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Direct Technology Diffusion in Higher Education: Evidence from Doctoral Students

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ABSTRACT

This study compares direct and indirect technology diffusion in higher education, focusing on plagiarism detection software in Indian doctoral education. Using a quantitative survey of research scholars, the study finds that direct diffusion significantly improves outcomes. Similarity levels decreased substantially under direct diffusion, indicating more accurate application of plagiarism rules. Additionally, direct diffusion reduced the time required and lowered costs considerably. The findings suggest that direct access empowers users, minimizes intermediary-related inefficiencies, and enhances both effectiveness and efficiency. The study highlights cost-effectiveness as a key enabler and recommends that policymakers and institutions promote direct technology diffusion to improve adoption and strengthen academic integrity in higher education.

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1. INTRODUCTION

Technology diffusion in higher education has attracted sustained scholarly attention, particularly in areas such as information technology, e-learning, and artificial intelligence adoption [1-3]. Prior research has extensively examined the determinants of technology adoption using theoretical frameworks such as the Technology Acceptance Model and Rogers' diffusion of innovations theory, highlighting factors such as perceived usefulness, ease of use, and social influence [4]. These studies have contributed significantly to understanding why individuals and institutions adopt technology. However, they largely focus on adoption outcomes and behavioral intentions, with limited attention to the structural pathways through which technology reaches end users.

Despite the richness of the technology adoption literature, the distinction between direct and indirect modes of technology diffusion remains underexplored in the context of higher education. Existing research tends to examine direct and indirect effects of technology diffusion rather than the modes of diffusion themselves, thereby overlooking the role of intermediaries in shaping user experience and outcomes. Evidence from other domains, such as e-government and international trade, suggests that direct diffusion mechanisms produce stronger, faster, and more efficient impacts compared to indirect ones mediated through institutional layers [5]. This gap is particularly relevant in higher education, where institutional structures often mediate access to critical technologies.

This study addresses this gap by examining the diffusion of plagiarism detection software in Indian doctoral education, a context characterized by both scale and regulatory complexity. Traditionally, plagiarism detection tools were made available indirectly through institutions, with research scholars relying on intermediaries such as librarians to access similarity reports. This indirect diffusion model limited user control, created delays, and often resulted in misapplication of academic integrity regulations due to inconsistent implementation practices [6, 7]. Recent developments, however, have enabled direct access to low-cost plagiarism detection tools, allowing research scholars to independently evaluate similarity, apply regulatory exclusions, and manage their own compliance processes.

Drawing on this context, this study conceptualizes two distinct modes of technology diffusion: direct diffusion, where technology is accessible to end users without intermediaries, and indirect diffusion, where access is mediated through institutional actors. The conceptual model illustrating these two modes and their pathways is presented in **Figure 1**. By comparing these two modes, this study seeks to examine not only differences in outcomes but also the underlying mechanisms that drive effectiveness and efficiency in technology adoption. Specifically, the study evaluates how direct diffusion influences similarity outcomes, time efficiency, and cost efficiency in the plagiarism checking process.

The novelty of this study lies in several key contributions. First, it introduces and empirically examines the concept of diffusion mode (direct versus indirect) in higher education, a dimension that has received limited attention in existing literature. Second, it shifts the analytical focus from adoption determinants to diffusion structure, thereby extending traditional technology adoption frameworks such as TAM and Rogers' diffusion theory. Third, the study provides large-scale empirical evidence from doctoral education, linking diffusion mode to measurable outcomes such as accuracy, time, and cost, which are rarely analyzed together in prior research. Fourth, it offers a novel conceptual parallel between direct technology diffusion and direct benefit transfer systems, highlighting how eliminating

intermediaries can enhance transparency, efficiency, and user empowerment. Finally, the study contributes practical insights by demonstrating that cost-effective technologies can enable scalable direct diffusion, with implications for policy design and institutional practices in higher education globally. Accordingly, this study addresses the following research questions: how and why direct technology diffusion is advantageous compared to indirect diffusion in higher education.

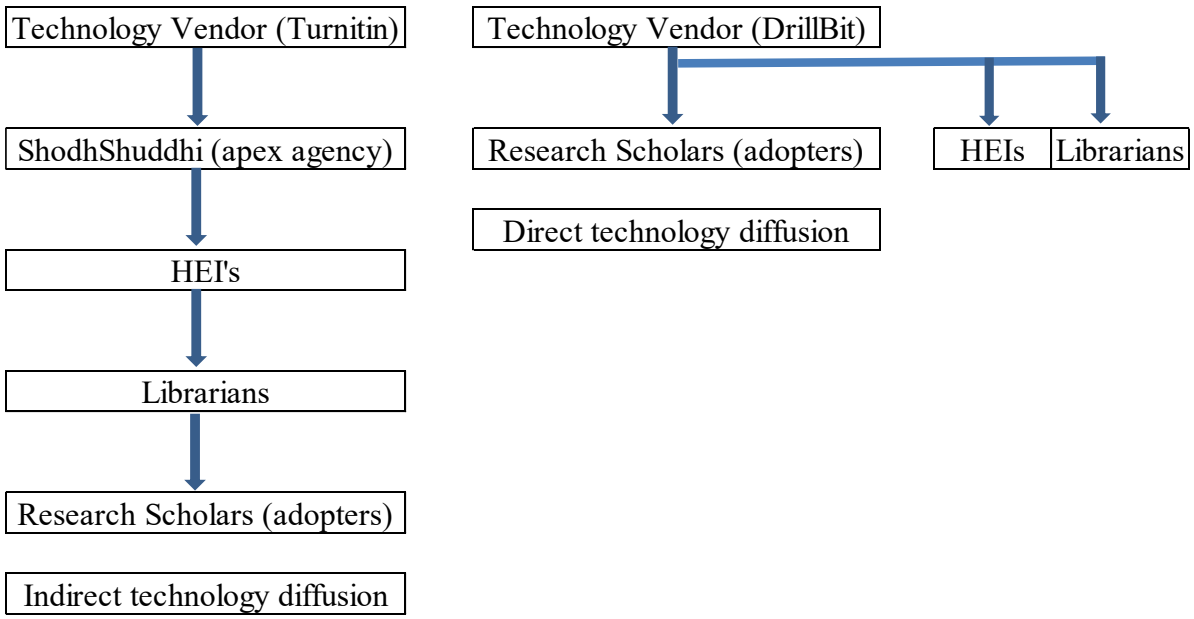

Figure 1. Conceptual model of direct and indirect technology diffusion in higher education.

2. METHODS

Technology adoption and diffusion in higher education have been widely studied through multiple theoretical and empirical perspectives. A substantial body of literature identifies key determinants influencing technology adoption, including performance expectancy, effort expectancy, social influence, and facilitating conditions [8]. These factors emphasize that perceived usefulness, ease of use, and institutional support play critical roles in shaping adoption behavior among students and faculty. Similarly, structural enablers such as infrastructure and technical assistance have been highlighted as essential for the successful implementation of educational technologies [9]. Despite these insights, challenges such as digital inequality, institutional resistance, and inadequate support systems continue to affect the effectiveness of technology adoption in higher education [8].

The Technology Acceptance Model has been extensively applied to explain technology adoption in educational settings, emphasizing the roles of perceived usefulness, perceived ease of use, and self-efficacy in shaping user attitudes and intentions [10-12]. These constructs are often influenced by contextual factors such as infrastructure, accessibility, and cultural norms, particularly in developing countries where resource constraints play a significant role [12]. Complementing this perspective, the Unified Theory of Acceptance and Use of Technology highlights effort expectancy and social influence as critical drivers of adoption intentions, while also recognizing the importance of users' technological capabilities [13, 14]. Together, these models provide a robust framework for understanding individual-

level adoption behavior but offer limited insights into how the structure of technology diffusion influences outcomes.

Rogers' diffusion of innovations theory further enriches this understanding by emphasizing the role of adopter characteristics such as self-efficacy, compatibility, and prior experience in shaping adoption decisions [15, 16]. The theory suggests that the positioning of adopters within the diffusion process significantly affects adoption outcomes. However, most applications of Rogers' framework in higher education focus on attributes of innovations and adopters rather than the pathways through which technology is delivered. As a result, the distinction between direct and indirect diffusion remains largely implicit in existing studies.

Although prior research acknowledges the existence of direct and indirect effects of technology diffusion, explicit examination of diffusion modes is limited. Evidence from other domains provides important insights into this distinction. Studies on e-government adoption show that factors such as resource availability, perceived ease of use, and compatibility have stronger positive associations with direct adoption compared to indirect adoption mediated by intermediaries [17]. Similarly, research on international technology diffusion indicates that direct diffusion mechanisms produce larger and faster impacts compared to indirect diffusion processes. These findings suggest that the mode of diffusion plays a critical role in shaping both efficiency and effectiveness, yet this dimension remains underexplored in higher education contexts.

To further understand the implications of direct versus indirect mechanisms, parallels can be drawn from the Direct Benefit Transfer system in India, which represents a large-scale shift from intermediary-based delivery to direct user access. The literature highlights that direct transfers improve efficiency by reducing delays, eliminating leakages, and enhancing transparency [18, 19]. Direct systems also increase inclusion and empower beneficiaries by giving them greater control over resources and lead to enhanced student performance, innovative thinking, and research efficiency [20, 21]. By contrast, intermediary-based systems are often associated with inefficiencies, corruption, and misallocation of benefits. These characteristics closely resemble the challenges observed in indirect technology diffusion in higher education, where multiple layers of intermediation can distort outcomes and reduce user autonomy.

Synthesizing the above literature reveals a clear research gap. While existing studies provide extensive insights into the determinants of technology adoption and the outcomes of diffusion, they largely overlook the structural dimension of diffusion modes. In particular, there is limited empirical evidence on how direct and indirect diffusion influence effectiveness and efficiency in higher education settings. Addressing this gap is important, as the mode of diffusion may shape not only adoption outcomes but also user empowerment, transparency, and overall system performance.

3. METHODS

This study adopted a mixed-methods approach to examine the effectiveness of direct and indirect technology diffusion in higher education. The quantitative component tested the impact of diffusion modes on similarity outcomes, time efficiency, and cost efficiency, while the qualitative component explored the underlying reasons for the observed differences. Based on the research objectives, the study tested two hypotheses: direct technology diffusion leads to more effective outcomes and results in savings in time and cost.

For the quantitative analysis, a survey method was employed targeting doctoral research scholars who had completed the similarity checking process for their theses. Participants were selected using a combination of convenience, purposive, and snowball sampling techniques. A total of 422 research scholars participated in the study, which was considered adequate based on standard sample size guidelines [22]. Data were collected through an online questionnaire administered via Google Forms. Respondents were required to report similarity levels, time taken, and costs incurred under both indirect and direct diffusion modes. The survey instrument included demographic variables such as region, gender, and field of study, along with key variables related to similarity outcomes, time, and cost. Time was defined as the duration from initial submission to final acceptance after reducing similarity to acceptable levels, while cost included expenses related to paraphrasing services and software access. Responses were captured using categorized ranges to ensure consistency and comparability.

To test the hypotheses, a two-sample t-test was applied to compare differences between the two diffusion modes across similarity, time, and cost variables. The analysis was conducted at a standard confidence level to determine statistical significance. The qualitative component employed expert interviews to gain deeper insights into the advantages of direct technology diffusion. A purposive sample of academic experts was selected. The experts were provided with a summary of the quantitative findings and were asked to explain the advantages of direct diffusion. Responses were collected via email and were analyzed using thematic analysis [23].

Ethical considerations were addressed throughout the study. Informed consent was obtained from all participants, and confidentiality was maintained. The study received institutional ethics approval and was conducted in accordance with established ethical guidelines.

4. RESULTS AND DISCUSSION

The results of the study are presented in two parts, beginning with the quantitative findings, followed by interpretive discussion. The demographic profile of the respondents is summarized in **Tables 1-3**, which provides an overview of the distribution of participants across regions, gender, and fields of study.

Table 1. Demographic profile of survey participants : Zone.

Category	Count	Percentage
North	101	24%
East	110	26%
West	120	28%
South	91	22%

Table 2. Demographic profile of survey participants: Gender.

Category	Count	Percentage
Male	211	50%
Female	206	49%
Prefer not to say	5	1%

Table 3. Demographic profile of survey participants: Field.

Category	Count	Percentage
STEM	216	51%
Humanities & Social Sciences	206	49%

The demographic distribution shows a relatively balanced representation across different regions of India, including North, East, West, and South zones. Similarly, gender distribution is nearly equal, with a marginal difference between male and female participants, while a very small proportion preferred not to disclose their gender. The sample also reflects a balanced representation of academic disciplines, with nearly equal participation from STEM, Humanities, and Social Sciences. This balanced distribution strengthens the reliability of the findings by ensuring that the results are not biased toward a specific group, thereby enhancing the generalizability within the studied context.

The descriptive statistics for the key variables (similarity percentage, time, and cost) under both indirect and direct technology diffusion modes are presented in **Table 4**. The results indicate a substantial difference between the two diffusion modes across all three variables. Under the indirect diffusion mode, the average similarity percentage is significantly higher compared to the direct diffusion mode. In contrast, direct diffusion results in considerably lower similarity levels, indicating a more accurate and appropriate application of plagiarism detection mechanisms. This finding is particularly important in the context of academic integrity, where inflated similarity scores under indirect systems may not necessarily reflect actual plagiarism but rather the misapplication of regulatory provisions [6, 7].

Table 4. Descriptive statistics of similarity, time, and cost under indirect and direct diffusion modes.

Variable	Diffusion Mode	Mean	Standard Deviation
Similarity (%)	Indirect	35.60%	0.085
	Direct	8.00%	0.042
Time (days)	Indirect	71	56.190
	Direct	7	5.938
Cost (INR)	Indirect	12,808 (USD 142)	6871.22
	Direct	1,770 (USD 20)	2181.66

A similar pattern is observed in terms of time efficiency. The time required under indirect diffusion is considerably higher, reflecting delays associated with intermediary involvement such as institutional processing and dependence on third-party services. By contrast, direct diffusion significantly reduces the time required for similarity checking and revision processes, as users are able to independently access and apply the technology without waiting for institutional intervention. This aligns with broader findings in technology diffusion literature, where reduced intermediation is associated with faster adoption and implementation. In terms of cost, the difference between the two modes is equally pronounced. Indirect diffusion is associated with higher costs, primarily due to the reliance on external paraphrasing services and institutional processes. Direct diffusion, on the other hand, significantly reduces costs, as users can perform similarity checks independently using low-cost tools and require minimal external assistance. This finding highlights the importance of affordability as a critical enabler of direct technology diffusion, consistent with prior research emphasizing the role of cost in technology adoption [24, 25].

To statistically validate these differences, hypothesis testing was conducted using a two-sample t-test, and the results are presented in **Table 5**. The results of the hypothesis testing strongly support both proposed hypotheses. The difference in similarity levels between the two diffusion modes is statistically significant, indicating that direct technology diffusion leads to more effective outcomes in terms of accurate similarity assessment. Similarly, the differences in time and cost are also statistically significant, confirming that direct diffusion leads to substantial efficiency gains. The very low p-values indicate a high level of confidence in these findings, reinforcing the robustness of the results.

Table 5. Results of hypothesis testing using a two-sample t-test.

Parameter	H1 (Similarity)	H2a (Time)	H2b (Cost)
Difference	0.276 (27.6%)	63.813 days	11037.915 (USD 122)
t (Observed value)	59.981	23.200	31.452
	t	(Critical value)	1.963
DF	842	842	842
p-value (Two-tailed)	<0.0001	<0.0001	<0.0001

To further illustrate the differences in similarity outcomes, **Figure 2** presents a comparative visualization of similarity percentages under indirect and direct diffusion modes. The figure clearly demonstrates a shift from higher similarity levels under indirect diffusion to significantly lower levels under direct diffusion. This shift can be interpreted as a correction effect, where direct access enables users to apply plagiarism detection rules more accurately. Under indirect diffusion, the involvement of intermediaries often leads to the inclusion of attributed text and other exempted content in similarity calculations, resulting in inflated similarity scores. In contrast, direct diffusion allows users to apply regulatory exclusions correctly, leading to more realistic and acceptable similarity outcomes.

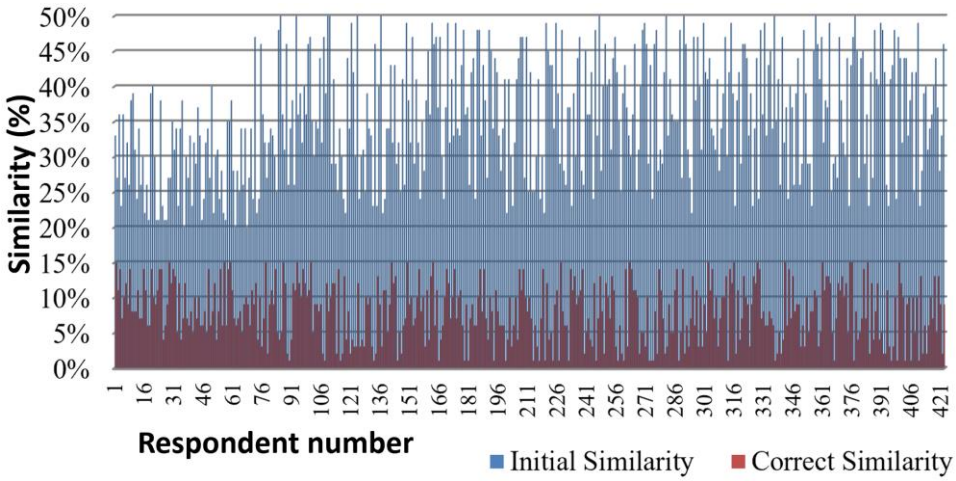

Figure 2. Comparison of similarity percentages under indirect and direct technology diffusion.

The impact of these differences extends beyond similarity scores to influence the time required for completing the plagiarism checking process. **Figure 3** illustrates the comparison of the time required under the two diffusion modes. The **figure** shows a significant reduction in time when moving from indirect to direct diffusion. Under indirect diffusion, the process involves multiple stages, including submission to institutional authorities, waiting for

processing, and engaging external paraphrasing services. Each of these stages introduces delays, contributing to the overall time burden. In contrast, direct diffusion streamlines the process by eliminating these intermediaries, allowing users to perform similarity checks and make revisions in a much shorter timeframe.

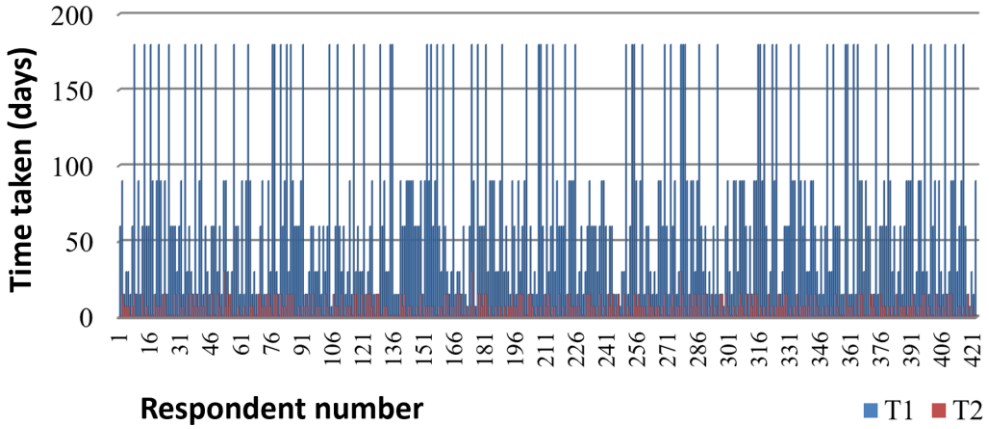

Figure 3. Comparison of the time required under indirect and direct technology diffusion.

Similarly, **Figure 4** presents a comparison of the costs incurred under the two diffusion modes. The cost comparison highlights the substantial financial burden associated with indirect diffusion, primarily driven by the need for external paraphrasing services. In many cases, users incur significant expenses to reduce similarity scores that may have been incorrectly inflated in the first place. Direct diffusion, by enabling accurate similarity assessment and reducing dependence on third-party services, leads to a significant reduction in costs. This finding underscores the economic benefits of direct technology diffusion, particularly for research scholars who often operate under limited financial resources.

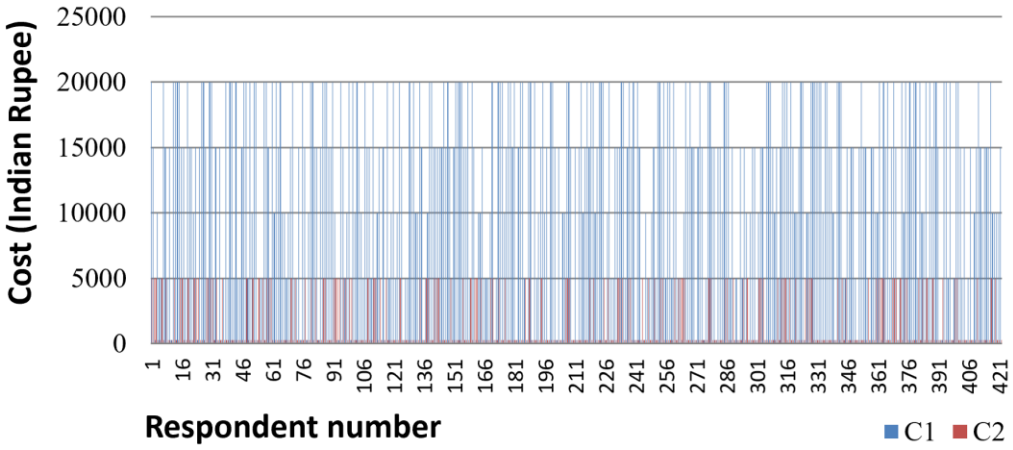

Figure 4. Comparison of costs under indirect and direct technology diffusion.

Taken together, the quantitative results provide strong evidence that direct technology diffusion outperforms indirect diffusion across key dimensions of effectiveness and efficiency. These findings not only validate the proposed hypotheses but also highlight the broader implications of diffusion structure in shaping technology outcomes. The consistent pattern across similarity, time, and cost suggests that the advantages of direct diffusion are systemic rather than incidental, pointing to the critical role of user-level access in technology adoption processes.

While the quantitative results clearly establish the superiority of direct technology diffusion in terms of effectiveness and efficiency, a deeper understanding of the underlying mechanisms requires further interpretation. The observed reduction in similarity levels under direct diffusion, as illustrated in **Figure 2**, is not merely a statistical outcome but reflects a fundamental shift in how technology is applied in practice.

Under indirect diffusion, users rely on intermediaries who may not fully adhere to regulatory provisions, particularly those related to exclusions in similarity calculations. As highlighted in prior studies, misapplication of plagiarism regulations often results in inflated similarity scores that do not accurately represent academic misconduct [6, 7]. In contrast, direct diffusion places the responsibility in the hands of users, enabling them to apply exclusion rules more accurately. This aligns with the principles of the Technology Acceptance Model, where perceived usefulness and perceived control significantly influence effective technology use [10, 11].

The improvement in similarity outcomes also reflects a shift in user engagement. Under indirect systems, research scholars act as passive recipients of similarity reports, with a limited understanding of how results are generated. Direct diffusion transforms them into active users who interact with the technology, interpret results, and make informed decisions. This transition is consistent with Rogers' diffusion of innovations theory, which emphasizes the role of user characteristics such as self-efficacy and experience in successful adoption [15, 16]. By enabling direct interaction with the technology, the diffusion process enhances these attributes, leading to more effective outcomes.

The significant reduction in time, as shown in **Figure 3**, further reinforces the advantages of direct diffusion. The delays associated with indirect diffusion are largely attributable to the involvement of multiple intermediaries, including institutional authorities and external service providers. Each layer introduces waiting time, coordination challenges, and inefficiencies. Direct diffusion eliminates these layers, enabling immediate access to the technology and faster decision-making. This finding is consistent with broader evidence from technology diffusion research, which shows that reducing intermediation accelerates adoption and implementation processes.

From a theoretical perspective, the reduction in time can also be linked to facilitating conditions, a key construct in the Unified Theory of Acceptance and Use of Technology. When users have direct access to tools and resources, the barriers to usage are significantly reduced, leading to faster and more efficient outcomes [13, 14]. In this context, direct diffusion can be seen as an enabling condition that enhances both accessibility and usability.

The cost advantages observed under direct diffusion, as illustrated in **Figure 4**, provide further evidence of the benefits of eliminating intermediaries. Under indirect diffusion, high costs are primarily driven by the need for external paraphrasing services, which are often required to reduce inflated similarity scores. This creates a paradox where users incur additional expenses to correct inaccuracies introduced by the system itself. Direct diffusion resolves this issue by enabling accurate similarity assessment at the outset, thereby reducing or eliminating the need for costly interventions. This finding highlights the importance of affordability as a driver of technology adoption, consistent with prior studies emphasizing cost as a critical factor influencing user behaviour [24, 25].

The qualitative findings provide deeper insights into these quantitative patterns by identifying key themes that explain why direct diffusion is more advantageous. One of the most prominent themes is the elimination of intermediation-related anomalies. Experts highlighted that indirect diffusion often leads to misinterpretation of regulations, unnecessary paraphrasing, and even opportunities for unethical practices. These issues arise from the lack of transparency and accountability in intermediary-driven systems.

The elimination of intermediaries under direct diffusion addresses these challenges by simplifying the process and reducing opportunities for distortion. This observation closely parallels findings from the Direct Benefit Transfer system, where direct delivery mechanisms have been shown to reduce inefficiencies, leakages, and corruption [18, 19]. The similarity between these contexts underscores the broader applicability of direct systems in improving efficiency and transparency across different domains.

Another key theme identified in the qualitative analysis is the shift of control to users. Under direct diffusion, research scholars gain greater autonomy over the similarity checking process, allowing them to make informed decisions and take responsibility for their work. This shift enhances user empowerment and aligns with the concept of self-efficacy, which is a critical determinant of technology adoption and effective use [10, 15].

User control also improves the accuracy of outcomes by ensuring that regulatory provisions are correctly applied. As experts noted, direct users are more likely to understand and implement exclusion rules, leading to more accurate similarity assessments. This finding reinforces the importance of user involvement in maintaining academic integrity, as highlighted in prior research [1].

The combined quantitative and qualitative findings suggest that the advantages of direct technology diffusion are not limited to individual outcomes but extend to systemic improvements. By eliminating intermediaries and empowering users, direct diffusion enhances transparency, efficiency, and effectiveness across the entire process. This supports the broader argument that diffusion structure plays a critical role in shaping technology outcomes, an aspect that has been largely overlooked in existing literature.

Furthermore, the findings provide empirical support for the conceptual link between direct technology diffusion and direct benefit transfer systems. In both cases, the removal of intermediaries leads to improved outcomes by reducing inefficiencies and increasing user control. This parallel offers a novel perspective on technology diffusion, suggesting that principles from public policy can be effectively applied to educational technology contexts.

Taken together, the results of this study highlight the importance of rethinking technology diffusion strategies in higher education. While traditional approaches have focused on institutional control and mediated access, the evidence presented here suggests that direct user access can lead to significantly better outcomes. This has important implications for policymakers, institutions, and technology providers, who must consider not only the adoption of technology but also the mechanisms through which it is delivered.

The findings of this study offer important implications for both theory and practice in the domain of technology diffusion in higher education. From a theoretical perspective, the study extends existing technology adoption frameworks by introducing diffusion mode as a critical dimension influencing outcomes. While prior models such as the Technology Acceptance Model and Rogers' diffusion of innovations theory primarily focus on individual perceptions

and adopter characteristics, this study highlights the importance of structural pathways through which technology is delivered. By demonstrating that direct diffusion leads to significantly better outcomes compared to indirect diffusion, the study emphasizes that adoption effectiveness is not solely determined by user attitudes but also by the configuration of the diffusion process itself.

The study also contributes to diffusion theory by reinforcing the role of the adopter as an active agent rather than a passive recipient. Direct access to technology enhances user control, self-efficacy, and engagement, which are key determinants of successful adoption [15, 16]. This finding aligns with prior research emphasizing the importance of user involvement in maintaining academic integrity and effective technology utilization [1]. Furthermore, the conceptual parallel drawn between direct technology diffusion and direct benefit transfer systems provides a novel interdisciplinary perspective, suggesting that principles of disintermediation can be applied across domains to improve efficiency and transparency [18, 19].

From a practical perspective, the findings have significant implications for higher education institutions, policymakers, and technology providers. Institutions should reconsider reliance on intermediary-driven systems for technology deployment, particularly in areas such as plagiarism detection where accuracy and transparency are critical. Enabling direct access to technology can reduce inefficiencies, minimize delays, and enhance user satisfaction. Policymakers should promote frameworks that encourage direct technology diffusion, supported by clear guidelines and awareness programs to ensure correct usage. Technology providers, on the other hand, should focus on developing affordable and user-friendly solutions that can be directly accessed by end users. The importance of cost-effectiveness as an enabler of direct diffusion is particularly evident in this study, reinforcing the need for scalable and accessible technological solutions [24, 25].

Overall, the implications of this study suggest a shift in focus from merely adopting technology to designing effective diffusion mechanisms. By prioritizing direct access and minimizing unnecessary intermediation, stakeholders can significantly improve both the effectiveness and efficiency of technology use in higher education.

This study has several limitations that should be considered when interpreting the findings. First, the study relies on non-probability sampling methods, including convenience, purposive, and snowball sampling, which may introduce selection bias. As a result, the findings may not be fully generalizable to the entire population of doctoral students. Second, the study is conducted within the specific context of Indian doctoral education, which may limit the applicability of the results to other countries with different institutional structures and regulatory environments.

Third, the quantitative data are based on self-reported responses, which may be subject to recall bias or subjective estimation, particularly in reporting time and cost variables. Although efforts were made to standardize responses through structured categories, some degree of variation in interpretation may remain. Fourth, the study focuses on a specific type of technology, namely plagiarism detection software, and the findings may not directly apply to other types of educational technologies without further validation.

Future research can address these limitations by employing probabilistic sampling techniques, expanding the study to multiple countries, and examining additional technology

contexts. Longitudinal studies may also provide deeper insights into the long-term impact of diffusion modes on technology adoption and outcomes.

5. CONCLUSION

This study demonstrates that direct technology diffusion is significantly more effective and efficient than indirect diffusion in the context of higher education. By enabling users to directly access and apply technology, direct diffusion improves accuracy in similarity assessment, reduces time delays, and lowers costs associated with the plagiarism checking process. These findings provide strong empirical support for the argument that diffusion structure plays a critical role in shaping technology outcomes.

The study also highlights that the advantages of direct diffusion extend beyond measurable outcomes to include increased user empowerment, improved transparency, and enhanced alignment with regulatory frameworks. By eliminating intermediaries, direct diffusion reduces the risk of misapplication, inefficiencies, and potential misuse, thereby contributing to better academic integrity practices. The findings reinforce the importance of designing technology systems that prioritize user-level access and affordability. As demonstrated in this study, cost-effective solutions can serve as key enablers of large-scale direct diffusion, making technology more accessible to a broader population of users. This insight is particularly relevant in developing country contexts, where resource constraints often limit technology adoption.

This study contributes to the growing body of literature on technology diffusion by highlighting the importance of diffusion mode as a determinant of effectiveness and efficiency. It provides both theoretical and practical insights that can inform future research, policy design, and institutional practices aimed at improving technology adoption in higher education.

6. AUTHORS' NOTE

The authors declare that there is no conflict of interest regarding the publication of this article. The authors confirmed that the paper was free of plagiarism.

7. REFERENCES

[1] Ahmed, H., Daim, T., and Basoglu, N. (2007). Information technology diffusion in higher education. *Technology in Society, 29*(4), 469–482.

[2] Pinho, C., Franco, M., and Mendes, L. (2021). Application of innovation diffusion theory to the e-learning process: Higher education context. *Education and Information Technologies, 26*(1), 421–440.

[3] Bouteraa, M., Bin-Nashwan, S. A., Al-Daihani, M., Dirie, K. A., Benlahcene, A., Sadallah, M., and Chekima, B. (2024). Understanding the diffusion of AI-generative (ChatGPT) in higher education: Does students' integrity matter? *Computers in Human Behavior Reports, 14*, 100402.

[4] Chen, R. (2024). A study applying Rogers' innovation diffusion theory on the adoption process of new teaching methods in secondary education. *Research and Advances in Education, 3*(2), 6–10.

[5] Kumar, R., Sachan, A., and Mukherjee, A. (2018). Direct vs indirect e-government adoption: An exploratory study. *Digital Policy, Regulation and Governance, 20*(2), 149–162.

[6] Raibagkar, S. S. (2021). Researchers do not fall prey to misuse of plagiarism regulations. *Publishing Research Quarterly, 37*(1), 55–68.
[7] Khaire, R., Dixit, N., Ghuge, A., Bhutada, D., Kasisomayajula, S. R., and Dhaigude, R. (2025). Implementation blues for the special Indian legislation to curb plagiarism in research in higher educational institutions. *Iberoamerican Journal of Science Measurement and Communication, 5*(2), 1–17.
[8] Feng, J., Yu, B., Tan, W. H., Dai, Z., and Li, Z. (2025). Key factors influencing educational technology adoption in higher education: A systematic review. *PLOS Digital Health, 4*(4), e0000764.
[9] Buchanan, T., Sainter, P., and Saunders, G. (2013). Factors affecting faculty use of learning technologies: Implications for models of technology adoption. *Journal of Computing in Higher Education, 25*(1), 1–11.
[10] Qashou, A. (2021). Influencing factors in m-learning adoption in higher education. *Education and Information Technologies, 26*(2), 1755–1785.
[11] Almaiah, M. A., Alhumaid, K., Aldhuhoori, A., Alnazzawi, N., Aburayya, A., Alfaisal, R., and Shehab, R. (2022). Factors affecting the adoption of digital information technologies in higher education: An empirical study. *Electronics, 11*(21), 3572.
[12] Kanwal, F., and Rehman, M. (2017). Factors affecting e-learning adoption in developing countries: Empirical evidence from Pakistan's higher education sector. *IEEE Access, 5*, 10968–10978.
[13] VanDerSchaaf, H. P., Daim, T. U., and Basoglu, N. A. (2021). Factors influencing student information technology adoption. *IEEE Transactions on Engineering Management, 70*(2), 631–643.
[14] Yakubu, M. N., and Dasuki, S. I. (2019). Factors affecting the adoption of e-learning technologies among higher education students in Nigeria: A structural equation modelling approach. *Information Development, 35*(3), 492–502.
[15] John, S. P. (2015). The integration of information technology in higher education: A study of faculty's attitude towards IT adoption in the teaching process. *Contaduría y Administración, 60*, 230–252.
[16] Menzli, L. J., Smirani, L. K., Boulahia, J. A., and Hadjouni, M. (2022). Investigation of open educational resources adoption in higher education using Rogers' diffusion of innovation theory. *Heliyon, 8*(7), e09885.
[17] Kumar, R., Sachan, A., and Mukherjee, A. (2018). Direct vs indirect e-government adoption: An exploratory study. *Digital Policy, Regulation and Governance, 20*(2), 149–162.
[18] Ahmad, S. (2022). Direct Benefit Transfer: The great technological move of India. *Journal of Digital Learning and Distance Education, 1*(1), 37–41.
[19] Sabherwal, R., Sharma, D., and Trivedi, N. (2019). Using direct benefit transfers to transfer benefits to women: A perspective from India. *Development in Practice, 29*(8), 1001–1013.
[20] Ghosh, B., Burman, R. R., Padaria, R., Mahra, G. S., Kumar, P., and Bhowmik, A. (2024). Assessing the operational constraints of direct benefit transfers: An empirical investigation of PM-KISAN scheme of India. *Journal of Experimental Agriculture International, 46*(9), 481–488.
[21] Parmasivan, C., and Arunkumar, G. (2018). Direct benefit transfer—An innovative approach to financial inclusion in India. *Journal of Emerging Technologies and Innovative Research, 5*(12), 409–418.

[22] Krejcie, R. V., and Morgan, D. W. (1970). Determining sample size for research activities. *Educational and Psychological Measurement, 30*(3), 607–610.
[23] Döringer, S. (2021). 'The problem-centred expert interview': Combining qualitative interviewing approaches for investigating implicit expert knowledge. *International Journal of Social Research Methodology, 24*(3), 265–278.
[24] Quigley, M., and Burke, M. (2013). Low-cost Internet of Things digital technology adoption in SMEs. *International Journal of Management Practice, 6*(2), 153–164.
[25] Foster, A. D., and Rosenzweig, M. R. (2010). Microeconomics of technology adoption. *Annual Review of Economics, 2*(1), 395–424.