Self-Directed Research Learning as a Mediator between Artificial Intelligence Utilisation and Research Productivity: A Hierarchical Regression Approach

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Abstract
This study examined how artificial intelligence (AI) utilisation and self-directed learning (SDRL) influenced research productivity among postgraduate students in public universities in Cross River State, Nigeria. A predictive correlational design was adopted to address four research questions. The population comprised 6,522 postgraduate students from two universities, and a sample of 450 was drawn using stratified random sampling to ensure fair representation across gender, degree levels, and age groups. Data were collected using a validated questionnaire that measured AI utilisation, SDRL, and research productivity, with high internal reliability ($\alpha > .80$). Data were analysed using simple and hierarchical regression models. Findings revealed that AI utilisation significantly predicted SDRL ($\beta = .32$, $p < .001$) and research productivity ($\beta = .23$, $p < .001$). SDRL exerted a stronger influence on research productivity ($\beta = .51$, $p < .001$) and fully mediated the relationship between AI utilisation and productivity. The study concluded that AI tools contribute to higher research productivity mainly by fostering independent learning habits and motivation for self-directed inquiry. It was recommended that postgraduate curricula incorporate AI literacy, mentorship, and digital learning environments that encourage autonomy and sustained scholarly engagement.

Keywords: Postgraduate Education, research engagement, Learning Autonomy, Digital Literacy, Higher Education

Introduction

Postgraduate education places a strong emphasis on developing research skills and scholarly output. In many Nigerian universities, however, postgraduate students face challenges such as weak training, limited mentorship, and infrastructure gaps that impede research progress (Owan et al., 2025). For example, previous work shows that students in Nigerian universities frequently report difficulties with literature review, study design, and data analysis during their research training (Undelikwo et al., 2022; Suleiman, 2025). These deficits are made worse by a shortage of experienced instructors and collaborative opportunities.

At the same time, advances in artificial intelligence (AI) are changing how research is done. Large language models like ChatGPT-4.1 offer automated support for writing, literature search, and data analysis (Ofem et al., 2025). This technology makes AI an increasingly common tool for postgraduate research. It has been noted that AI tools can transform how students learn and offer new research opportunities from home (Owan et al., 2023). By easing routine tasks, AI has the potential to supplement traditional research methods. Self-directed research learning (SDRL) occurs when students work independently to build research knowledge and skills. SDRL includes tasks such as formulating questions, choosing methods, analysing data and interpreting results. In practice, it means learners set their own goals and seek information on their own initiative. The literature suggests that more self-directed students tend to have better skills in research planning and execution (Owan et al., 2025). AI tools can support SDRL by providing tutorials, feedback and content generation, thereby improving research efficiency and precision.

Research productivity is typically defined as tangible research outputs, such as published papers, conference presentations and completed projects (Igiri et al., 2021). It reflects both the quantity and quality of knowledge students produce (Okon et al., 2022). In a

Nigerian context, factors affecting productivity include access to resources, digital skills, and institutional support (Chuktu et al., 2023; Owan, Ameh et al., 2024). For postgraduate students, productivity can be enhanced by better training in research methods and tools. For instance, studies have shown that using technological tools (such as citation managers and data analysis software) is associated with higher productivity among graduate students (Owan, Agama et al., 2024). One recent study in Nigeria found that the effective use of technology tools significantly improved students' writing accuracy and analytical capabilities, leading to more publications (Igiri et al., 2021).

Given these ideas, a key question is how the use of AI and SDRL relates to productivity. AI use might directly increase productivity by saving time (as one experiment with ChatGPT showed a 40% time reduction and 18% better output quality on writing tasks (Noy & Zhang, 2023). Alternatively, AI may work indirectly, as students who use AI may become more self-directed, and that increased autonomy then leads to better outputs. Indeed, previous work suggests that although individuals may accept or plan to use AI, such intention alone does not guarantee greater use or learning gains (Zhang et al., 2023). It appears more plausible that the main effect of AI on productivity would run through self-directed learning behaviour. In other words, AI use might promote SDRL (by providing tools and motivation), which then improves productivity.

Postgraduate students in Nigeria, especially in Cross River State, are an important group for studying the use of educational technology because they are actively involved in research and independent learning. Even though artificial intelligence (AI) is becoming more common as a tool to help learning and research, no study has yet explored how AI use, self-directed research learning (SDRL), and research productivity are connected in this setting. This is an important gap, because universities are introducing technology into research, but it is not clear whether AI actually helps students learn better or produce more research. Research shows that simply accepting or planning to use AI does not automatically lead to more use or better learning outcomes (Zhang et al., 2023). Therefore, it is important to study how AI can support independent learning and research productivity. In an attempt to bride this knowledge gap, the present study was conceived to: (1) determine the relationship between AI utilisation and SDRL among postgraduate students; (2) examine the relationship between AI utilisation and research productivity; (3) investigate the relationship between SDRL and research productivity; and (4) assess whether SDRL mediates the relationship between AI utilisation and research productivity among postgraduate students.

Literature review

2.1 AI utilisation and self-directed research learning

Students' willingness to adopt new technology is often framed by models like the Technology Acceptance Model (TAM) (Davis, 1989) and its successors. These models suggest that if students perceive a tool to be easy and useful, they will accept and use it. In the AI context, factors such as perceived usefulness and ease of use help explain AI adoption for learning (Ibrahim et al., 2025). Shahzad et al. (2024) found that awareness and attitudes towards AI strongly influenced students' intentions to use tools such as ChatGPT in higher education. In general, research shows many students are open to using AI for self-study, feeling that it boosts their motivation and confidence when working independently (Owan et al., 2025).

One key outcome of AI utilisation in learning is increased autonomy. Wang and Li (2024) report that when students have positive emotional engagement and confidence in AI tools, their willingness to engage in autonomous learning increases. In their survey of 721 university students, they found that digital self-efficacy was strongly linked to autonomy in learning: students who trusted their tech skills were more eager to learn on their own using AI (Wang & Li, 2024). This suggests that AI tools can bolster learners' readiness to direct their

own study. In research situations, AI-powered platforms (e.g. literature assistants, data analysis tools) can help students pursue knowledge independently, without waiting for instructor guidance (Owan et al., 2025). For example, AI-driven literature search tools and writing assistants can answer research questions on demand, effectively serving as a "virtual mentor" when faculty are unavailable (Bai & Stede, 2023).

Nonetheless, mere exposure to AI is not enough. Owan et al. (2025) noted that acceptance of AI often exceeds actual use: in their study, acceptance only weakly predicted real AI use. This implies that simply being aware of the benefits of AI does not ensure that students will engage deeply in self-directed learning. Instead, the usage of AI likely depends on students' active learning behaviours. In practice, this means that encouraging AI adoption should go hand in hand with encouraging self-directed learning strategies. In sum, the literature indicates that AI tools can support autonomous learning if students are motivated and digitally literate (Wang & Li, 2024). For our first objective, we expect that in CRS, students who report higher AI usage will also show higher SDRL.

2.2 AI utilisation and research productivity

While research on AI use for learning has grown, studies on the effect of AI on actual research output are still emerging. However, we can draw on related findings about technology and productivity. One large-scale experiment by Noy and Zhang (2023) showed that generative AI (ChatGPT) dramatically boosts productivity on writing tasks for professionals: participants with ChatGPT finished 40% faster and produced work rated 18% higher in quality. This suggests that AI can help users complete complex cognitive tasks more efficiently. If students similarly apply AI to research tasks, we might expect faster literature reviews or higher-quality drafts, potentially leading to more or better outputs over time.

In academic settings, research productivity is often aided by specialised tools. A recent Nigerian study found strong positive correlations between the use of digital research tools and student output. Postgraduate students who frequently used citation managers, data analysis software, and grammar checkers had much higher research productivity (Igiri et al., 2021). These tools help automate routine parts of research writing (formatting references, running statistics, polishing language), which frees students to focus on analysis and interpretation. Another study concluded that effective use of technological tools enhances productivity by improving reference accuracy, analytical capability and writing quality (Ramadhan et al., 2024).

AI tools extend this trend by automating even more complex tasks, such as AI-driven literature summarisation, automated data cleaning, and hypothesis generation. Owan et al. (2023) note that advanced AI could greatly ease information search and retrieval for research. Thus, greater AI use may directly translate to higher productivity by saving time and generating better outputs. On the other hand, if students use AI without learning, the productivity gain might be limited. Given existing evidence, we hypothesise a positive link between AI utilisation and research productivity (our second objective). We expect that students reporting high AI usage will, on average, score higher on productivity measures, mirroring the positive associations seen with other research tools.

2.3 Self-directed research learning and research productivity

Self-directed learning is linked to motivation and skill development, which are key to academic achievement. Students who take charge of their learning tend to set goals, seek resources, and monitor their progress. In theory, these habits should lead to better research outcomes. For example, knowledge of research methods and critical thinking developed through self-directed study could help students design stronger projects and produce more publishable results (Owan et al., 2025). While direct studies on SDRL and productivity are scarce, related

evidence suggests a connection. Nigerian scholars report that postgraduate researchers with better training and mentorship produce more scholarly work (Igiri et al., 2021). Training programmes often teach the skills involved in SDRL (such as goal-setting and information-seeking), suggesting that students who actively engage in such learning do better.

Moreover, when students develop their own research strategies, they may overcome the barriers others face. Indeed, a Nigerian survey found that lack of specialised skills and inability to collaborate hinder productivity (Oluwasanu et al., 2019). A student practising SDRL might proactively acquire those skills or seek opportunities for collaboration (Owan et al., 2025). Thus, we anticipate that higher SDRL will be associated with greater research productivity among postgraduates. Specifically, we expect a significant positive regression effect of SDRL on productivity (our third objective), consistent with the idea that more autonomous learners generate more academic output.

2.4 Mediating role of self-directed research learning

The above relationships suggest a possible mediation: AI utilisation might influence productivity primarily through its effect on SDRL. In other words, students who use AI tools may become more self-directed learners, and this increased autonomy leads to higher output. Such mediation is plausible given Owan et al.'s (2025) finding that AI acceptance alone had little direct effect on its use for SDRL. We surmise that any productivity gains from AI stem from its use encouraging students to explore, learn, and solve problems independently. For instance, a student using AI may feel empowered to tackle complex analyses on their own, thereby engaging in more SDRL, which in turn yields more research outputs.

Given this logic, we plan to test a hierarchical regression: first entering AI utilisation to predict productivity, then adding SDRL to assess whether the AI effect remains. If SDRL is truly mediating, the AI coefficient should drop substantially when SDRL is included. Prior work on technology acceptance suggests that user attitudes (such as autonomy) are often the pathway through which tools affect outcomes. Thus, for our fourth objective, we expect that SDRL will mediate the AI–productivity relationship. Showing this would reveal the importance of fostering self-directed learning as the mechanism by which AI tools translate into real academic gains.

Methods

Research design

The study adopted a correlational research design. This design suits investigations that seek to determine the nature and strength of relationships among variables without attempting to manipulate them. The approach allowed us to examine associations among artificial intelligence (AI) utilisation, self-directed research learning (SDRL) and research productivity among postgraduate students in public universities in Cross River State. The study addressed four research questions and objectives using survey data and regression procedures appropriate for testing predictive and mediational relations.

Population and sample

The target population comprised all registered postgraduate students at two public universities in Cross River State: University 1 (N = 5,312) and University 2 (N = 1,210), giving a total population of 6,522 postgraduate students. Sample size followed the item-to-respondent ratio rule. The questionnaire comprised 30 substantive items; applying a 1:10 ratio produced a baseline sample requirement of 300 respondents. To allow for attrition, non-response and unusable questionnaires, the baseline was increased by 50 per cent, yielding a planned sample of 450 participants. Proportional allocation of the 450 places to each institution resulted in approximately 367 places for university 1 and 83 places for university 2, reflecting each university’s share of the population.

Sampling technique

We used stratified random sampling to ensure proportional representation across institutions, gender, age groups, and degree level (master's versus doctoral). The registrar's office at each university provided an up-to-date sampling frame listing registered postgraduate students with information on gender, age band and programme. First, the sampling frame was divided into two strata by institution. Within each institutional stratum, we created sub-strata for degree level, gender and age band (e.g. 25–29, 30–34, 35–39, 40+). We computed the required number of respondents for each sub-stratum by proportional allocation (stratum population/total population × 450). Then we selected individuals from each sub-stratum using a computerised random number generator. This procedure ensured that the final sample reflected the population distribution on the key demographic variables named above.

Instrumentation

Data were collected using a structured, self-administered questionnaire comprising 30 items across three scales: AI utilisation (8 items), self-directed research learning (SDRL; 10 items) and research productivity (12 items). Items for AI utilisation focused on frequency and purpose of AI use in research tasks (e.g. information retrieval, draft generation, data analysis). SDRL items assessed goal setting, resource seeking, planning and self-monitoring in research learning. Research productivity items captured tangible outputs and activities (e.g. number of manuscripts submitted, conference presentations, completed proposals) and perceptions of recent research output. Respondents rated AI and SDRL items on a four-point Likert scale (1 = strongly disagree to 4 = strongly agree or 1 = never to 4 = always, as appropriate). Productivity items combined objective counts and ordinal response items; these were standardised and aggregated into a composite productivity index for regression analyses.

Validity and reliability

Content validity was established through expert review. A panel of five senior academics with postgraduate supervision experience examined the draft instrument for clarity, relevance and representativeness. Each item was rated for relevance and clarity, and a Content Validity Index (CVI) was computed at the item and scale levels; items with an I-CVI below 0.78 were revised or replaced. A small pilot study (n = 30 postgraduate students drawn from a neighbouring institution not included in the main sample) assessed face validity and initial psychometric properties. Internal consistency reliability for each scale was estimated using Cronbach's alpha. The pilot produced satisfactory reliability coefficients ($\alpha > 0.80$) for the three scales; in the main study, the instrument again demonstrated high internal consistency (Cronbach's alpha > 0.80 for AI utilisation, SDRL and the productivity index).

Data collection procedure

After obtaining institutional permissions and ethical clearance, the sampling frames were received from the registrars. Selected students received an invitation email containing an information sheet, consent form and a link to the online questionnaire. The information sheet explained the study purpose, voluntary participation, anonymity and data use. Where online access proved difficult, printed copies were made available through departmental offices and collection points agreed with programme coordinators. Data collection took place over four weeks. Reminders were sent after 1 and 2 weeks to improve the response rate. Completed questionnaires were screened for completeness and consistency; questionnaires with extensive missing data were excluded from analysis.

Ethical considerations

The study secured approval from the institutional ethics committee prior to data collection. All participants provided informed consent and were free to withdraw at any time without penalty. Questionnaires contained no

personal identifiers. Data were stored on encrypted drives, and access was limited to members of the research team. Results are presented in aggregated form to preserve confidentiality. The research conformed to principles of beneficence, respect and justice as set out in institutional research ethics guidelines.

Data analysis

Analyses were performed using SPSS version 27 software. We first calculated descriptive statistics (frequencies, means, standard deviations) and inspected the distributions of the variables for normality. Bivariate Pearson correlation analysis was performed to examine initial associations among AI utilisation, SDRL and research productivity. For inferential analyses, we used linear regression models. Objectives 1–3 were treated with simple linear regressions: (1) SDRL regressed on AI utilisation, (2) productivity regressed on AI utilisation, and (3) productivity regressed on SDRL. For Objective 4, a mediation analysis was conducted to examine the extent to which SDRL serves as a mediator in the relationship between AI utilisation and research productivity, using a hierarchical regression approach. In Step 1, productivity was regressed on AI utilisation; in Step 2, SDRL was entered, and the change in the AI coefficient and R^2 were examined to assess mediation. Regression assumptions (linearity, homoscedasticity, normality of residuals and absence of multicollinearity) were checked; variance inflation factors (VIF) and Durbin-Watson statistics were reported where appropriate. Statistical significance was set at $\alpha = 0.05$, and effect sizes were reported alongside p-values to aid interpretation.

Results

Relationship between AI utilisation and self-directed research learning

We first examined whether AI utilisation predicts SDRL using simple linear regression (Table 1). AI utilisation was the predictor, and SDRL the outcome. The regression model was significant ($F(1,298) = 35.2$, $p < .001$). AI utilisation accounted for about 10.7% of the variance in SDRL ($R^2 = 0.107$). The unstandardised regression coefficient for AI was positive and significant ($B = 0.33$, $p < .001$). In other words, students who reported using AI more frequently also scored higher on self-directed learning. This supports the idea that familiarity with AI tools is associated with stronger self-directed learning behaviours. AI utilisation was a significant predictor of self-directed learning ($\beta = 0.32$, $p < .001$). The positive coefficient indicates a direct relationship: more AI use goes with more SDRL.

Table 1. Simple linear regression of SDRL on AI utilisation (n = 450)

Predictor	B	SE B	β	t	p
(Constant)	–0.13	0.05	–	–2.64	0.009
AI utilisation	0.33	0.06	0.32	5.93	<.001

Relationship between AI utilisation and research productivity

Next, we regressed research productivity on AI utilisation (Table 2). The simple regression was statistically significant ($F(1,298) = 17.1$, $p < .001$), but the effect size was modest ($R^2 = 0.052$). The unstandardised coefficient for AI was positive ($B = 0.254$) and significant ($p < .001$), indicating that greater AI use predicted higher productivity scores. However, only about 5.2% of the variance in productivity was explained by AI alone. AI utilisation positively predicted research productivity ($\beta = 0.23$, $p < .001$), though the effect was weaker than for SDRL. This indicates that students with higher AI engagement tended to have somewhat higher research output. The relatively small R^2 suggests that other factors play a larger role in productivity.

Table 2. Simple linear regression of productivity on AI utilisation (n = 450)

Predictor	B	SE B	β	t	p
(Constant)	–0.15	0.05	–	–2.80	0.005
AI utilisation	0.25	0.06	0.23	4.13	<.001

Relationship between self-directed research learning and research productivity

We then tested the link between SDRL and research productivity. The regression of productivity on SDRL was highly significant ($F(1,298) = 105.1$, $p < .001$) with a substantial $R^2 = 0.261$ (Table 3). SDRL accounted for about 26.1% of the variance in productivity, a much larger effect than AI had. The unstandardised coefficient was also large and significant ($B = 0.565$, $p < .001$). This means that students who rated themselves higher on self-directed learning also reported notably higher research productivity. SDRL positively predicted productivity ($\beta = 0.51$, $p < .001$). The strong association suggests that autonomous learners tend to produce more research output.

Table 3. Simple linear regression of productivity on SDRL (n = 450)

Predictor	B	SE B	β	t	p
(Constant)	–0.08	0.03	–	–2.58	0.010
SDRL	0.56	0.05	0.51	10.26	<.001

Mediation of SDRL on the AI–productivity relationship

Finally, we tested whether SDRL mediates the AI–productivity link using hierarchical regression. In Model 1 (AI only), AI utilisation predicted productivity (as in Table 3), $R^2 = 0.052$. In Model 2 (AI + SDRL), the overall R^2 jumped to ≈ 0.265 (Table 5). Notably, once SDRL was included, the coefficient for AI utilisation dropped to near zero and became non-significant ($\beta = 0.08$, $p = 0.195$). Meanwhile, SDRL remained a strong predictor ($\beta = 0.54$, $p < .001$). The change in the coefficient of AI utilisation indicates full mediation. In Step 1, AI had a significant effect on productivity, but in Step 2, its effect disappeared after accounting for SDRL. The large increase in R^2 (from 0.052 to 0.265) shows that SDRL explains much of the variance. In summary, the direct effect of AI on productivity was not significant when SDRL was included, confirming that SDRL mediates the relationship. This suggests that the influence of AI on research productivity operates through self-directed learning. That is, AI tools help students become more autonomous learners, and these learning behaviours drive productivity.

Table 4. Hierarchical regression predicting productivity (n = 450)

Step	Predictor	B	SE B	β	t	p	R^2
1	AI utilisation	0.25	0.06	0.23	4.13	<.001	0.052
	(Constant)	–0.15	0.05	–	–2.80	0.005	
2	AI utilisation	0.076	0.059	0.07	1.30	0.195	0.265
	SDRL	0.54	0.058	0.54	9.29	<.001	
	(Constant)	–0.082	0.056	–	–1.47	0.142	

Discussion

This study examined how the use of artificial intelligence (AI) affects self-directed research learning (SDRL) and research productivity among postgraduate students in Cross River State. The first finding shows that students who use AI tools more often are better at directing their own learning. This means that the use of AI encourages students to study and solve research problems on their own without

relying too much on lecturers. This aligns with the Technology Acceptance Model (Davis, 1989), which posits that people are more likely to use a tool when they find it useful and easy to use. When students see that AI tools can help them write, search for information, or analyse data quickly, they become more willing to use these tools to learn independently. Earlier studies support this idea. For example, Wang and Li (2024) found that students who feel confident using digital tools are more willing to learn independently. Owan et al. (2025) also reported that students who regularly use AI tools become more active and responsible learners. In the Nigerian setting, where many postgraduate students face challenges such as poor supervision and limited access to research materials, AI tools can help fill this gap. By using AI applications for literature reviews, summarising, and idea generation, students can work more independently and keep their studies moving forward even when lecturers are unavailable.

The second finding shows that students who use AI tools tend to have higher research productivity, although the effect is not very strong. This means that AI tools help students work more efficiently in their research, but do not guarantee high productivity on their own. This aligns with studies by Noy and Zhang (2023) and Ramadhan et al. (2024), which found that AI tools can accelerate work and improve writing quality. Similarly, Igiri et al. (2021) found that students who use digital research tools such as citation managers and data analysis software produce better academic work. In Nigeria, many students struggle to make progress in their research due to inadequate facilities and limited mentoring. AI can help solve some of these problems by saving time and simplifying complex tasks. However, the modest influence of AI suggests that students still need strong research habits and motivation to fully benefit from these tools. This means that universities should not only teach students how to use AI but also help them build discipline and research skills. AI should be seen as a learning assistant, not a replacement for human effort.

The third major finding shows that self-directed learning has a strong effect on research productivity. Students who plan their own learning, set goals, and actively seek information tend to produce more research. This supports earlier findings by Igiri et al. (2021) and Owan et al. (2025), who noted that postgraduate students with strong self-management skills are more productive and complete their projects faster. The result also supports Knowles' (1975) view that independent learning leads to better academic outcomes. In the Nigerian context, where many students face inconsistent supervision, the ability to learn independently is crucial. Students who rely less on constant guidance are more likely to overcome challenges such as a lack of access to journals or research software. Therefore, universities should create programmes that build students' confidence and independence. Workshops on goal setting, research organisation, and time management can help students strengthen their self-directed learning abilities and increase their productivity.

The final finding shows that SDRL explains how AI affects research productivity. When SDRL is considered, AI use no longer directly affects productivity. This means AI improves productivity only when it helps students learn independently. In other words, AI tools increase productivity not by doing the work for students but by encouraging them to learn and manage their research more effectively. This result supports Owan et al. (2025), who found that AI produces real academic benefits only when students use it to support their learning habits. It also aligns with the Technology Acceptance Model, in which the usefulness of a tool influences user behaviour, which in turn leads to improved results. The finding suggests that for students to gain from AI, they must use it as a learning partner rather than just a source of quick answers. Universities and lecturers should guide students on responsible and effective AI

use so that it builds their skills rather than weakens them.

Generally, the findings show that AI helps postgraduate students become more independent learners, and this independence is what leads to better research output. The results form a clear pattern: students first use AI to make learning easier, this use increases their confidence and autonomy, and these qualities then lead to more productive research. For Nigerian universities, this has important implications. Schools can improve student productivity by teaching both AI skills and self-directed learning habits. Policies that promote responsible AI use can help postgraduate students work more efficiently, complete their projects on time, and publish more papers. Lecturers can also use AI to guide students and provide quicker feedback on research tasks. The weaker direct link between AI and productivity is also important. It shows that technology alone does not make students productive. Real improvement happens when the use of technology goes hand in hand with strong motivation and a disciplined approach to learning. This challenges the belief that AI automatically makes research easier or faster. It reminds educators that human effort, curiosity, and persistence remain at the centre of learning.

Conclusion

The study concludes that artificial intelligence improves postgraduate research outcomes mainly by strengthening self-directed learning. Students who use AI tools actively develop greater independence, confidence, and initiative in managing their research tasks. This independence, rather than reliance on technology alone, leads to higher productivity. The findings confirm the Technology Acceptance Model's expectations and support earlier research showing that technological tools are most effective when paired with strong learning habits. Within Nigerian universities, where supervision and resources are often limited, AI can serve as a valuable support for students who take responsibility for their learning. However, training is essential to ensure that the use of AI promotes genuine understanding rather than dependence. Universities should therefore combine AI literacy programmes with activities that encourage planning, critical thinking, and autonomous learning. This approach will help students use AI responsibly while improving the overall quality and quantity of postgraduate research output.

Recommendations

1. Universities should include structured training on the responsible and effective use of AI tools in postgraduate orientation and research methodology courses. This will help students understand how to use AI to support, rather than replace, their learning and research processes.
2. Faculties should organise workshops and mentorship sessions that build students' ability to plan, manage, and evaluate their own research work. Activities should focus on goal setting, time management, critical thinking, and information-seeking strategies.
3. Supervisors should guide students to apply AI tools for idea generation, literature review, and data analysis while maintaining academic integrity and originality in their work.
4. University management should invest in licensed AI-based academic platforms and ensure steady internet access to enable effective use of these tools for research.
5. Institutions should create clear policies that encourage innovation through AI while preventing misuse, plagiarism, or overdependence. Such policies will ensure that AI strengthens both research quality and student autonomy.

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