Effects of Trust Mechanisms on Knowledge Transfer in Research Collaboration

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Abstract

Purpose/Significance Trust is a critical factor sustaining collaboration among scientists and engenders knowledge transfer between them, transforming knowledge from individual ownership to collective possession, thereby further advancing scientific development. Research on trust mechanism-oriented knowledge transfer contributes to the maintenance of trust relationships among research collaborators, facilitates knowledge transfer, and consequently drives further scientific de velopment. Methods/Process This paper first quantifies the degree of trust among research collaborators using the American Physical Society (APS) dataset, analyzing the distribution patterns of trust among collaborators; subsequently, it categorizes knowledge transfer among research collaborators into tacit knowledge transfer and explicit knowledge transfer, mapping the pathways of knowledge transfer within collaboration networks; finally, it employs regression analysis to validate the effect of trust degree among collaborators on the volume of knowledge transfer. Results/Conclusion There exists a pronounced temporal resonance pattern between foundational trust among research collaborators and knowledge transfer; collaboration teams that generate tacit transfer exhibit lower trust levels compared to those that generate explicit transfer; explicit transfer demonstrates a higher correlation with trust degree but lower dependence. This study extends research on trust sentiment in scientific collaboration to trust behaviors, and by quantifying the degree of trust among research collaborators, mitigates the limitations inherent in measuring static trust within collaborative cross-sections.

Full Text

Research on the Knowledge Transfer Effect of Scientific Collaboration Based on Trust Mechanisms

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Abstract

[**Purpose/Significance**] Trust is a key factor in sustaining collaboration among scientists and facilitates knowledge transfer from individual to shared ownership, thereby promoting scientific development. Research on trust mechanism-oriented knowledge transfer helps maintain trust relationships among research collaborators, promotes knowledge transfer, and thus advances science. [**Methods/Process**] This study first quantifies the trust level among scientific collaborators using the American Physical Society (APS) dataset and analyzes the distribution patterns of trust among collaborators. It then classifies knowledge transfer between collaborators into implicit and explicit categories and maps the pathways of knowledge transfer within collaboration networks. Finally, regression analysis is employed to verify the effect of trust on the volume of knowledge transfer. [**Results/Conclusions**] Basic trust and knowledge transfer among scientific collaborators exhibit a clear temporal resonance pattern. Teams generating implicit transfer demonstrate lower trust levels compared to those producing explicit transfer. Explicit transfer shows higher correlation with trust but lower dependence on it. This study extends research on trust emotions in scientific collaboration to trust behaviors, reducing the limitations of measuring static trust at a single point in time by quantifying trust levels among collaborators.

Keywords: trust mechanisms; knowledge transfer; scientific collaboration
Classification Number: G203

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Scientific activities occur within a complex multidimensional network, making scientific collaboration one of the most critical and common phenomena in the scientific community. The advanced development of scientific fields brings together researchers from diverse backgrounds to solve interdisciplinary problems and improve research quality. An increasing number of scientists recognize that collaboration may produce impact more rapidly than individual work, leading to widespread scientific collaboration. Trust is the key factor sustaining such collaboration. For scientists, trust is a primary consideration when selecting collaborators, encompassing recognition of a collaborator's knowledge and capabilities, belief that the collaborator will prioritize the partnership, and confidence that the collaboration will yield satisfactory results. The openness of team communication is directly related to the level of trust among collaborators—the higher the internal trust within a team, the more willing members are to exchange their knowledge.

According to citation behavior norm theory, literature citation represents the manifestation of knowledge transfer, signifying recognition of the academic value of cited works. Motivated by trust, the sharer cites literature, which is then shared during collaboration. The recipient cites this literature, transferring trust to the shared document. This process represents trust transfer, emerging from collaboration and transforming into the recipient's recognition of the literature's academic value. After collaboration concludes, when the recipient conducts related research and cites the literature again, it demonstrates further extension of trust, indicating that knowledge transfer based on trust has occurred during collaboration.

Knowledge transfer can further promote scientific development by transforming knowledge from individual to collective ownership. The widespread practice of scientific collaboration amplifies this phenomenon. As Cui Yunxue et al. (2023) discuss, citation behavior is an unstable and unpredictable individual action, yet it is simultaneously influenced by social conditions such as the research culture environment. Therefore, examining the trust-oriented mechanisms behind knowledge transfer behavior is crucial. Research on trust mechanism-oriented knowledge transfer promotes more efficient and direct knowledge transfer, which is significant for advancing scientific collaboration toward greater comprehensiveness and efficiency, and for strengthening the dissemination and promotion of academic achievements.

Based on this foundation, this study quantifies the trust levels and knowledge transfer situations among scientific collaborators to clarify the status quo of trust-based knowledge transfer and employs regression analysis to explore the influencing mechanisms between them.

2.1 Trust in Collaboration

Scholarly understanding of trust consistently revolves around expectations, dependence, and commitment. Zhang Jidong et al. (2017) define trust as the expectation that the other party will perform specific actions, representing affirmation of the other's commitment and capabilities. When selecting collaborators, scientists typically consider whether the potential partner's abilities and priorities regarding collaboration meet their psychological expectations. Since these expectations are beyond the scientist's control, collaboration requires trust in the partner across multiple dimensions, despite the risk of betrayal. Trust relationships among researchers are typically connected through co-authored works produced by collaboration. Xusen Cheng et al. (2021) argue that trust originates from interactions and is actively attributed to other partners within the organization, meaning that collaborative outcomes represent the crystallization of trust among collaborators. Therefore, trust in scientific collaboration encompasses trust in collaborators, trust in information, and trust in oneself.

Based on existing definitions, this study conceptualizes trust as one party's expectation regarding the other party's ability and willingness to perform specific tasks, coupled with dependence on the other's behavior. For this research problem, trust possesses several key characteristics: (1) **Measurability**: Trust among collaborators varies in intensity and can be quantified through different methods in specific contexts; (2) **Dynamic nature**: Trust changes under various influences, with successful collaborations enhancing trust; (3) **Asymmetry**: Trust varies according to individual perceptions and is not necessarily identical; and (4) **Transferability**: During collaboration, the recipient's trust in the sharer transfers from the person to the shared knowledge.

Most existing research on trust in scientific collaboration employs questionnaires and interviews to study collaborators' trust perceptions and the impact of trust factors on collaborative teams. While this approach reflects collaborators' current trust perceptions, trust among collaborators dynamically changes due to collaborative behaviors and ongoing partnerships, making cross-sectional quantification prone to bias. Moreover, trust manifests in both psychological-emotional and behavioral dimensions, with survey methods neglecting behavioral considerations.

In quantitative research, scholars tend to use scientists' co-authorship information as a measurement dimension. Author ranking in co-authored works represents not only trust among collaborators but also contribution to the outcome. Avijit Gayen et al. (2014) quantified trust among research collaborators through the number of scientific papers and research articles they co-authored, though this approach is somewhat limited. In subsequent research, Gayen et al. (2017) further employed directed trust to represent trust relationships among research collaborators, using both the number of co-publications and mutual citations to calculate trust values.

Based on these quantitative indicators and trust analysis, this study argues that trust among scientific collaborators should be quantified through: (1) **Collaboration density**: Co-authored publications represent successful collaborations and fulfillment of trust expectations; (2) **Number of common collaborators**: More common co-authors indicate stronger connections and greater trust transmitted from other trusted collaborators; and (3) **Mutual citation count**: Represented by the number of mutual citations among co-authors, with more citations indicating higher trust.

2.2 Knowledge Transfer in Collaboration

Building on the analysis of trust in collaboration, knowledge transfer in scientific collaboration can be represented as knowledge-centered, trust among collaborators as the transfer orientation, and literature citations as the manifestation. Most knowledge workers believe knowledge is power and may be unwilling to fully share their knowledge, adopting attitudes that restrict knowledge flow or even deliberately concealing it. Trust mechanisms constrain such restrictions. Xiaomei Bai et al. (2021) utilized directed collaboration-citation networks to argue that sustained collaboration leads collaborators to cite previous collaborative outcomes. However, this study limited such transfer to original collaborators without measuring whether prior collaborative knowledge truly transferred to other collaborators, only measuring how knowledge outcomes transferred with collaborators to other groups. Thus, the knowledge largely remained with original collaborators, failing to examine individual-level knowledge transfer. Since scientific collaboration primarily occurs between individual scientists and knowledge spreads widely as collaboration expands, properly constructing scientific literature citation networks is crucial for studying knowledge transfer.

Based on this review, this study conceptualizes trust and knowledge transfer in collaboration as outcomes of behavioral relationships and interactions between two members. Therefore, a team is defined as any pair of authors among all coauthors of an article. In such teams, collaboration generates trust, with citation-represented explicit knowledge transfer as one outcome. Due to the concealed nature of implicit knowledge, this study focuses only on explicit knowledge transfer represented by citations.

2.3 Trust-Mechanism-Oriented Knowledge Transfer

Collaborators share knowledge during collaboration to obtain longer-term trust and partnership. Mohammad Alsharo et al. (2016) view knowledge sharing as a form of generalized social exchange, where the only clear return in collaboration is a longer-term commitment. Correspondingly, trust relationships can more actively promote knowledge sharing.

Furthermore, trust mechanisms facilitate knowledge transfer. Levin et al. (2004) argue that knowledge transfer effectiveness is closely related to trust and intimacy between knowledge senders and receivers, with cooperation degree and reputation promoting closer, more trusting relationships that facilitate knowledge exchange and transfer. Anna Pietruszka-Ortyl et al. (2021) contend that trust has special emotional dimension importance for knowledge workers, determining relationship openness that enables free idea sharing, difficulty discussion, and social commitment. Their research confirms that trust levels positively affect knowledge transfer among knowledge workers. The absence of trust makes scientists suspicious of knowledge shared by others; only when collaborators trust each other will shared knowledge be accepted and adopted. Knowledge transfer in scientific collaboration depends on mutual trust, requiring the sharer to believe the adopter will follow instructions and use knowledge for mutual benefit, while the adopter must acknowledge the need for help and trust that experts will provide necessary information rather than use their superior expertise against them.

Knowledge sharing among collaborators is triggered on the basis of trust, which in turn makes other collaborators willing to accept shared knowledge. That is, trust in collaborators transfers to recommended citations, completing trust mechanism-guided knowledge transfer through the shift from direct to indirect trust. This aligns with Clare Thornley et al.'s (2015) interview study conclusion that scientists trust citations recommended by trusted individuals.

Therefore, this study employs academic citations as knowledge representation in knowledge transfer. When scientists cite each other's previously cited literature after collaboration, it indicates knowledge transfer has occurred—explicit knowledge transfer represented by citations. Knowledge transfer is divided into implicit and explicit categories: explicit knowledge transfer involves immediate citation of shared literature in collaborative outcomes, while implicit knowledge transfer occurs when collaborators absorb each other's knowledge without immediate presentation in collaborative outputs.

3.1 APS Dataset

Given significant variations in collaboration scale and behavior across disciplines, and considering physics as a mature field with abundant data, this study selects the American Physical Society (APS) dataset as the data source. The APS database includes 10 core physics journals, 1 discontinued journal, and 6 free publications. Among them, *Physical Review Letters*, *Physical Review B*, *Physical Review D*, and *Physical Review A* rank 1st, 2nd, 6th, and 11th respectively in citation counts among all physics journals indexed by ISI, commanding extremely high prestige in the global physics community and related fields. As of the data acquisition date, APS encompassed 678,916 publications and 8,850,333 citation pairs from early 1893 to the end of 2020. Research literature metadata serves as the primary source for macro-level bibliometric analysis. The metadata obtained for this study includes article DOI, title, abstract, publication date, authors, and DOIs of both citing and cited literature.

Since the APS dataset does not provide unique author identifiers, two different scholars may share identical full names or initials. To address this, this study introduces S2ORC (Semantic Scholar Open Research Corpus). The Semantic Scholar database trained a binary classifier to merge author name pairs and progressively create author clusters. According to previous research evaluations, Semantic Scholar's author name disambiguation achieves an F1 score of 96.94%. This study uses the S2ORC version released on May 27, 2020, matching via article DOI and replacing APS author information with S2ORC author information to ensure each author's data corresponds to a unique ID.

3.2 Sample Selection and Data Processing

This study first preprocesses the obtained data. First, articles with author counts between 2 and 10 are selected. Since this research examines knowledge transfer behaviors generated by mutual trust, assuming any pair of scientists as the starting point, excessively large author counts mean not all trust relationships can be fully manifested. Therefore, author quantity is filtered to reduce measurement error in trust.

Second, author data is filtered: (1) authors with 20–500 published papers are selected; (2) since studying knowledge transfer among collaborators requires sufficient time span and publication volume, authors with career ages exceeding 10 years are selected to ensure more accurate measurement of internal trust and knowledge transfer; (3) to ensure selected collaborative teams have adequate collaboration foundations, author collaboration frequency is limited to more than 5 times.

From these filtered results, 50,000 samples are randomly extracted, each corresponding to a unique collaborative team. Sample information includes articles, authors, citation data, and each author's individual article and citation information. To ensure representativeness, three random extractions are performed, with similar distributions across the three results. Finally, outliers in collaborative teams are removed. Based on the constraint of author counts $ $10, teams where individual collaborators participate in collaborations larger than 10 are treated as error values and eliminated. This yields 16,471 sample records.

4.1 Trust Relationship Paths and Quantification in Collaboration-Citation Networks

As established above, this study measures trust among scientific collaborators through basic trust indicators: (1) collaboration density; (2) number of common collaborators; and (3) mutual citation count. Based on collaborative and citation behaviors, this study maps trust relationship paths among collaborators as shown in Figure [Figure 4: see original paper].1.

Figure [Figure 4: see original paper].1 illustrates the specific manifestation paths of basic trust within scientific collaboration teams through collaborative and citation behaviors. Among multiple authors of an article, any two authors form a collaborative team. Nodes A and B in the figure represent one such team, with collaboration frequency represented by co-authored publications P1 and P2. Besides A and B, P1 and P2 include additional authors C, D, and E as common collaborators. Collaboration density and common collaborator count between A and B are non-directional.

However, due to factors such as capability and position, mutual trust is typically not symmetrical. As shown in Figure [Figure 4: see original paper].1, A cites paper P5 co-authored by B and H, while B cites papers P3 and P4. Mutual citation counts between A and B differ, making mutual citations directional and requiring separate consideration.

Based on these paths, basic trust indicators (derived from actual author behaviors) are measured in the extracted samples: First, total volumes of collaboration density, common collaborator count, and mutual citation count are calculated for each collaborative team. Second, annual time-series data are computed from each team's first collaboration, representing newly added quantities. Finally, cumulative volumes within time windows of 3, 5, 10, 15, 20, and >20 years are calculated. Collaboration density here is not cross-sectional data; for example, 5-year collaboration density equals the total number of collaborations from the team's first partnership through the end of year 5, divided by time. Cumulative values across time windows are used because trust among collaborators evolves over time through interactions.

Notably, the mutual citation count indicator is directional, yielding two directed data points. Self-citations by collaborators are excluded to prevent errors in subsequent analysis. Mentor-mentor or dependency relationships between collaborators are also removed to avoid indicator bias. Based on extracted sample indicators, basic trust indicators across time series are summarized in Table .1.

Table .1 shows descriptive statistics for basic trust indicators across three metrics from 16,471 teams. Minimum and median values are small, with means close to medians, indicating clear concentration tendencies at lower values.

4.2 Correlation Analysis of Trust Among Collaborators

To further analyze the synergistic changes among trust indicators, this study conducts correlation analysis on basic trust indicators from collaborative team samples. Since indicator distributions do not follow normal distributions, Spearman correlation analysis is employed.

Table .2 presents Spearman correlation results for basic trust indicators. Overall, all basic trust indicators show highly significant correlations across time windows, ranked from high to low as: collaboration density vs. common collaborator count, mutual citation count vs. collaboration density, and mutual citation count vs. common collaborator count.

The correlation coefficient between common collaborator count and collaboration density increases until the 15-year window but declines at 20 years. This suggests that after 20 years, although both common collaborator count and collaboration density continue growing substantially, this growth is not simultaneous but occurs separately. In correlation analysis between mutual citation count and collaboration density, the growth rate slows at 20 years and declines in the >20-year window, indicating that citation impact on collaboration diminishes significantly after 20 years regardless of direction. Mutual citations and common collaborator count show consistently strong and strengthening correlations, suggesting strong interactive effects between these trust dimensions.

These findings demonstrate that during collaborative research, basic trust indicators are significantly correlated. The significant correlation between citation behavior and collaborative behavior partially validates collaboration behavior as representative of team trust, with clear temporal changes in correlations indicating that trust among collaborators grows with successful collaborations.

5 Quantification and Analysis of Knowledge Transfer in Scientific Collaboration

Based on the research content, this study posits that knowledge transfer in scientific collaboration can be represented through collaboration-citation relationships. Trust-based knowledge transfer among research collaborators is divided into implicit and explicit transfer, with the primary distinction being whether the transferred literature is cited immediately during collaboration. As shown in Figure [Figure 5: see original paper].1, black documents represent collaboratively published articles, blue documents represent citations, and solid arrows represent citation relationships. If A and B cited documents P1 and P2 before collaboration and cite them immediately in collaborative outcomes, this constitutes explicit knowledge transfer; delayed citation after collaboration represents implicit knowledge transfer.

Figure [Figure 5: see original paper].2 illustrates collaboration-citation knowledge transfer paths. Based on these paths, knowledge transfer within collaborative teams is quantified: First, conditions for indicator quantification are established to calculate the number of transferred documents according to definitions. Second, based on these conditions and randomly extracted collaborative team information, annual knowledge transfer volumes are calculated from each team's first collaboration, yielding directed time-series data. Finally, corresponding to basic trust, cumulative knowledge transfer volumes within each time window are calculated.

Based on extracted sample indicators, knowledge transfer indicators across time series are summarized in Table .3. Table .1 shows descriptive statistics for knowledge transfer indicators from 16,471 teams. Both indicators have small minimum and median values, with means close to medians and kurtosis far exceeding 3, indicating clear concentration tendencies at lower values. Skewness around 5 suggests long right tails in the data distributions.

6.1 Correlation Analysis Between Trust and Knowledge Transfer

Based on previous analysis showing that knowledge transfer volumes do not follow normal distributions, Spearman correlation analysis is used to measure temporal correlations between trust levels and knowledge transfer volumes in collaborative teams. Mutual citation counts in basic trust indicators and both implicit and explicit knowledge transfer volumes are directional variables.

Table .4 presents Spearman correlations between trust levels and implicit knowledge transfer. Table .5 shows correlations between trust levels and explicit knowledge transfer.

Overall, correlations between basic trust and knowledge transfer are highly significant across all time windows. Correlation coefficients for both explicit and implicit transfer only decline slightly in the >20-year window, with minimal changes. Common collaborator count shows similar correlation patterns with both explicit and implicit transfer as collaboration density does, but with more pronounced effects. Mutual citation count demonstrates clear directionality in its relationship with knowledge transfer: mutual citation count (A cites B) correlates lower with knowledge transfer (A transfers to B) than with knowledge transfer (B transfers to A). In other words, the more A cites B, the more trust A develops in B, and the less knowledge A transfers to B, and vice versa. Additionally, mutual citation count shows stronger correlations with implicit transfer.

6.2 Regression Analysis of Trust Levels and Knowledge Transfer Volume

Based on the above correlation results, this section further conducts regression analysis on the relationship between trust levels and knowledge transfer. Table .3 lists the variables involved in this analysis, and Figure [Figure 6: see original paper].1 illustrates the conceptual model.

Table .3 Variables for Regression Analysis of Trust Levels and Knowledge Transfer Volume

Variable Type	Variable Name	Description
Independent Variables (Trust Level)	Collaboration Density	Number of co-authored publications
	Common Collaborator Count	Number of shared co-authors
	Mutual Citation Count (A cites B)	Directional citation count
	Mutual Citation Count (B cites A)	Directional citation count
Dependent Variables (Knowledge Transfer)	Implicit Transfer (A transfers to B)	Papers cited by A but not B (implicit)
	Implicit Transfer (B transfers to A)	Papers cited by B but not A (implicit)
	Explicit Transfer (A transfers to B)	Papers cited by A but not B (explicit)
	Explicit Transfer (B transfers to A)	Papers cited by B but not A (explicit)
Control Variables	Career Age Difference	Difference in professional ages

Variable Type	Variable Name	Description
	Research Similarity	Similarity of research fields
	Collaborator A's Publication Count	Total publications by A
	Collaborator B's Publication Count	Total publications by B

Figure [Figure 6: see original paper].1 Conceptual Model for Zero-Inflated Negative Binomial Regression Analysis

6.2.1 Variance Inflation Factor Test Before regression analysis, multicollinearity among variable features—high correlations among explanatory variables that distort regression results—must be eliminated. Variance Inflation Factor (VIF) testing is employed using the formula:

$$VIF_j = \frac{1}{1 - R_j^2}$$

where R_j^2 is the coefficient of determination from regressing the jth independent variable on other independent variables.

Table .6 shows VIF test results. Since all variable VIF values remain below 5, no multicollinearity exists among indicators, ensuring precise and reliable regression results.

6.2.2 Hausman Test Given this study's emphasis on temporal effects of variables, panel data must be assessed before regression analysis. The Hausman test determines whether fixed-effects or random-effects models are appropriate. Fixed-effects models are more suitable for studying differences among samples, while random-effects models better infer population characteristics from samples. The test hypotheses are:

H_0: Random-effects model provides better fit
H_1: Fixed-effects model provides better fit

The Hausman test statistic is:

$$H = (b - B)'[V_b - V_B]^{-1}(b - B)$$

where n is the number of variables, b is the fixed-effects coefficient, and B is the random-effects coefficient. Separate Hausman tests are conducted for dependent variables SV1, SV2, SV3, and SV4 with other variables (see appendix tables). Results reject H_0, indicating that fixed-effects models are more appropriate for analyzing relationships between trust levels and knowledge transfer variables.

6.2.3 Zero-Inflated Negative Binomial Regression Analysis During knowledge transfer, cases where collaborators do not cite each other's papers are common. This special discrete variable with excessive zeros exceeds the predictive capacity of Poisson and negative binomial regression models, causing substantial variation. Therefore, zero-inflated regression analysis is applied to trust levels and knowledge transfer volumes. Statistical analysis (Table .4) shows that because mean and variance differ substantially, zero-inflated negative binomial regression provides better model fit.

Table .4 Descriptive Statistics of Dependent Variables

Variable	Sum	Mean	Min	Max

Since career age differences and research similarity among collaborators affect team trust levels, the model is fitted in two stages:

1. **Stage 1 (Zero-Inflation Model, Logit):** Models whether the dependent variable equals zero, incorporating inflation variables X (independent variables IV1, IV2, IV3, IV4).
2. **Stage 2 (Negative Binomial Regression):** The primary model of interest, using negative binomial regression.

Table .5 Zero-Inflated Negative Binomial Regression Results

Variable	Coef.	Std. Err.	z	P>	z

Results show that all trust indicators significantly affect knowledge transfer volume. Overall, trust indicators influence implicit transfer more than explicit transfer. Collaboration density significantly affects implicit transfer but poorly fits explicit transfer, suggesting that more frequent collaboration increases the likelihood of citing transferred knowledge after collaboration. Common collaborator count has minimal impact—while increasing common collaborators raises the probability of citing trusted literature, it fails to produce clear effects in practical analysis. Mutual citation count demonstrates significant directionality similar to correlation analysis results.

For control variables, career age difference and research similarity show contrasting effects. Career age difference promotes knowledge transfer—larger age gaps increase the likelihood of older collaborators transferring knowledge to younger ones, breaking temporal knowledge barriers and facilitating diffusion. Conversely, greater research similarity means overlapping knowledge scopes, reducing effective knowledge transfer during collaboration. Increasing interdisciplinary exchange in recent years has somewhat broken down disciplinary barriers, benefiting knowledge diffusion.

7 Conclusion and Implications

By mapping trust flow and knowledge transfer networks in scientific collaboration and conducting regression analysis on trust indicators and knowledge transfer, this study reveals that trust levels and knowledge transfer among collaborators exhibit clear temporal resonance patterns. Significant correlations appear before the 20-year window, with slight but minimal declines afterward. Mutual citation count shows clear directionality in its relationship with knowledge transfer. Regarding different transfer methods, higher team trust is more likely to produce explicit rather than implicit transfer, though implicit transfer depends more heavily on trust levels. This study also preliminarily demonstrates that larger career age gaps and smaller research similarity promote cross-disciplinary knowledge diffusion. By clarifying how trust mechanisms affect knowledge transfer in scientific collaboration, this study extends research from trust emotions to trust behaviors, providing support for scientists' research activities and citation recommendation system improvements.

For Researchers: Mutual trust is crucial for knowledge transfer. First, increase research interactions with others through more collaborations and citations to build mutual trust, breaking individual knowledge barriers and promoting transfer to acquire more relevant knowledge and improve research capabilities. Second, higher mutual citation counts lead to greater knowledge transfer volumes, so collaborating with citing authors—those who trust you more—helps diffuse knowledge beyond the team and advances field development. Third, for literature dissemination, most downloads occur within 5 months of publication, while citation peaks appear 3 years post-publication. Citing trusted collaborators' papers older than 3 years better facilitates further knowledge transfer for citing papers, increases their influence, and enhances diffusion likelihood. Additionally, collaborating with scientists of lower career age aids outward knowledge diffusion and raises researcher visibility, while collaborating with older scientists facilitates receiving shared knowledge and improves one's own academic capabilities.

For Citation Recommendation Systems: Extracting mutual citation patterns among collaborators is essential. First, recommendation systems can suggest citations based on mutual citation history, recommending papers published or cited by collaborators. Second, considering the temporal patterns of trust and knowledge transfer, systems can recommend literature during peak growth periods to improve recommendation success rates. This increases researcher attention to the system, aids system promotion, and facilitates further diffusion of cited literature, thereby enhancing its academic impact.

This study only uses APS dataset data, limiting research topic quantification to research similarity as a moderating factor, which somewhat weakens the influence of different disciplines on trust measurement and knowledge transfer, inadequately explaining cross-disciplinary transfer effects. Findings suggest that lower discipline similarity facilitates knowledge transfer, so future research should limit sample collection to cross-disciplinary teams during data collection and compare with existing studies to analyze how collaborators' disciplines affect mutual knowledge transfer.

Appendix Tables 1-4: Hausman Test Results

Appendix Table 1:
(b-B) Difference = 1500.4
chi2(11) = (b-B)'(V_b-V_B)^(-1)
Prob>chi2 = 0.0000

Appendix Table 2:
(b-B) Difference = 2976.98
chi2(11) = (b-B)'(V_b-V_B)^(-1)
Prob>chi2 = 0.0000

Appendix Table 3:
(b-B) Difference = 1748.54
chi2(11) = (b-B)'(V_b-V_B)^(-1)
Prob>chi2 = 0.0000

Appendix Table 4:
(b-B) Difference = 3056.4
chi2(11) = (b-B)'(V_b-V_B)^(-1)
Prob>chi2 = 0.0000

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Note: Figure translations are in progress. See original paper for figures.