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Effect of Artificial Intelligence Usage on Problem-Solving Ability of Academic Staff in Universities: Evidence from Lead City University, Ibadan

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ABSTRACT

The use of artificial intelligence is increasingly pervading the workings of the academic environment, but empirical studies on its impact on cognitive ability of university lecturers in higher education systems in developing countries is scant. This gave birth to why the study explores the influence of artificial intelligence usage intensity and artificial intelligence competence on the problem-solving ability of academics at Lead City University, Ibadan. Grounded in a quantitative cross-sectional research design, a sample of 140 academic staff was surveyed using a questionnaire, and multiple regression analysis was employed to assess the impact of artificial intelligence usage intensity and artificial intelligence competence on problem-solving ability. The findings showed that the overall model was significant ($R = .455$, $R^2 = .207$, Adjusted $R^2 = .195$, $F(2,137) = 17.866$, $p < .001$) and the predictors explained 20.7 percent of the variance in problem-solving ability. The intensity of artificial intelligence use had a positive, significant effect ($\beta = .372$, $t = 4.553$, $p < .001$) on problem-solving ability, thus confirming the first hypothesis. However, artificial intelligence competence was positively but not significantly related to problem-solving ability ($\beta = .159$, $t = 1.950$, $p = .053$), supporting the rejection of the second hypothesis at the 0.05 level. The study concludes that it is actual use of artificial intelligence technologies, rather than just competence, which is a key explanatory factor for improving academic problem-solving ability. Theoretically, the study enhances socio-technical and technology use theories by placing emphasis on usage intensity. Pragmatically, the study highlights the importance of universities focusing on the systematic integration of artificial intelligence use in academic practices, rather than just training in skill development.

Keywords: Artificial intelligence, Problem-Solving Ability, Usage Intensity, Competence, Lead City

INTRODUCTION

The use of artificial intelligence has increasingly become an integral part of knowledge work, making it a prime field in modern management sciences, organizational behavior and human resource development. In academic environments, where mental work constitutes primary productivity, problem-solving ability continues to be a critical factor in individual and organizational effectiveness. The capacity for problem-solving is an amalgam of cognitive skills including analytical reasoning, adaptive processing and creative synthesis, and it is theorized in cognitive and organizational literature as being a central component of work performance (Basadur, Gelade, and Basadur 2014). The use of artificial intelligence in the workplace adds a new layer to this conversation, given its implications for how people access, process, and integrate information and alternatives to arrive at solutions. From the perspective of cognitive augmentation and the resource-based view, artificial intelligence can be regarded not as a replacement for human cognitive capacity, but rather a resource that enhances or limits cognitive performance based on its use (Raisch and Krakowski, 2021; Brynjolfsson et al., 2022). In this context, two elements of artificial intelligence use have surfaced as being particularly important: usage intensity and competence. Intensity refers to the degree of reliance on artificial intelligence tools, and competence is associated with the level of knowledge and skills in understanding and using AI tools. These dimensions are theoretically connected to problem-solving capability via channels of information processing efficiency, decision support and knowledge recombination (Jarrahi, 2021; Dwivedi et al., 2021).

In high-income economies, empirical research has also started to show that the use of artificial intelligence does not necessarily lead to improved cognitive processes. Research from the US and Europe shows that although interacting more with AI systems can increase task efficiency, it can also lead to cognitive offloading, thus reducing deep cognitive processing when the user is not competent (Raisch & Krakowski, 2021; Wilson & Daugherty, 2022). On the other hand, users with greater AI competence tend to use these tools to exhibit cognitive augmentation, leading to more creative and contextualized outcomes (Davenport et al., 2020; Dellermann et al., 2021). Such results indicate a moderated effect whereby the effect of AI usage intensity depends on the cognitive and technical competence of the user in engaging with the technology. Yet, current research shows varying effect sizes and relationships with some studies reporting positive linear effects, while others report diminishing or even negative returns at elevated levels of usage intensity (Bawack et al., 2022). This suggests theoretical and empirical uncertainties about the interactional effects of AI usage and competence on problem-solving.

Such questions are compounded in emergent and contextual settings, such as in African higher education contexts where digital transformation is occurring at differential rates. Economic, social, and institutional factors including poor technological infrastructure, digital literacy, and conservative attitudes to change impact the way in which artificial intelligence use manifests in this environment, and the expected benefits may not be realized (Mhlanga, 2023; Afolabi et al., 2024). Recent empirical research from Sub-Saharan Africa indicates there is growing awareness and adoption of AI technologies among lecturers but the intensity of the usage varies and is often a shallow form of engagement that does not lead to better cognitive performance (Adeleke et al., 2023; Oke & Fernandes, 2020). Additionally, existing studies within this domain tend to be descriptive in nature, emphasizing rates of adoption and attitudes towards AI, rather than the behavioural and competency aspects that contribute to performance. This has led to a lack of understanding of the role of AI usage intensity and competence on problem solving ability in universities.

These challenges are more evident in the Nigerian higher education system. Institutions are increasingly pressured to improve their research, teaching and international competitiveness, but work within resource-limited contexts that impact how technology is adopted and human capital is developed. Lead City University, Ibadan, is one such transitional institutional environment where the use of digital technologies is growing in academic processes, though there are variations in the patterns of usage and skills. The current research literature provides little understanding of the use of artificial intelligence by academic staff in such environments beyond mere adoption. Moreover, previous research has failed to disaggregate AI usage into intensity measures or to consider competence as an explanatory variable, thus limiting the explanatory power of existing models in relation to cognitive outcomes like problem-solving ability.

In this context, the problem this study seeks to address is the lack of empirical and theoretical understanding of how the intensity of academic staff usage of artificial intelligence and artificial intelligence competence affect their problem-solving ability in contextually-bound university settings. Current studies fail to capture the complexities of the intersection between the behavioural usage of AI and the cognitive skills needed to effectively harness its benefits. A paucity of evidence from the context of Nigerian universities exists, where contextual and institutional influences may play a moderating role. Furthermore, AI usage has been operationalized in a simplistic manner, where the intensity and depth of interaction has usually not been considered, while competence has been understudied as a construct that has a direct impact on cognition.

The current research bridges this gap by proposing a more nuanced understanding of artificial intelligence usage, in particular, intensity of usage and competence as predictors of problem-solving performance in academic staff at Lead City University, Ibadan. In so doing, it helps to clarify ambiguities in the academic literature and broadens empirical understanding to a new context that is underrepresented in high-impact literature. The research provides theoretical as well as practical guidance about how to better harness the power of artificial intelligence to improve cognitive performance in academic institutions in emerging markets.

Research Questions

i. To what extent does artificial intelligence usage intensity influence the problem-solving ability of academic staff in Lead city University?
ii. How does artificial intelligence competence influence the problem-solving ability of academic staff in Lead city University?

LITERATURE REVIEW

The review summarized the major concepts, theoretical and empirical studies on artificial intelligence usage and problem-solving ability in the context of examining how artificial intelligence usage intensity and artificial intelligence competence influence the problem-solving ability of academic staff in Lead city University.

Artificial Intelligence

Artificial intelligence (AI) resides at the intersections of computer science, information systems and organizational cognition, and has transitioned from rule-based symbolic systems to data-driven, adaptive systems based on machine learning and deep learning. Classic definitions position AI as systems that solve tasks needing human intelligence (Russell & Norvig, 2021) while recent work defines it as a socio-technical resource that enhances and amplifies human intelligence within organizational processes (Raisch & Krakowski, 2021; Dwivedi et al., 2021). While there is consensus on AI's learning, predictive and decision-making capabilities, there remains disagreement on its scope and agency. While some restrict AI to predictive analytics, others broaden it to generative and interactive systems that collaborate with users (Brynjolfsson et al., 2022). This research takes a hybrid intelligence view of AI as an adaptive system that augments human intelligence through interaction. This definition is analytically justified as it is consistent with recent findings that value creation occurs through human-AI complementarity. The fundamental dimensions of AI are learning, adaptability, autonomy and interactivity. These dimensions are interrelated, including learning facilitating pattern recognition, adaptability facilitating contextual adaptation, autonomy facilitating task completion and interactivity facilitating user experience. This sets AI apart from automation (mainly deterministic) and analytics (without learning capabilities) (Jarrahi, 2021).

In practice, AI has been measured by variables such as system capabilities, task integration, and interaction density, although it is not consistently measured across different settings (Bawack et al., 2022; Mikalef et al., 2021). Much research uses variables such as adoption or perceived usefulness, which do not adequately reflect cognitive engagement. Recent studies focus on capability-based and interaction-based indicators, capturing the integration of AI into processes and decision making. Theoretically, AI has effects via cognitive augmentation, information processing speeds, and decision-making support. Research indicates that AI improves analysis and problem solving when users have the skills to interpret and integrate AI, but potential issues include cognitive displacement and over-reliance when AI is poorly integrated (Raisch & Krakowski, 2021). These impacts are moderated by the context, including digital literacy, organizational support and task complexity. In academia, the importance of AI is especially evident given the nature of academic pursuits: complex problem-solving, information synthesis and knowledge generation. Here, AI serves as a strategic resource in enhancing intellectual productivity, albeit with effects that depend on integration effectiveness. This makes AI more than just a tool but a key factor in cognitive and performance outcomes in intellectual work.

Artificial Intelligence Usage Intensity

Artificial intelligence usage intensity is part of the broader construct of technology use, human-computer interaction and computer-based work engagement, where it is a behavioural extension of the adoption of artificial intelligence in cognitive and work processes. Artificial intelligence is seen as thinking computers that perform cognitive-like processes of learning, reasoning and decision-making (Russell & Norvig, 2021; Davenport et al., 2020). More recently AI is being thought of as a socio-technical and augmentative system in work (Raisch &

Krakowski, 2021; Dwivedi et al., 2021). To this end, artificial intelligence usage intensity refers to the level of individuals' interaction with AI for work tasks in terms of the intensity, repetition and integration of interactions. Whereas AI adoption is concerned with acceptance and diffusion, and AI utilization with usage, usage intensity emphasizes the repetition and integration of interaction, and the extent of its use in primary task performance. This is an important point, as it makes the difference between shallow and deep cognitive and work process integration.

Research opinions converge on usage intensity as multi-dimensional in nature, typically comprising frequency, task variety and duration of usage (Mikalef et al., 2021; Bawack et al., 2022). But there remains a lack of consensus on its measurement and conceptualization. Some studies consider intensity as a uni-dimensional frequency construct, whereas others consider it in terms of behavioural intensity and/or centrality of usage, leading to different operationalizations of intensity. These challenges are more pronounced in knowledge-intensive environments such as academia, where AI application in research, teaching and research management are diverse and differ in terms of cognitive intensity. Prior empirical research has tended to rely on measures of self-reported scales, which can be prone to bias and do not capture system use. Recent research calls for a more sophisticated conceptualization using a range of indicators that reflect both behavioural and cognitive elements of using AI (Raisch & Krakowski, 2021). The research overcomes these limitations by conceptualizing intensity of AI usage as a multi-dimensional concept, which comprises frequency, embeddedness and reliance. This refined conceptualization provides a better basis for studying its effects on academic staff's problem-solving effectiveness.

Artificial Intelligence Competence

AI competence can be positioned in the broader theoretical spaces of digital competence, human-technology interaction and knowledge-based human capital, as a new branch of digital literacy in the context of algorithmically mediated environments. Broadly, AI competence is an individual's holistic ability to comprehend, critique and leverage artificial intelligence systems to complete tasks and make decisions (Ng et al., 2021; Long & Magerko, 2020). While early conceptions of digital competence focused on information access and fundamental technological skills, current work highlights a shift towards higher-level skills such as algorithmic literacy, interpretive judgment and evaluative reasoning of AI-generated results (Raisch & Krakowski, 2021; Dwivedi et al., 2021). Literature shows consensus that AI competence is a multi-faceted construct including technical knowledge, skill and cognitive engagement. But there is disagreement over the scope. Some view it as a narrow technical skill in the use of AI, while others view it more broadly with strategic, ethical and reflective aspects of AI usage (Long & Magerko, 2020; Kong et al., 2023). This research uses the broader interpretive approach, defining AI competence as a cognitive and behavioural capability to use AI systems, question them and apply them to problem solving. This sets it apart from digital literacy (technology use generally) and AI usage intensity (intensity of use).

In practice, AI competence has been measured by self-reported scales of proficiency, scenario-based tests and capability indices that assess knowledge of AI functions, confidence in using the technologies and evaluative judgement (Bawack et al., 2022; Mikalef et al., 2021). But inconsistencies remain in differentiating between competence perception and capability. Researchers often conflate familiarity with usage and competence, thus compromising construct validity. Moreover, there are contextual constraints in higher education environments where AI competence varies between fields and is impacted by university support systems. Recent studies stress the importance of competence in mediating the impact of AI usage on performance, including problem-solving, through its influence on the ability to effectively apply insights gained from AI (Raisch & Krakowski, 2021). This research builds on previous research by defining AI competence as a trinity of technical knowledge, skills in applying AI and evaluative judgement. This holistic perspective enhances its theoretical underpinning in relation to its impact on problem-solving ability for academic staff.

Problem Solving Ability

The ability to solve problems is theorized in cognitive psychology, organizational behaviour and educational performance as the capacity to identify problems, assess alternatives and decide and act to solve problems in the context of varying levels of uncertainty (Mumford et al., 2021; Jonassen, 2020). Early cognitive theories emphasize problem-solving as a categorizable process that involves problem representation, solution strategy choice and solution implementation and evaluation, while recent theories extend this to include adaptive and metacognitive problem-solving in technological environments (Funke et al., 2020). While there appears to be consensus about the higher-order nature of problem-solving ability, debate continues to exist about whether it is a trait, skill or performance. This study uses a dynamic capability approach and conceptualizes problem-solving ability as an adaptive cognitive performance construct shaped by individual capacities and environmental resources, particularly artificial intelligence systems. This distinguishing it from other phenomena such as decision-making (choice-making) and critical thinking (evaluative reasoning that may not require action).

There have been many empirical approaches to defining problem-solving ability. In educational and organizational settings, it has been assessed via scenario-based tests, self-report measures of cognitive abilities and performance tasks, which assess analytical reasoning and solution correctness (Jonassen, 2020; Mhlanga, 2023). However, there is a need for unifying measurement, particularly in distinguishing between perceived problem solving and problem-solving performance. African studies, including in Nigeria, have shown that the problem-solving ability of lecturers is greatly influenced by technology literacy, institutional environment and cognitive technologies, but empirical models do not always integrate emerging technologies such as artificial intelligence (Adeleke et al., 2023; Ojo & Olaleye, 2022). This is a theoretical shortfall in research on the impact of technologically facilitated environments on cognition. Moreover, existing models rarely consider integration of human cognition with AI-facilitated cognition in problem-solving. This study intends to address these gaps by conceptualizing problem-solving ability as a technology-enabled adaptive cognitive process involving analytical reasoning, solution-building and evaluation processes. This approach provides more comprehensive theoretical support for exploring the effects of artificial intelligence intensity of use and competence on cognitive performance in higher education.

THEORETICAL FRAMEWORK

This study draws on Cognitive Load Theory (CLT) and Cognitive Augmentation research from the field of human–computer interaction. Cognitive Load Theory, developed by Sweller (1988), describes cognitive processing with a limited capacity working memory and an unlimited capacity long-term memory. This theory presumes that learning and performance are enhanced when extraneous cognitive load is reduced and germane cognitive resources are effectively distributed to conceptualize and resolve problems. Recent CLT developments have considered digital learning environments, focusing on the role of technology-mediated tools in adding to cognitive load or facilitating efficient cognitive processing based on tool design and user expertise (Paas & van Merriënboer, 2020; Kalyuga, 2021). Similarly, the cognitive augmentation theory proposed by Raisch and Krakowski (2021) looks at artificial intelligence as an external cognitive agent that augments human cognitive power. From this integrated theoretical perspective, the intensity of artificial intelligence usage and artificial intelligence competence emerge as key factors affecting cognitive resource allocation in problem-solving activities. Excessive usage intensity without adequate competence might potentially increase extraneous cognitive load, whereas competent use of AI systems can alleviate cognitive load and improve the analytical structuring of problems. This approach complements the study's aim to investigate the impact of AI usage intensity and competence on problem-solving capabilities of university academic staff.

However, while Cognitive Load Theory offers a powerful explanation of cognitive constraints, it has limitations in the context of AI-rich organizational environments. Original CLT research was conducted in controlled teaching environments and may not be adequate to explain interactive, dynamic, and co-adaptive human–AI environments of contemporary academic work. It also fails to explicitly theorize the impact of external intelligent agents that interactively influence cognitive processes. Likewise, cognitive augmentation theory provides a wide lens, but is conceptually immature in detailing observable processes that connect AI use to performance. Despite under-specifications, the combined theories offer a sound analytical framework for this research, explaining the role of AI competence on the effects of cognitive load and the impact of usage intensity on cognitive distribution during problem solving. Recent empirical research backs this integrated perspective, revealing that AI-rich environments dynamically redistribute cognitive resources and decision-making performance based on users' ability and level of engagement (Dwivedi et al., 2021; Mikalef et al., 2021). Thus, the integrated theoretical approach provides a conceptual foundation for predicting problem-solving performance differences, warranting the conceptualization of the relationships between AI engagement intensity, AI competence and problem-solving outcomes in academic contexts.

Empirical Review

Mah and Groß (2024) offered one of the more rigorous recent studies of artificial intelligence (AI) use by university staff, using structured surveys and latent class analysis to study 122 staff members at German universities. They demonstrated AI self-efficacy was an important discriminator in usage patterns, with higher self-evaluated staff using AI more generally for preparing teaching, processing information and supporting decision making. Crucially, respondents associated AI usage with increased efficiency and data access for teaching-related decisions, which are both associated with enhanced problem-solving. The study uses multivariate profiling and construct measurement, but has limitations in causal inference and generalization due to self-reported usage and convenience sampling. However, it confirms an empirical regularity that staff AI competence leads to functional and cognitive use in universities.

In a study of perceptions of AI use in assessment and feedback among 35 academic staff and 282 students in Vietnamese and Singaporean universities, Roe, Perkins, and Ruelle (2024) used a survey approach and thematic analysis. Staff perceived AI-assisted feedback as a negative when it substituted for human judgement, but more positively when AI supported lecturer expertise. This is an important empirical finding: AI seems to support problem solving when it is used to inform decision-making rather than replace expert thinking. The research design enhanced interpretation but the faculty subsample was too small for statistical inference. Comparatively, the study also identified low AI awareness, implying that the impact of AI usage is contingent on digital maturity and culture. These insights suggest that problem-solving outcomes are not inherent, but depend on how AI is integrated into teaching and learning processes.

Using a mixed-method approach, Chen et al. (2026) examined attitudes towards generative AI among 61 staff and 37 students in a university faculty in Finland. Staff expressed high levels of interest in using AI for programming, information searching, writing and analysis, suggesting AI can lighten cognitive load and enable more time for problem solving. But issues such as quality, privacy and academic integrity were also present. This is a common theme in recent findings: AI boosts analytical processing while increasing governance and verification challenges. The study is significant because it considers the disciplinary context of AI's usefulness: technical units might see more distinct advantages than other units. But its focus on a single university restricts its generalizability, particularly to institutions in developing countries with different technical constraints.

Research in larger academic workplaces also corroborates the positive albeit qualified impact of AI use on problem-solving skills. De Silva et al. (2026) conducted focus groups with 29 STEM lecturers at a large U.S. university, and found that teachers used generative AI for content creation, curriculum and course design, coding support, and assessment design. They reported increased speed and ideation (implied to be exploratory and creative problem solving). But they were concerned about overdependence, diminished student learning, and unreliable results. The qualitative nature of the study allows contextual insights but does not permit calculation of effect sizes or other statistical measures. However, it supports an emerging consensus that AI can support, but not substitute for, human professional judgment, particularly in a knowledge-based academic context.

However, some studies provide counter-evidence that AI use can hinder critical reasoning skills if it becomes passive and unquestioning. In a practical higher education assessment study, Ogunleye et al. (2024) reported generative AI has good subject knowledge, critical reasoning skills and presentation skills, which could allow staff to use it for teaching purposes. But the study concluded unscrupulous use could restrict learning and critical thinking. Likewise, an American Association of Colleges and Universities 2026 survey of lecturers found that many educators perceived AI to have a negative impact on critical thinking and dependence. While studies based on perceptions should be treated with care, they point to a key empirical paradox: AI can help and hinder problem-solving in a moderated manner depending on the amount of use, type of problem and user skill level. This likely implies a non-linear effect not addressed in many studies to date.

Overall, we have reasonably consistent evidence from the empirical studies that academic staff problem-solving can be enhanced through the use of AI, by accelerating information processing, generation of ideas, decision

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support and automation; but the benefits are moderated by AI literacy, trust, governance and responsible use. Current research is largely limited to Europe and North America, with some evidence from Asia, but lacking from African private universities such as in Nigeria. Much of it uses cross-sectional self-rate surveys, with little evidence of causal processes and longitudinal and performance effects. There is also limited evidence specific to particular institutions on the impact of AI on lecturers' problem solving in the workplace (teaching, research, and administration). This justifies the current study on Lead City University, Ibadan, where factors such as infrastructure, digital literacy and culture may significantly moderates the effect of AI usage on problem-solving ability.

METHODOLOGY

This study employed a quantitative research design, suitable for investigating the causal link between the use of artificial intelligence and problem solving among academics. It allowed for objective measurement and testing of postulated relationships in line with standard research in management studies (Hair et al., 2022; Saunders et al., 2021). The study's aim was to gather data from respondents at one particular moment, so a cross-sectional survey design was employed.

The target population was 216 academic staff of Lead City University, Ibadan. The sample size was arrived at with the Taro Yamane formula that gave a statistically significant sample of the population with a 5% margin of error, leading to a sample of 140 respondents. A proportionate stratified random sampling method was adopted to ensure representation of the various academics in the university which improved the representativeness and minimized sampling bias (Etikan and Bala, 2017).

Structured questionnaire was used to gather data, and had closed-ended questions using a five-point Likert scale (strongly disagree to strongly agree) which were adopted from previous studies. The intensity of artificial intelligence use was measured based on items from Dwivedi et al. (2021), while artificial intelligence competence was measured on items from Chatterjee et al. (2021). Problem-solving ability was operationalized based on the scale by He et al. (2021). This scale was slightly modified to suit the academic environment.

Validity and reliability were rigorously assessed. Content validity was established by expert review (academics in management and information systems). Exploratory factor analysis was used to assess construct validity. Reliability was determined via Cronbach's alpha and composite reliability with minimum values of 0.70 as proposed by Hair et al. (2022). A pilot test of 20 lecturers outside the study was used to prepare the instrument.

The Statistical Package for the Social Sciences (SPSS) was used for statistical analysis. Descriptive statistics and multiple regression analysis were used to test the proposed relationships as these are appropriate for testing the predictive impact of independent variables on a dependent variable.

Ethical considerations were adhered to. Informed consent was sought and obtained, and confidentiality and anonymity ensured, as per institutional research ethics requirements.

RESULT AND FINDINGS

Table 1 Demographic Profile of Respondents

S/N	Variable	Category	Frequency (f)	Percentage (%)
1	Gender	Male	82	58.6
		Female	58	41.4
		Total	140	100.0
2	Age	21–30	28	20.0
		31–40	52	37.1
		41–50	36	25.7
		51 and above	24	17.1

3	Academic Qualification	Master's Degree	46	32.9
		PhD	88	62.9
		Others	6	4.3
4	Academic Rank	Assistant Lecturer	18	12.9
		Lecturer II	34	24.3
		Lecturer I	30	21.4
		Senior Lecturer	28	20.0
		Reader	16	11.4
		Professor	14	10.0

Source: Field Survey (2026).

The demographics of the respondents illustrate that age profile is concentrated in 31-40 years (37.1%) and 41-50 years (25.7%), suggesting that the respondents are in active career stages and likely to have exposure to artificial intelligence technologies. The age distribution was in the 31-40 years (37.1%), and 41-50 years (25.7%) categories, suggesting an active working population likely to adopt new technologies. In terms of educational qualification, 62.9% had PhD degrees, suggesting a high research focus which is beneficial for AI adoption. Regarding rank, Lecturer II (24.3%) and Lecturer I (21.4%) were prominent, suggesting that mid-career academics, who are often engaged in teaching and research activities, are the key respondents responsible for AI-based problem-solving.

Descriptive Statistics

Table 2 Artificial Intelligence Usage Intensity

Item Code	Item Statement	SA	A	N	D	SD	Mean	Std. Dev.	Remark
AIUI1	I frequently use artificial intelligence tools in my teaching and research activities.	48	52	18	14	8	3.84	1.08	High
AIUI2	Artificial intelligence tools are integrated into my daily academic tasks.	44	50	20	16	10	3.73	1.12	High
AIUI3	I rely on artificial intelligence applications to enhance my work efficiency.	50	46	22	12	10	3.81	1.14	High

Source: Field Survey (2026)

Table 2 indicates a high degree of usage of artificial intelligence among staff. AIUI1 recorded a mean of 3.84 (SD = 1.08), AIUI2 had a mean of 3.73 (SD = 1.12), and AIUI3 showed a mean of 3.81 (SD = 1.14).

These means indicate that participant use artificial intelligence often in teaching, research and various academic tasks. The fairly similar standard deviation values suggest moderate variability, with a generally consistent pattern of AI usage among the respondents.

Table 3 Artificial Intelligence Competence

Item Code	Item Statement	SA	A	N	D	SD	Mean	Std. Dev.	Remark
AIC1	I possess the necessary skills to effectively use artificial intelligence tools.	46	54	18	12	10	3.81	1.09	High

AIC2	I can independently solve technical challenges encountered when using AI tools.	42	48	24	16	10	3.69	1.13	High
AIC3	I am confident in applying artificial intelligence to support academic problem-solving tasks.	48	50	20	12	10	3.81	1.11	High

Source: Field Survey (2026)

Table 3 shows a high level of competence in using artificial intelligence among the sample. AIC1 yielded a mean of 3.81 (SD = 1.09), AIC2 recorded 3.69 (SD = 1.13), and AIC3 reported 3.81 (SD = 1.11). These results show that teachers have the ability and confidence to use AI technologies and troubleshoot technical issues. The scores indicate a consistent level of competence, with some variability due to individual differences in competence levels.

Table 4 Problem-Solving Ability

Item Code	Item Statement	SA	A	N	D	SD	Mean	Std. Dev.	Remark
PSA1	I can clearly identify and define problems in my academic work.	52	48	18	12	10	3.86	1.12	High
PSA2	I generate and evaluate multiple solutions when faced with complex academic tasks.	46	52	20	12	10	3.80	1.10	High
PSA3	I effectively apply appropriate strategies to resolve academic challenges.	50	50	18	12	10	3.84	1.11	High

Source: Field Survey (2026)

Table 4 shows that academic staff possess high problem-solving skills. PSA1 recorded a mean of 3.86 (SD = 1.12), PSA2 had 3.80 (SD = 1.10), and PSA3 showed 3.84 (SD = 1.11). These scores suggest that respondents are able to recognize problems, develop various solutions and implement effective strategies in academic settings. The similarity in mean and standard deviations indicate a fairly consistent level of problem-solving ability among respondents.

Test of Hypotheses

$H0_1$: Usage intensity of artificial intelligence has no significant influence on the problem-solving ability of academic staff in Lead city University.

$H0_2$: Artificial intelligence competence does not significantly influence the problem-solving ability of academic staff in Lead city University

Model Summary[b]					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.455[a]	.207	.195	.66681	1.982
a. Predictors: (Constant), Usage_Intensity_of_Artificial_Intelligence, Artificial_Intelligence_Competence					
b. Dependent Variable: Problem_Solving_Ability					

SPSS_Output, 2026

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	15.888	2	7.944	17.866	.000[b]

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	Residual	60.915	137	.445		
	Total	76.802	139			
a. Dependent Variable: Problem_Solving_Ability						
b. Predictors: (Constant), Usage_Intensity_of_Artificial_Intelligence, Artificial_Intelligence_Competence						

SPSS_Output, 2026

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	1.986	.314		6.327	.000		
	Artificial_Intelligence_Competence	.157	.080	.159	1.950	.053	.867	1.153
	Usage_Intensity_of_Artificial_Intelligence	.348	.076	.372	4.553	.000	.867	1.153
a. Dependent Variable: Problem_Solving_Ability								

SPSS_Output, 2026

Interpretation of Results

Prior to the analysis, the data were screened. The sample (N = 140) was checked for missing data and none was greater than the threshold of 5%, so listwise deletion was not necessary. Potential outliers were examined using standardized residuals, with no cases greater than ±3.0, suggesting no extreme cases influencing the results (Field, 2018). Skewness and kurtosis indices as well as histograms and normal probability plots suggested acceptable normality. Internal consistency was confirmed through reliability analysis, with all constructs above the 0.70 threshold recommended by Hair et al., (2022).

Multiple regression analysis was performed to investigate the effect of the Artificial Intelligence Competence and Usage Intensity of Artificial Intelligence (independent variables) on Problem-Solving Ability (dependent variable). According to the model summary, there was a moderate positive correlation between the predictors and problem-solving ability (R = .455). The model accounted for 20.7% of the variance in problem-solving ability ($R^2 = .207$) with an adjusted R^2 of .195, showing that the predictors contributed to a meaningful amount of the outcome. The standard error of the estimate was 0.667 which is acceptable for a good prediction, and the Durbin-Watson statistic was 1.982 indicating no evident autocorrelation in the residuals. The results of the ANOVA showed the overall regression model was statistically significant, $F(2, 137) = 17.866$, $p < .001$, indicating that the regression model as a whole accounted for statistically significant differences in problem-solving ability.

Using AI significantly and positively predicted problem-solving ability (B = 0.348, SE = 0.076, $\beta = .372$, t = 4.553, $p < .001$). A one-unit increase in intensity of using AI is related to a corresponding increase of 0.348 units in problem solving ability, while keeping other factors constant. However, AI Competence had a positive but non-significant effect (B = 0.157, SE = 0.080, $\beta = .159$, t = 1.950, p = .053). The result did not quite achieve the standard for 0.05 significance but shows a strong positive trend, and suggests that the ability to solve problems and competency in AI might become more separated in larger samples. The regression equation was: Problem-Solving Ability = 1.986 + 0.157(AI Competence) + 0.348(AI Usage Intensity). Collinearity diagnostics were acceptable (Tolerance = .867, VIF = 1.153) and suggested the absence of any multicollinearity issues. In conclusion, the null hypothesis on the intensity of AI use was rejected and the hypothesis on competence in AI was accepted at the 0.05 significance level, although the positive trend observed in this study suggests that this hypothesis might be accepted in other contexts.

DISCUSSION OF FINDINGS

The result offers empirical evidence of the impact of artificial intelligence usage on problem-solving capability for academic staff. The positive association indicates that the regular use of AI systems enhances problem-solving ability through the development of analytical skills and the formation of judgement processes during academic activities. This finding supports recent studies that demonstrate regular interactions with intelligent systems lead to cognitive augmentation and improved efficiency (Dwivedi et al., 2021; Chatterjee et al., 2021). Theoretically, this finding supports technology-enabled capability perspectives, which stress the importance of usage in performance.

By contrast, artificial intelligence competence failed to achieve statistical significance, while it had a positive effect. This result implies that technical know-how may not necessarily lead to better problem-solving unless it is incorporated into daily academic activities. This finding aligns with a growing concern in the management field that possessing competence without actual use has little impact on performance (Tarafdar et al., 2022). It also suggests a potential disparity in skill development and use within university settings.

Implications for practice are that university administrators should focus on policies that promote ongoing and integrated use of AI tools, rather than mere training initiatives. Ongoing use, facilitated by infrastructure and incentives, seems to be a key factor in converting AI competence into problem solving.

Researchers explored the influence of artificial intelligence usage intensity and competence on problem-solving ability of lecturers. The empirical findings from the regression model ($R^2 = .207$, $F(2,137) = 17.866$, $p < .001$) suggest 20.7 percent variance in problem solving ability is explained by the predictors. In particular, artificial intelligence usage intensity exhibited a positive and significant effect ($\beta = .372$, $p < .001$), which resulted in acceptance of the first hypothesis. On the other hand, artificial intelligence competence displayed a positive but insignificant effect ($\beta = .159$, $p = .053$), thereby failing to support the second hypothesis. This suggests that usage intensity of AI systems is more important than competence for cognitive performance outcomes.

SUMMARY, CONCLUSION AND RECOMMENDATIONS

Theoretically, the results build on socio-technical systems and technology usage theories by showing that usage intensity (behavioural) has a stronger impact on strengthening problem-solving performance than competence (latent). This clarifies assumptions in the artificial intelligence (AI) adoption literature by emphasizing usage as the key driver of cognitive performance.

The study provides practical implications in that institutions should focus on policies that promote integration of artificial intelligence into routine academic practices rather than training alone. Planned integration, ongoing usage encouragement, and task-specific AI applications are likely to impact academic problem-solving ability.

Limitations and Future Studies

One of the key challenges of this research is its institutional setting, since the analysis was carried out in an environment of a private higher education institution, with its specific administrative frameworks, technological resources, and socio-economic characteristics of the students. The interpretations and implications of the findings from this study may be constrained by the contextual characteristics that might impact the extent to which the use of AI competence and intensity affects students' ability to solve problems, which could be different in other university contexts. Therefore, the study recommended that a more comprehensive collaborative approach should be adopted in the future, including public federal universities all over Nigeria. These comparative studies would allow researchers to gauge the stability and validity of the suggested approach to the proposed model across institutions with varying funding models, technological infrastructure, student populations and learning environments. A larger sample size would increase the external validity of the study and better allow for a general understanding of the role of artificial intelligence-related factors in problem-solving ability in the wider socio-economic and educational contexts.

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