<0.05, \*p<0.1

number of citations of dissertations depends on the accumulation of time, we rebuilt the negative binomial regression model with publication age as the exposure variable. The results are shown in Table 5. A comparison of the new model with the benchmark regression in Table 3 reveals a significant difference in the proportion of reciprocity in relational capital ( $P < 0.05$ ). This finding supports hypothesis H2b. In terms of the signs and significance of the coefficients, the results for other core independent variables were consistent across both models, with only minor variations in the magnitude of the coefficients. Furthermore, a zero-inflated negative binomial regression model was constructed, and the conclusions derived from this model were found to be consistent with those of the benchmark regression model presented in Table 3. In addition, the negative binomial regression model was determined to be optimal based on the AIC and BIC criteria, with the smallest AIC and BIC values. The zero-inflated negative binomial regression model was the second-most optimal model. Due to space limitations, supplementary materials are provided online to elaborate on the models' outcomes.

Doctoral dissertations typically have higher academic quality, and we analyzed a subset of doctoral dissertations to examine the robustness of the findings. Comparing Table 6 and Table 3, there are no statistically significant differences between the dissertation sub-sample and the full sample. Although the signs of the coefficients change for some indicators in the cognitive dimension, they are not statistically significant at the 0.1 level. The results of the study are robust.

In the cognitive dimension, the field match between supervisor and student is not significant in doctoral dissertations, unlike the significant negative effect in the full sample; the positive effect of differences in supervisor seniority on citation count is partially supported in doctoral dissertations ( $p < 0.10$ , in Models 4, 5, and 7), while there is not sufficient evidence to support it in the full sample. In the relational dimension, average tie strength continues to negatively affect dissertation citations in doctoral dissertations,

**Table 6**  
Results of negative regression models for doctoral dissertation samples.

| Models                               | (1)                 | (2)                 | (3)                  | (4)                 | (5)                 | (6)                  | (7)                 |
|--------------------------------------|---------------------|---------------------|----------------------|---------------------|---------------------|----------------------|---------------------|
| Moderator (M)                        |                     |                     |                      |                     | CoSupervision       | SDSupSeniority       | InterSupDiv         |
| SupStuMatch                          | 0.108<br>(0.220)    |                     |                      | 0.0304<br>(0.221)   | 0.0546<br>(0.219)   | 0.0863<br>(0.212)    | 0.0445<br>(0.220)   |
| InterSupDiv                          | -0.802<br>(0.931)   |                     |                      | -0.678<br>(0.821)   | -0.611<br>(0.791)   | 0.531<br>(0.687)     | 0.462<br>(1.027)    |
| AvgCoSupSimilarity                   | -0.252*<br>(0.145)  |                     |                      | -0.0564<br>(0.193)  | -0.0880<br>(0.183)  | -0.0421<br>(0.179)   | -0.102<br>(0.185)   |
| SDSupSeniority                       | 0.0797<br>(0.059)   |                     |                      | 0.0842*<br>(0.050)  | 0.0907*<br>(0.050)  | 0.110<br>(0.071)     | 0.0902*<br>(0.050)  |
| AvgTieStrengthSup                    |                     | -0.138*<br>(0.073)  |                      | -0.0383<br>(0.092)  | -0.0275<br>(0.092)  | -0.0281<br>(0.089)   | -0.0360<br>(0.091)  |
| ReciprocityRatioSup                  |                     | 0.889*<br>(0.505)   |                      | 0.643<br>(0.393)    | 0.604*<br>(0.357)   | 0.330<br>(0.281)     | 0.654*<br>(0.390)   |
| DegreeCentralitySup                  |                     |                     | -0.213**<br>(0.094)  | -0.222**<br>(0.087) | -0.203**<br>(0.082) | -0.237***<br>(0.080) | -0.187**<br>(0.085) |
| DegreeCentralitySup <sup>2</sup>     |                     |                     | 0.0414***<br>(0.016) | 0.0389**<br>(0.016) | 0.0341**<br>(0.015) | 0.0398***<br>(0.014) | 0.0325**<br>(0.015) |
| M × DegreeCentralitySup              |                     |                     |                      |                     | -0.360<br>(0.386)   | -0.231**<br>(0.090)  | -1.736<br>(1.497)   |
| M × DegreeCentralitySup <sup>2</sup> |                     |                     |                      |                     | 0.104<br>(0.097)    | 0.0823***<br>(0.029) | 0.337<br>(0.446)    |
| Control Variables                    | YES                 | YES                 | YES                  | YES                 | YES                 | YES                  | YES                 |
| Constant                             | 0.395<br>(0.276)    | 0.415<br>(0.256)    | 0.349<br>(0.261)     | 0.403<br>(0.272)    | 0.407<br>(0.272)    | 0.417<br>(0.268)     | 0.418<br>(0.273)    |
| lnalpha                              | 0.298***<br>(0.070) | 0.299***<br>(0.072) | 0.303***<br>(0.078)  | 0.286***<br>(0.069) | 0.284***<br>(0.069) | 0.261***<br>(0.066)  | 0.283***<br>(0.070) |
| N                                    | 1447                | 1447                | 1447                 | 1447                | 1447                | 1447                 | 1447                |
| Log Likelihood                       | -4391.34            | -4392.34            | -4393.80             | -4383.58            | -4382.39            | -4368.32             | -4381.59            |
| AIC                                  | 8816.7              | 8814.7              | 8817.6               | 8809.2              | 8810.8              | 8782.6               | 8809.2              |
| BIC                                  | 8906.4              | 8893.8              | 8896.7               | 8920.0              | 8932.2              | 8904.0               | 8930.5              |
| Pseudo R2                            | 0.0527              | 0.0525              | 0.0522               | 0.0544              | 0.0546              | 0.0576               | 0.0548              |

Standard errors in parentheses

\*\*\*  $p < 0.01$ ,

\*\*  $p < 0.05$ ,

\*  $p < 0.1$

but with reduced statistical significance. Consistent with the entire sample, the U-shaped relationship between structural capital and citation count is significantly established in doctoral dissertations. According to Model 4 in Table 6, the minimum point of the U-shaped curve is 2.853, which falls within the range of degree centrality values. Differences in supervisor seniority play a significant moderating role in doctoral dissertations, while there is insufficient evidence to support the moderating role of supervisor team size and field differences in doctoral dissertations. As can be seen from Fig. 4, the overall trend of the moderating effect of the supervisor team's seniority is basically consistent with that of the entire sample. The difference is that as the differences in the seniority of the supervisor team increase, the minimum value shifts to the left, and the extreme values under the three different conditions are 2.9774, 1.5091, and 1.4581, respectively. This indicates that in doctoral dissertations, teams with large differences in supervisor seniority have a lower tolerance for excessive cooperative relationships in co-supervision, so the critical point of negative effects appears earlier. This could potentially be because doctoral dissertations place a greater emphasis on the originality and depth of the research content.

## 6. Conclusion and discussion

In response to the increasing global emphasis on research excellence, from the perspective of dissertations, this study investigates the direct impact of social capital of author team and supervisors on the citation impact of graduate dissertations within the context of co-supervision. Furthermore, we explore how supervisor team diversity moderates the influence of the supervisors' social capital on dissertation citation impact. Our empirical analysis is based on a dataset comprising 21 years (2000–2020) of graduate dissertations from two specialties of statistics in Chinese graduate education. China boasts a vast graduate education system. The number of graduate students enrolled in China reached 3.88 million in 2023 (MOE, 2024). Co-supervision practices for graduate students have become increasingly common in China, driven by factors such as pressure from the expansion of graduate enrollment, growing demand for interdisciplinary research that requires diverse expertise from supervisors, and related policy and institutional incentives (Shen & Jin, 2020). Meanwhile, the CNKI dissertation database systematically archives essential information about dissertations, clearly documented co-supervision relationships, and citation counts, thereby providing an invaluable data foundation for this study.

According to social capital theory, the social capital possessed by authors can significantly influence their citation impact of research achievements. Examining the complex relationship between an author's social capital and their citation impact of paper not only deepens our understanding of the underlying mechanisms driving academic success but also aids in predicting and evaluating such outcomes. Our research subject at the dissertation level is a powerful supplement to existing journal articles and scholar-oriented research. Unlike other forms of papers, dissertations are written by supervisors and students, who have different roles. We took note of this difference and focused on examining the impact of supervisors' social capital on the citation counts of dissertations in the context of co-supervision, from the perspective of the dissertation author team. The main reasons for choosing co-supervision are, first, that scientific collaboration is becoming increasingly common, and collaborative networks have become an important carrier of social capital for scholars, significantly influencing the citation impact of academic achievements. Second, scientific collaboration in dissertations is mainly reflected between supervisors and students, as well as between co-supervisors, and with the expansion of graduate enrollment, the increasing complexity of research issues, and the emphasis on interdisciplinary research, co-supervision has become an important form of graduate student training and dissertation writing.

Based on the three-dimensional framework theory of social capital proposed in (Nahapiet & Ghoshal, 1998), this paper designs and constructs a measurement indicator system for team social capital in dissertations based on objective bibliometric data and co-supervision relationship data, which consists of structural, cognitive, and relational capital. Based on the research context and relevant theories, we established research hypotheses on the impact of team social capital in different dimensions on the citation count

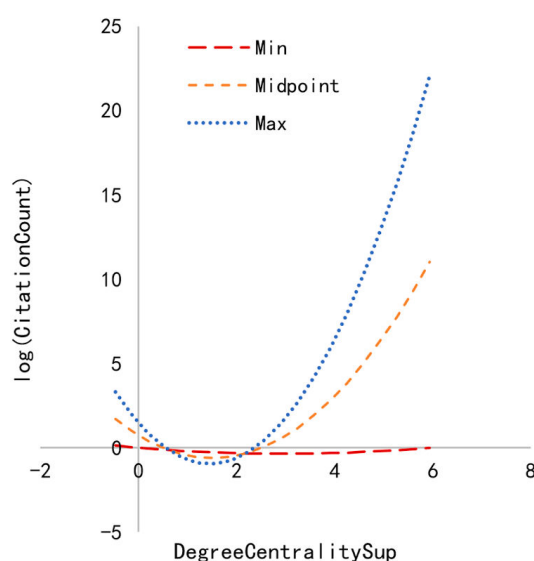


Fig. 4. The moderating effect of supervisor team diversity in seniority on the relationship between degree centrality and citation count (based on Model 6 in Table 6).

of dissertations, and conducted empirical analysis based on the negative binomial regression model. A series of robust analyses showed that the research results were highly robust.

The study found that the cognitive capital of the team significantly affects the citation impact of the dissertation, and cognitive diversity has a positive effect on the citation count of the dissertation. The outcome supports our hypothesis and concurs with scholar-level evidence from [Yin, et al. \(2024\)](#). It underscores that cognitive diversity is a pivotal mechanism for fostering academic impact within the distinctive knowledge-production framework of graduate student supervision. In particular, in terms of the differences in cognition between supervisors and students within the team, the more consistent the research areas of the supervisor and student dissertations are, the lower the citation count of the dissertation will generally be. Therefore, for supervisors, an overly single research direction may not be conducive to generating more citations. Under China's current academic system, where quantitative evaluation and project continuity serve as strong incentives, highly congruent supervisor-student teams tend to entrench research in the supervisor's established academic trajectory. This fosters a safe yet conservative mode of knowledge production, which, while conducive to completing predefined tasks, may come at the expense of originality and novelty, thereby limiting its external impact. From the perspective of author teams, this insight suggests that co-supervision involving supervisors from different fields can effectively enhance the diversity of a dissertation's research scope. Therefore, the findings support the implementation of co-supervision for graduate students, providing a rationale for selecting co-supervision arrangements.

At the same time, the relational capital of supervisors significantly affects the citation impact of the dissertations they supervise. Contrary to the research hypothesis, our analysis found that the strength of the relationship of supervisors in co-supervision significantly negatively affects the citation count of dissertations. This contradicts the conclusions reached in research on journal articles and scholars ([Fronzetti Colladon, et al., 2020](#)). The strength of the relationship is measured by the average tie strength of supervisors in the co-supervision network (i.e., the average number of collaborations with other supervisors), and is averaged at the dissertation level. This indicator can reflect the sustainability and trust of collaborative relationships ([Zhang & Wang, 2017](#)). Therefore, this result suggests that supervisors' over-reliance on a fixed set of collaborators and frequent work together in co-supervision are not conducive to the formation of high-impact dissertations. A possible reason is that this may limit scholars' access to heterogeneous information and resources in new fields, leading to convergence in research perspectives and a lack of innovation. However, it should also be noted that in the practice of co-supervision of graduate students in China, many co-supervision arrangements suffer from deficiencies such as formalistic collaboration, unclear division of labor, and inefficient communication ([Xu, et al., 2024](#)). Some frequent co-supervisions stem from institutional arrangements, such as established teams, academic lineage, or evaluation requirements, rather than being driven entirely by complementary academic interests. In such cases, the high tie strength may be formal, lacking substantive knowledge integration and intellectual exchange. This not only fails to fully leverage the innovative and empowering potential of collaboration but may also dilute supervisory resources due to divided responsibilities and internal coordination friction, ultimately undermining the academic dissemination and impact of the dissertation. Consequently, the negative effect of average tie strength on dissertation citation counts will be amplified. Therefore, establishing a causal relationship based on the above results necessitates further investigation in combination with the quality of collaboration.

On the other hand, the proportion of reciprocal relationships of supervisors in co-supervision network positively influences the citation count of the dissertation. This further illustrates that collaboration frequency alone serves merely as a formal measure of relationship sustainability and trust, failing to capture the qualitative essence of relationship quality, such as trust, rapport, and genuine intellectual exchange. In the common Chinese dual-supervisor system, where there is a primary and a secondary supervisor, reciprocity often indicates that the supervisory relationship extends beyond formal hierarchies and divisions of responsibility. This reflects more substantive, bidirectional and equal exchanges of knowledge and academic support, which are likely to be driven by genuine mentoring needs and shared academic interests. Therefore, the negative effect of average tie strength and the positive effect of the proportion of reciprocal ties both point to the same core conclusion: the effectiveness of co-supervision depends not only on how frequently the supervisors collaborate, but also on whether it involves high-quality interactions that are substantive and reciprocal. To further explore and clarify this mechanism, as well as to establish causality, future studies should be based on objective bibliometric data, and should also incorporate surveys and interviews in order to conduct more comprehensive mixed-methods research.

Structural capital is an important dimension of social capital. It can even predict cognitive capital and relational capital ([Li, et al., 2013](#)) and is one of the important variables in this study. We use degree centrality to measure structural capital, which is one of the most important indicators for measuring structural capital in scientific collaboration. This study found that the number of collaborators (degree centrality) of supervisors in the co-supervision network has a significant U-shaped effect on the citation count of dissertations. This is consistent with the research hypothesis we proposed. Additionally, it is important to note that although co-supervision for graduate students in China has become increasingly common, its institutionalization and standardization remain underdeveloped, with issues such as unclear division of responsibilities and superficial collaboration ([Shen & Jin, 2020](#)). This may also explain the observed result. When supervisors rely on a small number of familiar collaborators, coordination is easier and responsibilities are clearly defined. On the other end, a larger number of collaborators may correspond to more institutionalized, interdisciplinary supervisor teams that provide broad academic support. In the context of the co-supervision culture of the primary-secondary supervisor system in China, medium-sized teams are most likely to fall into the dilemma of ambiguous responsibilities and increased communication costs, thereby failing to realize the potential of co-supervision. Further analysis shows that differences in the seniority of supervisor team have a significant moderating effect on the above U-shaped relationship, while the moderating effects of supervisor team size and cognitive differences are not statistically significant. Unlike the knowledge conflicts that may arise from disciplinary barriers or the dilution of cohesion brought about by expanding team sizes, the moderating effect of supervisor seniority differences reveals the unique value of intergenerational complementarity in activating resources and balancing risks. Maintaining a reasonable seniority difference and encouraging intergenerational collaboration provides specific guidance for



team configuration and scientific research management. When constructing co-supervision networks, seniority diversity may be more effective than pursuing co-supervision scale or disciplinary diversity in improving the conversion efficiency of social capital.

While the analysis of structural capital reveals meaningful statistical associations, it should be noted that the interpretation of the underlying mechanisms remains speculative in the absence of qualitative data, such as motivations for co-supervision and interaction behaviors in co-supervisory relationships, and cannot establish causality. The degree centrality (that is, the number of collaborators) cannot distinguish whether a supervisor team is established based on genuine intellectual complementarity, project requirements, personnel arrangements, or merely nominal inclusion.

In summary, this study focuses on citation differences in dissertations. Based on the context of co-supervision, this study is the first to incorporate the three dimensions of social capital (structural, relational, and cognitive), as well as supervisor team diversity, into a citation analysis framework. This study constructs measurable indicators within and outside the team, examines the influence mechanism of social capital and the moderating effect of diversity, fills the gap in quantitative research on co-supervision, and provides theoretical and strategic insights for optimizing supervisor co-supervision, enhancing the citation impact of dissertations, and improving graduate student training.

The limitations of the research and suggestions for future studies are as follows.

First, this study focuses only on co-supervision as a form of collaboration. Future research could examine other aspects of supervisors' collaboration such as co-authorship, joint conference participation, collaborative research projects, or co-teaching. A more comprehensive framework could also be developed based on these factors. Furthermore, aside from formal supervisory relationships listed in dissertations, other individuals—such as additional scholars or peers—often contribute to dissertation completion. These contributions are typically mentioned in the acknowledgments section. Analyzing this section could reveal more detailed collaborative relationships and provide valuable data for future studies.

Second, this paper utilizes objective dissertation data and co-supervision relationship data to construct a three-dimensional measurement indicator system for the social capital of supervisors. This system has the advantages of operability and comparability. From the perspective of the team's internal members, supervisor-student cognitive alignment and disciplinary differences within the supervisor team were established to measure internal team relationships from the perspective of cognitive capital. Meanwhile, based on the objective co-supervision data, indicators for relational capital were established from the perspectives of sustainability, trust, and reciprocity in relationships. However, the more detailed communication and interaction between supervisors and between supervisors and students within the team from the perspective of relational capital was not further studied. Therefore, it remains challenging to fully capture the qualitative nature of relational capital, such as trust, rapport, and genuine knowledge exchange, in co-supervision. This limitation may prevent a deeper interpretation of the relationships among variables. While the interpretation of the mechanisms behind statistical relationships is theoretically reasonable and resonates with the Chinese context, direct behavioral evidence is lacking. This evidence would include the actual motivations of supervisors, the dynamic interactions within teams, and the real experiences of graduate students. Therefore, future research should adopt a mixed-methods approach that integrates objective data on co-supervision networks with interviews or surveys of supervisors and students. This will yield more detailed insights into intra-team communication, helping to unveil the "black box" of collaborative motivations and interactive processes. This approach will provide a more comprehensive understanding of how co-supervision actually influences the citation impact of dissertations and the mechanisms underlying its effects. Among the extant literature, the survey scale proposed by Zuccala, et al. (2024) to measure scholars' social capital from the perspectives of cognition, relationships, and structural preferences can be used as a reference and extended to the dissertation scenario.

Third, this study conducted an empirical analysis within two statistical disciplines in China. Future research should extend to a wider range of disciplines and incorporate data from different countries to assess the broader geographical applicability and disciplinary variation of the findings. The systems, cultures, and motivations for co-supervision in graduate education vary internationally. Findings from a single-country context like China cannot easily distinguish universal mechanisms from context-specific phenomena. Therefore, the theoretical generalizability and external validity of the proposed recommendations require systematic cross-national comparisons in the future to identify both universal patterns and context-dependent conditions that influence the effectiveness of co-supervision. From a disciplinary perspective, although these two disciplines are primarily classified into two different categories, namely the natural sciences and the humanities and social sciences, and the influence of specific research fields has been considered, due to the disciplinary heterogeneity in the effects of co-supervision (Xu, et al., 2024), the impact generated by disciplinary differences still needs to be compared and analyzed across more disciplines in the future.

Finally, due to limitations in the CNKI data, this study used citation count to measure the dissertations' academic influence, and self-citation data are not excluded here. The tendency of self-citation among researchers may be attributed to the internal continuity of the research context. However, this practice may also lead to an amplification of the scale of citation, thereby complicating the accurate assessment of the impact of dissertations on external academic entities. Future research will be improved by distinguishing between self-citations and external citations.

#### **CRedit authorship contribution statement**

**Li Zhai:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Xiangbin Yan:** Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization.

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## Supplementary materials

Supplementary material associated with this article can be found, in the online version, at [doi:10.1016/j.joi.2026.101781](https://doi.org/10.1016/j.joi.2026.101781).

## References

- Abbasi, A., & Jaafari, A. (2013). Research impact and scholars' geographical diversity. *Journal of Informetrics*, 7(3), 683–692.
- Abbasi, A., Jalili, M., & Sadeghi-Niaraki, A. (2018). Influence of network-based structural and power diversity on research performance. *Scientometrics*, 117(1), 579–590.
- Abbasi, A., Wigand, R. T., & Hossain, L. (2014). Measuring social capital through network analysis and its influence on individual performance. *Library & Information Science Research*, 36(1), 66–73.
- Almlöv, C., & Grubbström, A. (2023). Challenging from the start: Novice doctoral co-supervisors' experiences of supervision culture and practice. *Higher Education Research & Development*, 43(1), 17–31.
- Badar, K., Hite, J. M., & Badir, Y. F. (2013). Examining the relationship of co-authorship network centrality and gender on academic research performance: The case of chemistry researchers in Pakistan. *Scientometrics*, 94(2), 755–775.
- Bai, X., Zhang, F., Li, J., Xu, Z., Patoli, Z., & Lee, I. (2021). Quantifying scientific collaboration impact by exploiting collaboration-citation network. *Scientometrics*, 126(9), 7993–8008.
- Bangani, S. (2018). The impact of electronic theses and dissertations: A study of the institutional repository of a university in South Africa. *Scientometrics*, 115(1), 131–151.
- Belkhouja, M., Fattoum, S., & Yoon, H. D. (2021). Does greater diversification increase individual productivity? The moderating effect of attention allocation. *Research Policy*, 50(6), Article 104256.
- Bornmann, L., & Daniel, H. D. (2008). What do citation counts measure? A review of studies on citing behavior. *Journal of Documentation*, 64(1), 45–80.
- Bu, Y., Li, H. L., Wei, C. L., Liu, M. J., & Li, J. (2022). On the relationship between supervisor-supervisee gender difference and scientific impact of doctoral dissertations: Evidence from Humanities and Social Sciences in China. *Journal of Information Science*, 48(4), 492–502.
- Casanueva, C., & Gallego, Á. (2010). Social capital and individual innovativeness in university research networks. *Innovation: Management, Policy & Practice*, 12(1), 105–117.
- Chaparro, N., & Rojas-Galeano, S. (2021). Revealing the research landscape of Master's degrees via bibliometric analyses. arXiv:2103.09431.
- Chen, K., Ding, Y., Zhao, B., Guo, R., & Ning, L. (2025). Benefits beyond the local network: Does indirect international collaboration ties contribute to research performance for young scientists? *Research Policy*, 54(5), Article 105233.
- Chen, S., Arsenault, C., & Larivière, V. (2015). Are top-cited papers more interdisciplinary? *Journal of Informetrics*, 9(4), 1034–1046.
- Chen, Y., Wu, K., Li, Y., & Sun, J. (2023). Impacts of inter-institutional mobility on scientific performance from research capital and social capital perspectives. *Scientometrics*, 128(6), 3473–3506.
- D'Este, P., Llopis, O., Rentocchini, F., & Yegros, A. (2019). The relationship between interdisciplinarity and distinct modes of university-industry interaction. *Research Policy*, 48(9), Article 103799.
- Donner, P. (2021). Citation analysis of Ph.D. theses with data from Scopus and Google Books. *Scientometrics*, 126(12), 9431–9456.
- Egghe, L., & Rousseau, R. (1990). *Introduction to Informetrics. Quantitative Methods in Library, Documentation and Information Science*. Elsevier Science Publishers.
- Fronzetti Colladon, A., D'Angelo, C. A., & Gloor, P. A. (2020). Predicting the future success of scientific publications through social network and semantic analysis. *Scientometrics*, 124(1), 357–377.
- Garfield, E. (1972). Citation Analysis as a Tool in Journal Evaluation. *Science (New York, N.Y.)*, 178(4060), 471–479.
- Gonzalez-Brambila, C. (2014). Social capital in academia. *Scientometrics*, 101(3), 1609–1625.
- Granovetter, & Mark. (1985). Economic Action and Social Structure: The Problem of Embeddedness. *American Journal of Sociology*, 91(3), 481–510.
- Guan, J., Yan, Y., & Zhang, J. J. (2017). The impact of collaboration and knowledge networks on citations. *Journal of Informetrics*, 11(2), 407–422.
- Guan, J. C., & Pang, L. X. (2018). Bidirectional relationship between network position and knowledge creation in Scientometrics. *Scientometrics*, 115(1), 201–222.
- Guan, J. C., Zuo, K. R., Chen, K. H., & Yam, R. C. M. (2016). Does country-level R&D efficiency benefit from the collaboration network structure? *Research Policy*, 45(4), 770–784.
- Hansen, M. T. (1999). The search-transfer problem: The role of weak ties in sharing knowledge across organization subunits. *Administrative Science Quarterly*, 44(1), 82–111.
- Hsu, J., & Huang, D. (2011). Correlation between impact and collaboration. *Scientometrics*, 86(2), 317–324.
- Klofsten, B. M. (2012). Creating entrepreneurial networks: Academic entrepreneurship, mobility and collaboration during Ph.D education. *Higher Education*, 64(2), 207–222.
- Kousha, K., & Thelwall, M. (2019). Can Google Scholar and Mendeley help to assess the scholarly impacts of dissertations? *Journal of Informetrics*, 13(2), 467–484.
- Li, E. Y., Liao, C. H., & Yen, H. R. (2013). Co-authorship networks and research impact: A social capital perspective. *Research Policy*, 42(9), 1515–1530.
- Li, W., Zhang, S., Zheng, Z., Cranmer, S. J., & Clauset, A. (2022). Untangling the network effects of productivity and prominence among scientists. *Nature Communications*, 13(1), 4907.
- Liao, C. H. (2011). How to improve research quality? Examining the impacts of collaboration intensity and member diversity in collaboration networks. *Scientometrics*, 86(3), 747–761.
- Liao, S., Lavender, C., & Zhai, H. (2024). Factors influencing the research impact in cancer research: A collaboration and knowledge network analysis. *Health Research Policy and Systems*, 22(1), 96.
- Liénard, J. F., Achakulvisut, T., Acuna, D. E., & David, S. V. (2018). Intellectual synthesis in mentorship determines success in academic careers. *Nature Communications*, 9(1), 4840.
- Lopaciuk-Gonczaryk, B. (2016). Collaboration strategies for publishing articles in international journals – A study of Polish scientists in economics. *Social Networks*, 44, 50–63.
- Martín-Alcázar, F., Ruiz-Martínez, M., & Sánchez-Gardey, G. (2019). Assessing social capital in academic research teams: A measurement instrument proposal. *Scientometrics*, 121(2), 917–935.
- Miramontes, J., & Gonzalez-Brambila, C. N. (2016). The effects of external collaboration on research output in engineering. *Scientometrics*, 109(2), 661–675.
- MOE. (2024). Number of students of formal education by type and level. In *2023 Education Statistics: Ministry of Education of the People's Republic of China*.

- Muscio, A., Lopolito, A., & Nardone, G. (2019). Evaluating social dynamics within technology clusters: A methodological approach to assess social capital. *Land Use Policy*, 88, Article 104161.
- Nahapiet, J., & Ghoshal, S. (1998). Social capital, intellectual capital, and the organizational advantage. *The Academy of Management Review*, 23(2), 242–266.
- Nasir Ahmad, A., & Maarten Pieter, R. (2013). Profit (p)-index: the degree to which authors profit from co-authors. *PLOS ONE*, 8(4), Article e59814.
- Onodera, N., & Yoshikane, F. (2015). Factors affecting citation rates of research articles. *Journal of the Association for Information Science and Technology*, 66(4), 739–764.
- Pyhältö, K., Tikkanen, L., & Anttila, H. (2024). The more the merrier? PhD supervisors' perspectives in engaging in co-supervision. *Innovations in Education and Teaching International*, 61(6), 1460–1471.
- Reagans, R., & McEvily, B. (2003). Network structure and knowledge transfer: The effects of cohesion and range. *Administrative Science Quarterly*, 48(2), 240–267.
- Rodriguez Miramontes, J., & Gonzalez-Brambila, C. N. (2016). The effects of external collaboration on research output in engineering. *Scientometrics*, 109(2), 661–675.
- Rossi, L., Damaceno, R. J. P., Freire, I. L., Bechara, E. J. H., & Mena-Chalco, J. P. (2018). Topological metrics in academic genealogy graphs. *Journal of Informetrics*, 12(4), 1042–1058.
- Shen, W., & Jin, W. (2020). Global diffusion of joint supervision in doctoral education: An analysis since 1980s. *China Higher Education Research*, (12), 89–95.
- Tahamtan, I., Safipour Afshar, A., & Ahamdzadeh, K. (2016). Factors affecting number of citations: A comprehensive review of the literature. *Scientometrics*, 107(3), 1195–1225.
- Tang, X., Wang, L., & Kishore, R. (2014). Why do is scholars cite other scholars? An empirical analysis of the direct and moderating effects of cooperation and competition among is scholars on individual citation behavior C3. In *In 35th International conference on information systems "building a better world through information systems"*, ICIS 2014 (2014 ed.).
- Tian, S., Xu, X., & Li, P. (2021). Acknowledgement network and citation count: The moderating role of collaboration network. *Scientometrics*, 126(9), 7837–7857.
- Tsai, W., & Ghoshal, S. (1998). Social capital and value creation: the role of intrafirm networks. *The Academy of Management Journal*, 41(4), 464–476.
- Woolcock, M., & Narayan, D. (2000). Social capital: implications for development theory, research, and policy. *The World Bank Research Observer*, 15(2), 225–249.
- Xu, H., Shen, W., & Zhao, Y. (2024). The heterogeneous impact of joint supervision system on the quality of doctoral training: an empirical analysis based on National Survey of Doctoral Graduates in 2021. *Fudan Education Forum*, 22(2), 64–74.
- Yin, D. H., Zhang, X., Zhao, H. K., & Tang, L. (2024). Predicting scholar potential: A deep learning model on social capital features. *Scientometrics*, 129(12), 7851–7879.
- Yu, T., Yu, G., Li, P. Y., & Wang, L. (2014). Citation impact prediction for scientific papers using stepwise regression analysis. *Scientometrics*, 101, 1233–1252.
- Zeng, M., Han, X., Zhang, G., & Zhang, M. (2022). A research about the influence of social capital on scientists'scientific research performance. *Studies in Science of Science*, 2022(2), 288–296.
- Zhai, L., Yan, X., & Zhu, B. (2014). The HI-index: Improvement of H-index based on quality of citing papers. *Scientometrics*, 98(2), 1021–1031.
- Zhang, B., & Wang, X. (2017). Empirical study on influence of university-industry collaboration on research performance and moderating effect of social capital: Evidence from engineering academics in China. *Scientometrics*, 113(1), 257–277.
- Zhang, L., Sun, B., Jiang, L., & Huang, Y. (2021). On the relationship between interdisciplinarity and impact: Distinct effects on academic and broader impact. *Research Evaluation*, 30(3), 256–268.
- Zhang, X., Liu, X., Wang, X., Zhao, H., & Zhang, W. (2022a). Exploring the effects of social capital on crowdfunding performance: A holistic analysis from the empirical and predictive views. *Computers in Human Behavior*, 126, Article 107011.
- Zhang, Y., Ding, J., Yan, H., He, M., & Wang, W. (2022b). A study of the influence of collaboration networks and knowledge networks on the citations of papers in sports industry in China. *Complexity*, 2022(1), Article 9236743.
- Zuccala, A. A., Jensen, M. S., Wærn, E. K., & Hertzum, M. (2024). Social capital in academia: Measuring researchers' collaboration habits versus preferences. *Research Evaluation*, 33, rvae028.