



AI-Enabled Research Practices and Knowledge Diversity: A Moderation Model of Generative AI Competency

Pankaj Adatiya Tiwari^{*} and Renu Rathi

¹ Senior Assistant Professor, School of Commerce, Jain (Deemed to be University),
Bangalore, India

² Professor, School of Commerce, Jain (Deemed to be University), Bangalore, India
adatiya.pankaj@gmail.com; r.renu@jainuniversity.ac.in

Abstract. The increasing usage of artificial intelligence (AI) in academic research has dramatically altered the nature of knowledge discovery, but its impact on the variety of knowledge has not been studied much in depth. This paper examines how AI-supported research practices such as using AI, multilingual search, and access to various databases can contribute to increasing knowledge diversity in higher education. According to data provided by academic researchers, who had to fill out a structured questionnaire and analyze it with the help of PLS-SEM, AI use, multilingual search, and multi-database practices increase knowledge diversity. The research concludes that the beneficial effect of using AI on knowledge diversity is higher among individuals who have high generative skills in AI. As a result, it is equally important that AI tools be implemented and user proficiency be developed to improve the outcome of the research. The research provides viable solutions to improve the quality and inclusivity of research in higher education by proposing knowledge diversity as an outcome variable.

Keywords: AI in Research, Knowledge Diversity, Generative AI Competency, Multilingual Search Methods, Multi-Database Handling, AI-Enabled Research Practices, Higher Education Research.

1 Introduction

Productive development in the field of artificial intelligence (AI) and generative AI in particular is quickly transforming the academic research of higher education, making the discovery of knowledge, its synthesis, and sharing more effective.[11] The use of AI tools [11]in research processes is expanding among the researchers – they are used to review the literature, generate ideas, and analyze data, which results in a higher productivity [1–4]. There is also an increased availability of sources outside English language publication, through the development of wider global databases and the increased focus on multilingual scholarship [5,7]. Nevertheless, these developments do not eliminate the fact that numerous of the existing research practices continue to be largely dependent on small data sets and are characterized by language bias, which inhibits the inclusivity and diversity of knowledge generation [6,7].

The concept of knowledge diversity, i.e., the integration of other disciplines and cultural background perspectives, is becoming increasingly accepted as a crucial requirement in the quality of research, innovation, and international significance [8]. However, it is not clear how AI-enhanced research practices are likely to affect the

diversity of knowledge particularly in the context of multilingual and multi-database searches. Available literature indicates that the usefulness of AI usually determines how well the user is acquainted with generative AI tools [2,3]. It is against this background that the current research seeks to address some research questions:

1. How does AI usage affect knowledge diversity in academic research?
2. What influence do multilingual search practices have on knowledge diversity?
3. How does using multiple databases promote knowledge diversity?
4. Is there a connection between knowledge diversity and expertise with generative AI tools?

By discovering these queries, the study contributes to the existing discourse on AI-based research environments and gives new information on how to enhance inclusivity and quality of research in higher education.

2 Review of Literature

2.1 AI in Research

AI is transforming scholarly literature by automating the process of knowledge creation, processing, and transfer. The generative AI tools assist researchers in literature review, idea generation, and synthesis of large amounts of information in an efficient manner [1–4]. Such tools increase productivity and aid pattern recognition across sources and research indicates that they increase the discovery range by linking fragmented data [2,3]. The role of AI hinges on how it is incorporated in the working process, especially in terms of diversity and inclusivity in the research results.

2.2 Multilingual Search Practices

The use of multilingual search has become a very necessary inclusion in research and is applicable worldwide. Traditionally, the scholarly literature on academic research has been monopolized by works published in English, limiting the access to local knowledge and marginalizing scholarly literature in other languages [5]. Multilingual search strategies enable the researcher to use a broader spectrum of knowledge sources to develop the importance and comprehensiveness of research implications in their context [7]. According to previous research, knowledge bias can be reduced and epistemic diversity enhanced through the integration of multilingual resources since they introduce perspectives of different linguistic and cultural backgrounds [7]. Multilingual search techniques are increasingly required to encourage inclusiveness and diversity in knowledge generation due to the increasing globalization of research.

2.3 Multi-Database Usage

Extensive coverage of literature and the increased quality of the research can be achieved only with the help of several academic databases, as the scope and criteria of each of the databases differ. Research indicates that there is [16]a significant platform difference [16]between websites such as Scopus, Web of Science, and Google Scholar

[5,6], thus the use of multiple sources expands the access to information, minimizes publication bias, and increases the reliability of the research, particularly in interdisciplinary studies where the knowledge is diverse across multiple fields.

2.4 Knowledge Diversity

The concept of knowledge diversity, which is the subject of this paper, is incorporating the various perspectives, disciplines, and cultures into academic research. It is believed to be essential to the quality of research and innovation [8], as different sources introduce better understanding and teamwork [26–28]. Nevertheless, the issue of structure such as language barriers, computerization of databases and dependence on mainstream publication practices often diminish diversity [6,7]. These problems can be solved by using AI tools, multilingual searches, and various databases and promoting a more inclusive knowledge creation.

3 Theoretical Background and Framework

The research relies on the commonly known theories like Technology Acceptance Model (TAM), and knowledge-based perspective of the organization to highlight the issues of effective adoption and utilization of technology in academic research. According to TAM, the intention and actual adoption of technology is determined by its perceived usefulness, and ease of use [9]. The AI is viewed as useful in enhancing the efficiency of research, processing of information, and discovery of information, thereby facilitating its application in academic workflows [1,3]. The usage of generative AI in research underscores the importance of TAM in comprehending the interaction with new technologies by the researchers.

Moreover, the knowledge-based perspective highlights the importance of knowledge as resource that is crucial to organizations and individuals. It emphasizes the need to learn, synthesize and implement various sources of knowledge [10]. The principle of this approach implies the utilization of multilingual search methods and the employment of multiple databases, which allows accessing a larger spectrum of information and enhancing the variety of knowledge. Also, the framework includes the concept of personal competency which means that the usefulness of AI tools will be conditioned by the likelihood of the user to communicate with and critically analyze AI-generated outputs. Generative AI competency is proposed as a moderator that improves the connection between the use of AI and diversity in knowledge. The research provides a framework relating AI-based research to knowledge diversity, and competency was one of the boundary conditions.

4 Hypotheses Development and Conceptual Framework

AI is rapidly changing academic research, streamlining literature review, data analysis, and idea generation. Researchers can quickly process large datasets and spot patterns across fields with AI tools [1–4]. Studies show that using AI boosts productivity and broadens knowledge exploration, leading to better research outcomes [2,3]. By

supporting cross-disciplinary synthesis and expanding access to information, AI is expected to increase the diversity of knowledge in academic work. Thus, it is hypothesized that:

H1: AI usage in research influences knowledge diversity.

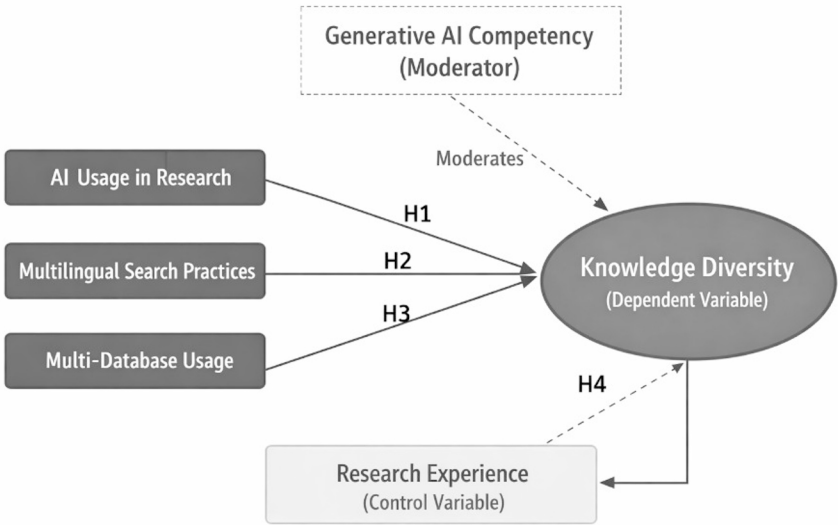


Fig. 1. Conceptual Framework (Source: Author’s interpretation).

The phenomenon of multilingual search is very important as it expands the academic research horizons by allowing access to non-English and region-specific articles. The traditional research practices have been criticized as not necessarily using English dominated sources to include different perspectives [5]. Inter-integration of multilingual resources enables researchers to gain access to more knowledge and thus enhances inclusivity and bias in research findings [7]. Multilingual search practices ought to have a positive impact on knowledge diversity since the diversity of knowledge is determined by the presence of different linguistic and cultural views. Accordingly:

H2: Multilingual search practices influence knowledge diversity.

To guarantee sufficient coverage of literature and reduce the chances of incomplete or biased information, the application of various academic databases is necessary. Because different databases vary in how far they index and in the disciplinary areas they cover, the use of one database can limit access to useful research [6]. The use of multiple databases will allow the researcher to gain access to a wider base of academic publications, increasing the credibility and variety of sources of knowledge [5,6]. This method is especially valuable when conducting interdisciplinary research, whereby the knowledge is spread through various platforms. Thus:

H3: Multi-database usage influences knowledge diversity.

Although the use of AI has many benefits, its usefulness will be determined by how well the user can use and critically analyze AI-generated results. The expertise required

to use AI tools efficiently, such as timely design, comprehension of the outcomes, and the capacity to integrate them with traditional research methods, is represented by generative AI competency [3,23]. Research on the interaction between humans and AI has recommended that people with higher competency can more effectively use AI to make better decisions and integrate knowledge [4]. Therefore, generative AI competency is expected to strengthen the relationship between AI usage and knowledge diversity.[11] Hence:

H4: Generative AI competency moderates the association between AI usage and knowledge diversity.

5 Methodology

The research design used in this study is a quantitative research design in order to investigate the relationships between AI-enabled research practices and knowledge diversity in higher education. The target group will include academic researchers such as PhD scholars, faculty members, and research professionals who are actively involved in scholarly activities. Convenience and snowball sampling methods were [8] used to collect a total of 128 valid responses using academic networks and online platforms with the assistance of a questionnaire. Inclusion criteria were intended to keep data quality on par by including those respondents who were actively involved in research and previously worked with AI tools, with those who never used AI tools or those who did not submit full responses being excluded. The sample size is deemed to be sufficient in regard to PLS-SEM that suits exploratory research with relatively small to medium sample sizes and complex models [15,16].

The measurement tool is formulated on the basis of the available scale construction protocols to ascertain reliability and validity [19,20]. AI usage items were based on previous research on technology adoption and AI-enabled research practices [1,3,22], and multilingual search practices were based on the literature on inclusive and multilingual knowledge systems [5,7]. The items of multi-database usage relied on bibliometric and database coverage studies [6], and the conceptualization of knowledge diversity was on the existing frameworks of interdisciplinarity and diversity in research [26,27]. Moderating variable, generative AI competency was based on technology competency and self-efficacy literature [23,24]. Responses were recorded on 7-point Likert scale with options as 1 for strongly disagree to 7 for strongly agree. The survey form was presented online which ensured accessibility and expanded participation of respondents.

Smart-PLS was applied to conduct data analysis to perform PLS-SEM. Internal consistency was measured using Cronbach's alpha (α), and composite reliability (threshold greater than 0.70) [19], and convergent validity was determined using AVE greater than 0.50) [17]. The HTMT ratio (< 0.85) was used to evaluate discriminant validity [18]. Path coefficients, t-values, and levels of significance obtained through bootstrapping were used to evaluate the structural model [15]. Explanatory and predictive power were measured with the coefficient of determination (R^2)[14] and predictive relevance (Q^2) [14], respectively. The Normed Fit Index (NFI > 0.90) and Standardized Root Mean Square Residual (SRMR < 0.08) were used to assess the

model fit. Also, effect size (f^2) was computed to identify the contribution made by each predictor and the moderating effect of generative AI competency was analyzed through the product indicator approach. To counter possible common method bias, procedural remedies and statistical checks were implemented as suggested in earlier studies [21]. These steps of analysis guarantee soundness, legitimacy and dependability of the research results.

5.1 Descriptive analysis

The data was first explored to investigate the central tendency, and variability of the study variables. The findings show that AI usage ($M = 3.84$, $SD = 0.72$) has the highest mean, which implies a high level of AI usage by the respondents, then there is knowledge diversity ($M = 3.79$, $SD = 0.69$). There is a moderate level in the use of multi-databases ($M=3.68$, $SD = 0.75$) and generative AI competency, ($M = 3.61$, $SD = 0.77$) and relatively lower levels of multilingual search ($M = 3.56$, $SD = 0.81$).

Table 1. Descriptive Statistics.

No	Variable	Mean	Std. Deviation	Cronbach's Alpha (α)
1	AI Usage (AIU)	3.84	0.72	0.88
2	Multilingual Search (MSP)	3.56	0.81	0.85
3	Multi-Database Usage (MDB)	3.68	0.75	0.83
4	Knowledge Diversity (KD)	3.79	0.69	0.87
5	Generative AI Competency (GAIC)	3.61	0.77	0.89

(Source: Primary data of the Study)

Table 2. Correlation Statistics.

No	Variable	1	2	3	4	5
1	AI Usage (AIU)	1				
2	Multilingual Search (MSP)	0.52**	1			
3	Multi-Database Usage (MDB)	0.48**	0.55**	1		
4	Knowledge Diversity (KD)	0.61**	0.58**	0.54**	1	
5	Gen.AI Competency (GAIC)	0.57**	0.49**	0.46**	0.60**	1

Note: ** Significance level at $p<0.01$

(Source: Primary data of the Study)

Correlation analysis indicates that, all the variables are positively correlated, and the AI usage has the highest correlation with the knowledge diversity, followed by

multilingual search and multi-database usage. These findings point to stable interrelations between variables and allow further structural analysis.

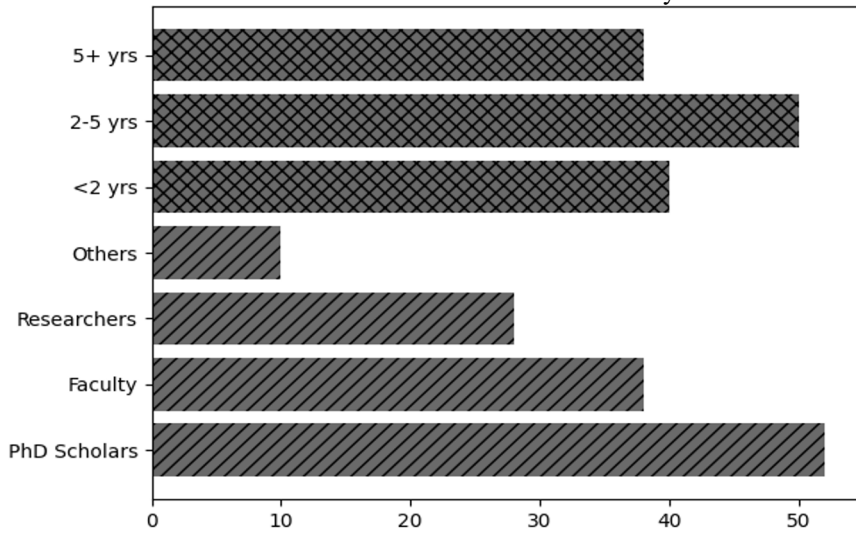


Fig. 2. Respondents' profile (Source: Primary data of the Study).

The distribution of respondents[20] using black and white patterned horizontal bar chart is shown in Fig. 2. The categories of respondents are expressed in diagonal line patterns, and the levels of the research experience are expressed in the cross-hatched patterns. Clear and interpretable grayscale printing is guaranteed using separate patterns. The values indicate that the largest group is that of PhD scholars and most respondents are in the category of 2–5 years of research experience.

6 Research Findings

The PLS-SEM was used to analyze the structural model to estimate the direct, indirect and moderating effects among the study variables. The findings reveal that the use of AI has a considerable positive impact on the diversity of knowledge ($\beta = 0.32$, $p = 0.01$), which implies that the more AI tools are used, the more knowledge integration becomes diverse in academic research. Hence, H1 is supported. Likewise, the positive impact on the diversity of knowledge is also significant with the utilization of multilingual search ($\beta = 0.28$, $p < 0.01$) and multi-database ($\beta = 0.25$, $p < 0.05$) as well, which means that access to diverse linguistic sources and multiple databases do lead to wider knowledge views. Hence, H2 and H3 are supported. In terms of the indirect effects, the findings [32] indicate that the AI usage has an indirect effect on the diversity of knowledge by improving research practices, but the primary emphasis is on direct relationships.[11] Moreover, the moderating role of the generative AI competency was significant ($\beta = 0.18$, $p < 0.05$), which suggests that the association between the AI usage and the diversity of knowledge is stronger in the case of those with greater abilities to use

generative AI tools. This brings out the relevance of user capability in maximizing the benefits of AI in research. Hence H4 is supported.

Overall, the model demonstrates moderate explanatory power, with an R^2 value of 0.57 for knowledge diversity. The findings disclose that AI-enabled research practices play a critical role in enhancing[2] knowledge diversity, particularly when supported by higher levels of generative AI competency[7].

Table 3. Regression Statistics (Moderation Effect).

Mo del	Relationship			β	t- value	p- value	df	F- value	R^2
M1	AI	Usage	→	0.32	4.85	<0.01	126	28.12	0.41
	Knowledge Diversity								
M1	Multilingual Search		→	0.28	4.21	<0.01	126	–	–
	Diversity								
M1	Multi-Database Usage		→	0.25	3.67	<0.05	126	–	–
	Knowledge Diversity								
M2	AI	Usage	→	0.29	4.36	<0.01	125	31.45	0.52
	Knowledge Diversity								
M2	GAIC (Moderator)			0.26	3.98	<0.01	–	–	–
M3	AIU × GAIC		→	0.18	2.74	<0.05	124	35.67	0.57
	Knowledge Diversity								

(Source: Primary data of the Study)

Figure 3, Figure 4 and Figure 5 showcase different regression frameworks involved in the present study. Figure 6 shows that the association between AI usage and knowledge diversity is more at high values of generative AI competency.

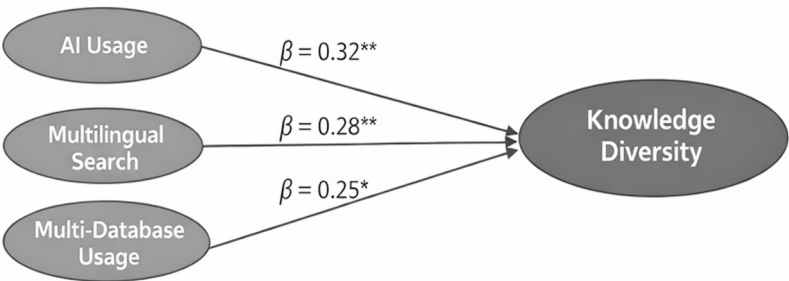


Fig. 3. M1 – Direct Effects Model (Source: Primary data of the Study).

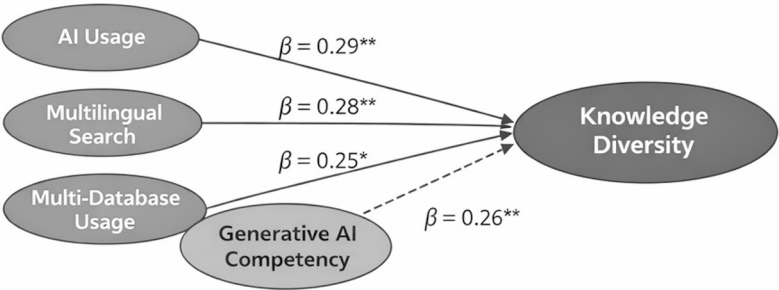


Fig. 4. M2 – Moderation Model (Source: Primary data of the Study).

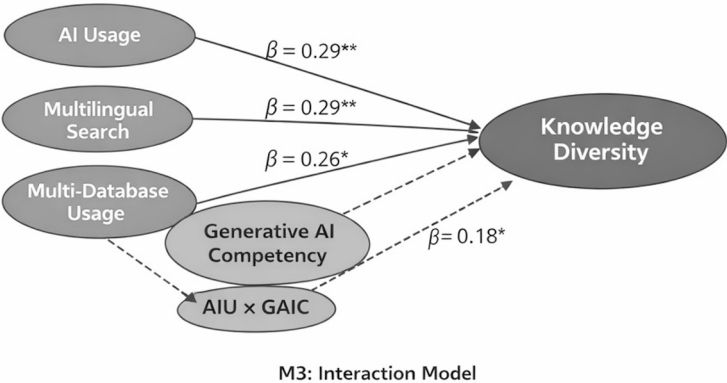


Fig. 5. M3 – Interaction Model (Source: Primary data of the Study).

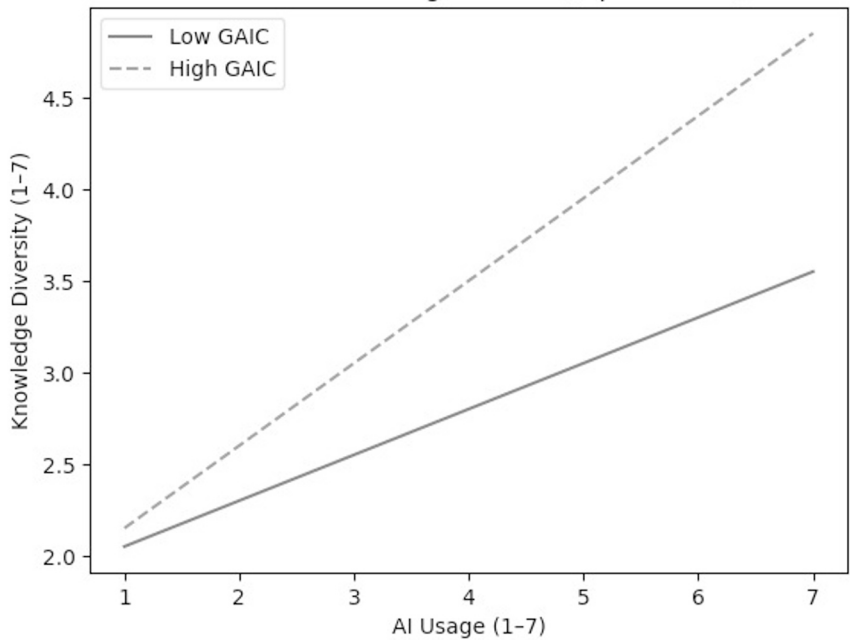


Fig. 6. Generative AI Competency vs AI Usage Interaction Graph (Source: Primary data of the Study).

7 **Discussion**

The results of this research are highly empirical evidence of how AI-enabled research practices can help to increase the diversity of knowledge in higher education. The findings indicate the impact of AI use on knowledge diversity is the strongest, which implies that AI tools cannot be seen as efficiency-only instruments but rather as the ones that support the integration of wider knowledge. This correlates with previous studies which emphasized the disruptive nature of generative AI in changing the academic processes and broadening access to a wide range of information sources [1,2]. The current research also indicates that generative AI helps researchers to gain, assess, and synthesize information more efficiently, thus enhancing the richness and breadth of knowledge generation [11]. Pattern recognition and synthesis across several sources can be facilitated by AI-driven tools, [1]which can help to produce more thorough research results [3,4]. Moreover, the extensive impact of the multilingual practices of search and the use of multi-database support the necessity of an inclusive research method, since the use of a narrow range of linguistic and database sources can restrict the variety of knowledge [5,6]. These results are in line with the findings of studies that reiterate the importance of having varied and internationally representative knowledge systems in scholarly research [7,8].

Another important contribution of the study is that it has revealed the moderating effect of generative AI competency in enhancing the relationship among AI use and knowledge diversity. According to the findings, the usefulness of AI depends on whether the user can successfully use and critically analyze the results of AI. This helps in proving the fact that technological implementation itself does not ensure that the research results are going to be better but needs to be supplemented with human skills [2,3]. The latest studies point to the fact that the AI competency frameworks started to emphasize not merely on technical skills as well as on cognitive and evaluative skills, which supports the idea of the vital role played by user expertise in maximizing AI efficiency [12]. Also, recent findings confirm the usefulness of structured AI competency models in higher education, which proves that competency has a strong impact on AI use and research related outcomes [13]. The moderation impact is consistent with the emerging body of research on human-AI collaboration that highlights the fact that competent users are in a better position to use AI to enable a wide range of sources of knowledge and reduce bias [4]. This result strengthens the argument that competency is a critical limitation in AI-based research settings.

7.1 Implications

Theoretically and practically, the study has a few implications. Theoretically, it adds to the expanding body of research about AI-enabled studies, introducing knowledge diversity as an outcome variable of critical concern and integrating technological, methodological, and behavioral dimensions into a single framework [1,8]. In practice, the results show the development of generative AI competency in universities and colleges should be based on systemic training, workshops, and support systems within the institution. The latest views in the global context also indicate that the future of academic performance is increasingly hinged on adaptive AI-related capabilities as well as interdisciplinary skills in a transformed digital ecosystem [14]. Introducing multilingual research practices and increasing the availability of various academic databases is another way to make research more inclusive and internationally relevant [5,7]. These insights can be used by policymakers and institutional bodies to come up with policies that facilitate innovation, interdisciplinary cooperation, and research excellence. Overall, the study highlights the importance of [20] adopting a balanced approach that integrates advanced technologies with human capability development to fully leverage the possible of AI in enhancing knowledge diversity.[20]

8 Limitations and Future Scope

One of the restrictions of this research work is the use of a relatively[39] small sample size ($N = 128$), which could restrict the extrapolation of the research results to other institutional and geographical settings. Second, convenience and snowball sampling can result in selection bias since the respondents are mostly selected based on the available academic contacts. Third, the research is based on self-reported data, which is also prone to common method bias and respondent subjectivity. Also, the cross-sectional nature of the data restricts the establishment of causal relationships between variables. [39] Lastly, research is narrow-based with only a few variables being

examined and other possible variables like institutional backing, the differences in discipline, and technological infrastructure were not addressed.

These limitations can be overcome by future studies using bigger and more varied samples in different countries and institutional contexts to increase the generalizability. Longitudinal studies may be carried out to improve the knowledge of the causal relations and the changing influence of the AI-enabled research practices over the course of time. It is also possible that more variables, including institutional support, digital infrastructure, and interdisciplinary collaboration, can be included in further research to create a more comprehensive model. Additionally, qualitative or mixed methods may be used to identify the researchers' interaction with AI tools and multilingual resources. Finally, future studies can also examine novel opportunities like the ethical aspect of AI usage, biases created by AI-generated information, and knowledge environments affected by AI.

References

1. Akanksha Srivastava, A.V. Senthil Kumar, Disha Maheshwari, Samrat Ray. *Artificial Intelligence and Human Existence: Insights on Education, Technology, and Society*. CRC Press, 2025.
2. Abhishek N, Keyurkumar M. Nayak, Mallikarjun M. Muttappa Maradi, Ujwala Jain, M.S. Divyashree. "Reconceptualizing instructor roles and institutional readiness in the AI era: stakeholder perspectives on Gen Z competency development in higher education", *Asian Education and Development Studies*, 2026
3. Bill Serrano-Orellana, Jessica Ivonne Lalangui Ramírez, Néstor Daniel Gutiérrez Jaramillo, Lia Rodríguez-Jaramillo et al. "Identification of Organizational Efficiency Profiles Based on Human Capital Management: A Study Using Principal Component Analysis and Clustering Algorithms." *Sustainability*, 2025.
4. Brynjolfsson, E., Li, D., Raymond, L.R. Generative AI at work. *Quarterly Journal of Economics*, 140(2), 889–942 (2025).
5. Compeau, D.R., Higgins, C.A. Computer self-efficacy: Development of a measure and initial test. *MIS Quarterly*, 19(2), 189–211 (1995).
6. Davis, F.D. Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319–340 (1989).
7. DeVellis, R.F. *Scale Development: Theory and Applications* (4th ed.). Sage Publications, Thousand Oaks (2016).
8. Dhananjay Beura, Mihir Ranjan Nayak. *Navigating Digital Disruption: Strategies for Sustainable Business Management*. Routledge, 2026.
9. Dwivedi, Y.K., Kshetri, N., Hughes, L., Slade, E.L., Jeyaraj, A., Kar, A.K., Wright, R. So what if ChatGPT wrote it? Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management*, 71, 102642 (2023).

10. Fornell, C., Larcker, D.F. Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39–50 (1981).
11. Francisco Tigre Moura. *Artificial Intelligence, Co-Creation and Creativity: The New Frontier for Innovation*. Routledge, 2024.
12. Hair, J.F., Hult, G.T.M., Ringle, C.M., Sarstedt, M. *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)* (2nd ed.). Sage Publications, Thousand Oaks (2017).
13. Hair, J.F., Risher, J.J., Sarstedt, M., Ringle, C.M. When to use and how to report the results of PLS-SEM. *European Business Review*, 31(1), 2–24 (2019).
14. HCI in Business, Government and Organizations. Springer Science and Business Media LLC, 2021.
15. Henseler, J., Ringle, C.M., Sarstedt, M. A new criterion for assessing discriminant validity in variance-based SEM. *Journal of the Academy of Marketing Science*, 43, 115–135 (2015).
16. Innocent Musonda, Erastus Mwanaumo, Adetayo Onososen, Retsepile Kalaoane. *Development and Investment in Infrastructure in Developing Countries: A 10-Year Reflection*. CRC Press, 2024.
17. Joanna Paliszkievicz, Marta Mendel, Charles J. Priolo, Trang Nguyen. *Trust and Human Resource Management: Navigating Human Capital in the Age of Transformation*. Routledge, 2026.
18. K. C. Tan, V. R. Kannan, R. Narasimhan. The impact of operations capability on firm performance. *International Journal of Production Research* (2007).
19. Kasneci, E., Sessler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Kasneci, G. ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences*, 103, 102274 (2023).
20. Krishna Koppa, Manita D. Shah, Srimantoora S. Appadoo. *Empowering Inclusive Innovation: Shaping Sustainable Business Ecosystems*. CRC Press, 2026.
21. Li, H., Zhang, Y., Sun, Q. AI competency frameworks in higher education: A multidimensional perspective. *Computers & Education*, 198, 104789 (2026).
22. Martín-Martín, A., Thelwall, M., Orduna-Malea, E., Delgado López-Cózar, E. Google Scholar, Web of Science, and Scopus: A systematic comparison of citations in 252 subject categories. *Journal of Informetrics*, 15(1), 101104 (2021).
23. Mongeon, P., Paul-Hus, A. The journal coverage of Web of Science and Scopus: A comparative analysis. *Scientometrics*, 106, 213–228 (2016).
24. N A, Nayak K.M., Maradi M.M.M., Jain U., Divyashree M. Reconceptualizing instructor roles and institutional readiness in the AI era: Stakeholder perspectives on Gen Z competency development in higher education. *Asian Education and Development Studies*, Ahead-of-Print (2026).
<https://doi.org/10.1108/AEDS-01-2026-0046>
25. Nonaka, I. A dynamic theory of organizational knowledge creation. *Organization Science*, 5(1), 14–37 (1994).
26. Nunnally, J.C., Bernstein, I.H. *Psychometric Theory* (3rd ed.). McGraw-Hill, New York (1994).

27. OECD. *Digital Education Outlook 2026: Artificial Intelligence and the Future of Learning*. OECD Publishing, Paris (2026).
28. Pavlou, P.A., Fygenon, M. Understanding and predicting electronic commerce adoption. *MIS Quarterly*, 30(1), 115–143 (2006).
29. Peters, M.A., Zhu, X., Jandrčić, P. Artificial intelligence and knowledge production: Future directions in higher education. *Educational Philosophy and Theory* (2024).
30. Podsakoff, P.M., MacKenzie, S.B., Lee, J.Y., Podsakoff, N.P. Common method biases in behavioral research: A critical review. *Journal of Applied Psychology*, 88(5), 879–903 (2003).
31. Porter, A.L., Rafols, I. Is science becoming more interdisciplinary? *Scientometrics*, 81, 719–745 (2009).
32. Pranjall Jain, Pooja Jain, Anju Jain, Pawan Kumar. *AI in Public Policy and Business: Strategies, Ethics, and Impact*. Routledge, 2026.
33. Rafols, I., Meyer, M. Diversity and network coherence as indicators of interdisciplinarity. *Scientometrics*, 82, 263–287 (2010).
34. Stirling, A. A general framework for analyzing diversity in science and technology. *Journal of the Royal Society Interface*, 4(15), 707–719 (2007).
35. Tarafdar, M., Pullins, E.B., Ragu-Nathan, T.S. Technostress: Negative effect on performance. *Journal of Management Information Systems*, 24(1), 301–328 (2007).
36. Tennant, J.P. Web of Science and Scopus are not global databases of knowledge. *European Science Editing*, 46, e51987 (2020).
37. Venkatesh, V., Morris, M.G., Davis, G.B., Davis, F.D. User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425–478 (2003).
38. Wang, Y., Li, X., Chen, Z. Generative AI and knowledge integration in academic research: Emerging perspectives. *Journal of Academic Research*, 18(2), 145–162 (2026).
39. Xuhong Nan, Linmei Tang, Xue Fang, Xinlei Yang, Yu Kang. “Application of multimodal ultrasound in the biomechanical evaluation of carotid intima-media thickness in type 2 diabetes mellitus: A focus on subclinical vascular changes.” *Frontiers in Endocrinology*, 2026.
40. Zhai, X. ChatGPT for scientific writing: A study on productivity, efficiency, and user perceptions. *Education and Information Technologies*, 28, 1–17 (2023).
41. Zhang, T., Liu, W., Chen, Y. Measuring generative AI competency in academic environments: Scale development and validation. *Education and Information Technologies* (2026).

Open Access This chapter is licensed under the terms of the Creative Commons Attribution-NonCommercial 4.0 International License (<http://creativecommons.org/licenses/by-nc/4.0/>), which permits any noncommercial use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons license and indicate if changes were made.

The images or other third party material in this chapter are included in the chapter's Creative Commons license, unless indicated otherwise in a credit line to the material. If material is not included in the chapter's Creative Commons license and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder.

