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ASSESSMENT OF UNIVERSITY LECTURERS' PERSONAL VARIABLES AND ATTITUDE TOWARDS LARGE LANGUAGE MODELS AS TOOLS FOR PROFESSIONAL DEVELOPMENT IN CROSS RIVER STATE

Ita, Caroline, Otu, Bernard Diwa & Egbai, Julius Michael Ph.D

carolineita@unical.edu.ng, Bernardotu@unical.edu.ng & juliegbai@gmail.com
Department of Educational Foundations, University of Calabar, Calabar, Nigeria

Abstract

This study evaluated the attitudes of university lecturers at the University of Calabar, Calabar (UNICAL), and the University of Cross River State (UNICROSS) regarding large language models (LLMs) as professional development tools. The study used a descriptive survey approach with a sample of 420 academic staff members -220 from UNICAL and 200 from UNICROSS. Three hypotheses and two research questions were put out to direct the investigation. The 16-item "Teachers' Attitude Questionnaire on Large Language Models as Tools for Professional Development" (TAOLTP), which was validated by experts and has a reliability coefficient of 0.83 according to Cronbach Alpha, was used to gather the data. The mean, standard deviation, t-test, and Analysis of Variance (ANOVA) were used in the data analysis. The findings showed that lecturers' opinions on Large Language Models (LLMs) as instruments for professional growth are highly influenced by their age and level of education. The findings showed that professors at both schools had a favorable opinion of LLMs, with no discernible difference between the two groups. The findings also demonstrated that lecturers' opinions of Large Language Models (LLMs) as professional development tools were not much impacted by their gender. Providing sufficient training and assistance to improve the successful incorporation of LLMs into professional development activities is one important suggestion.

Keywords: assessment, Lecturers' attitudes, large language models, Professional development

Introduction

Numerous disciplines have been profoundly influenced by artificial intelligence (AI). AI is a collection of technologies that provide computers with the capacity to carry out a wide range of sophisticated tasks, including seeing, comprehending, and translating written and spoken language, analysing data, formulating suggestions, and more. It is the capacity of machines to think and act similarly to people.

Along with Natural Language Processing (NLP) approaches, AI models, including Large Language Models (LLMs) like GPT-4, BAND, PALM, Megatron-Turing, NLG, Jurassic-1, and Jumbo, have significantly advanced our knowledge and use of AI in various fields (Kumar,2024). Narrow or weak artificial intelligence (AI) is made to do specialized tasks, whereas strong AIs, often called artificial general intelligence (AGI), are made to have general cognitive capacities. Generative artificial intelligence is a branch of AI that uses patterns found in existing data to create content, text, messages, pictures, music, or codes. After being educated on input data, they produce new output. Artificial general intelligence (AGI) can learn, think, and adapt like humans by imitating human intelligence. They can also solve problems and pick up new skills in ways that are similar to those of humans (UNESCO, 2022). The technique is not new because it is based on research from almost fifty years ago, namely the Markov Chain (process), which was named for the Russian mathematician Andrey Markov (1906). The complexity of the objects created and the scale at which the models are taught differ between what is generated now and what was generated back then. Models are trained on more considerable data sets with hundreds of millions or even billions of data points to produce remarkable outcomes. The Transformer architecture model is one such model that has been crucial to the advancement of generative AI. In 2017, this deep neural network technique was introduced. The purpose of transformers is to process sequences, including text in natural language. Language models like BERT and GPT were developed as a result of the use of this architecture in Natural Language Processing (NLP) (Popenici & Kerr, 2017). One recent development in natural language processing is the Generative Pretrained Transformer, or GPT. OpenAI developed ChatGPT, the initial iteration of GPT. This neural network uses a deep learning architecture to produce text, have user discussions, and do other tasks. Its development signaled a sea change in the widespread application of machine learning. Nowadays, a wide range of operations, from producing advertising materials and translating texts to coding and conducting in-depth research, may be automated and improved with the help of this technology. This model's processing speed and operational size are worth it. With its ability to produce up to 25,000 words of text, GPT4 was introduced in 2024 and represents a major advancement over earlier iterations, such as GPT-2 and GTP-3. Based on the enormous volume of text data they have been trained on, large language models—a kind of generative AI—are intended to comprehend and produce content that is human-like (Brown et al., 2020).

Instead of creating and training domain-specific models for each of these use cases separately, which is prohibited under many criteria (most notably, cost and infrastructure), they offer the fundamental capabilities required to drive multiple use cases and applications and solve a multitude of tasks like Natural Language Understanding (NLU) and Natural Language Processing (NLP). This stifles synergies and may result in inferior performance (Popenici & Kerr, 2017). LLMs can produce texts like humans, along with other types of content, infer from context, produce contextually relevant and coherent responses, translate to languages other than English, summarize texts, respond to questions, and even help with creative writing or code generation tasks, all thanks to the enormous amounts of data that are used to train them. Large language models (LLMs), such as GPT-3 and GPT-4, have become revolutionary tools in a number of domains, including education, and have made significant contributions to our comprehension and use of artificial intelligence (AI) and natural language processing methods (Nejjar, Zacharias, Stiehle, Ingio, 2024).

LLMs are increasingly being included in teaching and learning contexts as a result of the advancements in educational technology, which provide new options for teachers and students. Delivering and consuming educational information might be entirely transformed by large language models. They improve personalised learning by helping to create learning experiences that are specifically suited to each student's needs. LLMs, for example, are able to create adaptive learning resources that accommodate students' differing skill levels and offer focused assistance when required (Zhang et al., 2021). Similarly, Korpimies, Laaksonen, and Luukkainen (2024) have shown that these models have a variety of applications, and many students find them useful for addressing problems successfully. The models are said to allow for greater efficiency in many aspects of life. For example, they may act as virtual teaching assistants, providing students with immediate feedback and assistance, so reducing the workload of human teachers. Nejjar and associates, 2024; Hirsch & Ng, 2020). The LLMs can serve as online tutors, helping students with difficult tasks, providing clarifications, and responding to inquiries. According to Popenici and Kerr (2017), this can be especially helpful in big classrooms where teachers are unable to provide individual attention. In addition to offering possibilities for ongoing education, these models may assist kids outside school hours. Lesson plans, tests, and interactive exercises are just a few educational resources educators may produce using LLMs. As a result, teachers can save time and concentrate more on direct student interaction (Alam, 2020). In order to guarantee that educators have access to current and reliable information for their professional growth, large language models (LLMs) may also help filter pertinent instructional materials from extensive web databases. LLMs can assist students who are not fluent in the primary language of instruction to better grasp the topic by offering real-time translation services in multilingual classrooms (Chiu, 2021). This is especially important in Nigeria, where several languages are spoken, since language obstacles can make teaching and learning less efficient. Instructors of research in other nations where English is not the official language, such as Algeria, China, Ivory Coast, Germany, France, and Japan, among others, also find it very helpful. By automating tasks like grading, scheduling, attendance, tracking, report generation, and managing communications with students and parents, the models can reduce administrative burdens on lecturers and free up more time for activities that are student-centered and instructional (Popenici & Kerr, 2017; Holmes et al., 2019).

Special potentials and difficulties are associated with incorporating LLMs into the Nigerian educational system. In order for this procedure to be implemented successfully, Nigerian professors' opinions regarding the demands for professional development are crucial. By offering materials and activities that accommodate a range of skills and interests, LLMs can assist differentiated instruction in classes with varying learning levels. This is especially pertinent given the vast diversity of student skills in Nigerian classrooms (Uwadiae, 2020). Teachers may create a more inclusive learning environment by using LLMs to ensure all students receive the proper support and challenges. The models may automate numerous administrative duties, including report preparation, attendance monitoring, and grading. This decrease in administrative duties might improve overall teaching efficacy and efficiency for Nigerian teachers, who frequently deal with big class numbers and few resources. By granting access to a wealth of learning materials, research, and best practices, the LLMs may also aid in the professional growth of teachers. By keeping abreast of the most recent advancements in educational theory and practice, teachers may utilize LLMs to enhance their instructional practices over time (Darling-Hammond et al., 2017). LLMs can also provide professional development modules and on-demand training specifically designed to meet the needs of Nigerian educators. LLMs can help close the gap in Nigeria, where educational disparities are common. LLMs can help under-resourced schools and give students in underserved or rural places access to learning materials they might not otherwise have by offering high-quality educational resources and content (Uwadiae, 2020). This can provide more equal educational opportunities for all kids and help level the playing field.

When it comes to incorporating new technology into teaching methods, lecturers are essential. Teachers are essential when it comes to the acceptance and use of new technology in the classroom. How well these technologies are embraced and used in classrooms is greatly influenced by their attitudes, preparedness, and professional growth. To improve teaching and learning results in Nigeria, evaluating lecturers' professional development requirements for the successful integration of Large Language Models (LLMs) is essential. In order to bridge the gap between new technology and traditional classroom methods, lecturers play a crucial role. They act as mentors and role models, exemplifying the successful integration of new technology into the classroom. Their views about technology greatly influence their propensity to embrace and support new tools (Ertmer & Ottenbreit-Leftwich, 2010). Fostering an innovative culture in educational institutions requires positive attitudes and a proactive approach to technology. Determining if their personal characteristics—such as gender, age, education, and kind of university—can affect this and how they see these tools is also crucial. Giving preservice and in-service teachers training and assistance is one of the lecturers' main duties. This involves giving educators the abilities and information they need to successfully employ emerging technology, like LLMs. Fostering an innovative culture in educational institutions requires positive attitudes and a proactive approach to technology.

Technology has been a driving force behind educational innovation, allowing teachers to use student-centered pedagogies that accommodate a range of learning preferences and skill levels. Digital technologies have drastically changed the way that people study (Ralyani, 2024). Students may learn more, do better on tests, and cultivate higher-order thinking abilities with the aid of educational tools. According to key studies, instructional technology may improve information retention, increase student engagement, and develop higher-order thinking abilities when it is properly incorporated (Akintayo, Eden, Oyebola, Ayani, and Onyebuchi, 2024; Goretti & Caroline, 2019). For instance, enhanced student engagement and more efficient classroom administration have been linked to the usage of interactive whiteboards and learning management systems (LMS) (BECTA, 2004). Nonetheless, some instructors have voiced doubts regarding the efficacy of technology, pointing to issues with dependability, distraction potential, and inadequate support and training (Ertmer, 1999). Students who use LLMs for moderate code generation, brainstorming, general information retrieval, or diligent code improvement, for instance, generally performed better, according to Korpimiesetal (2024). This is probably because these activities foster a deeper comprehension of the code material. On the other hand, performance was somewhat impacted by an over-reliance on LLMs, especially when it came to producing vast amounts of code documents, which may indicate problems with surface-level learning. Evaluating lecturers' opinions on LLMs is especially pertinent given the historical background of educators' views toward technology (Egbai & Eke, 2024). Positive perceptions of LLMs can make it easier for them to be incorporated into professional development programs, improving the caliber and efficacy of such programs (Sahlgren, Karlgren & Hammarström, 2021). People will demonstrate interest in an activity if they have a good attitude about it, according to Ita & Egbai (2018). On the other hand, unfavorable opinions may act as obstacles to adoption, reducing the potential advantages of LLMs in learning environments. The impact of these instructors' individual characteristics on their attitudes toward LLMs is more significant. By customizing professional development materials to each educator's unique requirements and interests, the LLMs may offer individualized and flexible learning experiences (Huang et al., 2022). Both efficacy and engagement may rise as a result of this customisation. The LLMs can assist continuous professional development by providing instant access to a multitude of research, best practices, and instructional materials (Hirsch & Ng, 2020). This might assist teachers in keeping up with the most recent advancements in their industry. LLMs can save up time for instructors to concentrate on more significant professional development activities by automating repetitive operations like grading and giving feedback (Zhang et al., 2021). In order to overcome any opposition to new technology, educators' concerns must be recognized and addressed. This entails offering continuing assistance and showcasing the observable advantages of LLMs (Ertmer, 1999).Even though a lot of research has been done on the use of artificial intelligence (AI) and large language models (LLMs) in education, there are still a number of unanswered questions, especially when it comes to lecturers' professional growth. (Egbai and Ita, 2018) By concentrating only on lecturers' attitudes regarding LLMs as instruments for professional growth, this study seeks to close these disparities. The public launch of ChatGPT, a generative AI chatbot driven by LLMs, and experts' forecasts of how the technology would impact education, especially the role of instructors, have been contested by Jeon and Lee (2023). Nevertheless, despite its impact on education, little is known about how instructors could utilise the technology and how it relates to their characteristics. Instead of concentrating on lecturers, the majority of current research on the application of AI and LLMs in education tends to concentrate on students and classroom teachers. For example, studies by Luckin, Holmes, Griffiths, & Forcier (2016) and Holmes et al. (2019) focus mostly on how AI might improve teaching practices and student learning in secondary school settings. The perception of teachers and students was the main topic of Egbai and Eke (2024) and Korpimiesetal (2024). Comprehensive research on the factors that impact prospective teachers' relationships and use of LLMs in their own professional development, including lecturers' gender, age, education, and university, is lacking. Few studies have explicitly examined teacher educators' personal factors in relation to their attitudes toward LLMs, despite the fact that some have examined educators' attitudes toward educational technologies generally (Teo, 2011; Ertmer, 1999; Cabaleiro-Cervino & Vera, 2020; Egbai & Eke, 2024). Understanding the particulars of lecturers' individual characteristics regarding these instruments is essential, given the special powers and ramifications of LLMs. By offering actual data on the connection between lecturers' personal factors and LLMs, this study seeks to close this gap. A large portion of the research on AI and LLMs in education seeks to generalize results without taking into account the unique circumstances of lecturers' professional growth. Studies such as those by Holmes et al. (2019) and Bender et al. (2021) frequently talk about the wide-ranging uses of AI, but they don't go into detail on how these tools might be customized to meet lecturers' requirements for professional growth. In their study of lecturers' attitudes about LLMs as professional development instruments, Egbai and Eke (2024) did not take into account how their characteristics interacted with their attitudes toward LLMs. Examining how these individual factors may affect their views toward using these tools to explicitly leverage and improve their knowledge and abilities, this study aims to contextualize the usage of LLMs within the framework of professional growth. The influence of teacher educators' personal characteristics on attitudes toward LLMs and professional development outcomes is not well supported by empirical research. The majority of the material now in publication is theoretical or anecdotal. Huang, Zhang, and Cheng (2022) conducted a thorough literature study on the impacts of artificial intelligence (AI) in education, but they did not include empirical evidence about the precise effects of LLMs on professional growth. By gathering and examining information on lecturers' individual characteristics, experiences, and results when using LLMs, this study seeks to close this empirical gap. Research has already shown how crucial assistance and training are to successfully integrating educational technology (Liu & Huang, 2021; Ertmer, 1999). Nevertheless, there is currently little to no recorded data about the relationship between lecturers' personal characteristics and their perception of LLM models as instruments for professional growth. This study intends to provide empirical literature and useful suggestions for policymakers and educational institutions by determining if lecturers' gender, age, education, and kind of university have any bearing on their stance on LLM models as instruments for professional development.

Research Questions

The following Research questions were raised to guide the study:

1. What is the attitude of UNICAL and UNICROSS lecturers on large language models as tools for professional development?

2. What is the difference in the attitude perception response of UNICAL and UNICROSS lecturers on large language models as tools for professional development?

Hypotheses

The following hypotheses were raised to guide the study:

1. There is no significant difference in the lecturer's attitude towards Large Language Models as tools for professional development on their gender.
2. There is no significant difference in the lecturer's attitude towards Large Language Models as tools for professional development based on their age
3. There is no significant difference in the lecturer's attitude towards Large Language Models as tools for professional development based on their qualification

Methodology

Ex-post facto design was the research methodology used for this investigation. According to Isangedighi, Joshua, Asim, and Ekuri (2004), *Ex-post facto* is a methodical empirical investigation in which the researcher lacks direct control over independent variables because their manifestations have already taken place or are intrinsically unmanageable. The study's population comprises the 3,153 lecturers at the two public universities in Cross River State, Nigeria. 200 teachers from the University of Cross River State, UNICROSS, and 221 lecturers from the University of Calabar, UNICAL, were chosen using the purposeful sampling approach. This resulted from the researcher's deliberate choice to conduct the study only with professors. 441 respondents from both campuses, or 14% of the total population, were selected using the accidental sampling approach. This was due to the fact that the researcher only gave the instrument to lecturers who were willing to answer it throughout the data collecting period. The survey, "Lecturers' Attitude Towards Large Language Models as Tools for Professional Development Questionnaire (TAOLTPQ)", served as the data gathering tool. There are two parts to the instrument. Respondents' personal information, including gender, age, and qualifications, is gathered in Section A. The 16 questions in Section B assessed attitudes about big language models as instruments for professional growth. Strongly Agree (SA, 4 points), Agree (A, 3 points), Disagree D, 2 points, and Strongly Disagree (SD, 1 point) are the four points on the modified Likert scale used in the questionnaire. Three measurement and evaluation specialists from the Department of Computer Science and the Faculty of Education separately evaluated the items created to demonstrate face validity. The Cronbach Alpha reliability coefficient technique was used to determine the instrument's dependability, and the reliability coefficient was 0.83. With the assistance of three research assistants, the researchers individually distributed the surveys. Only 420 of the 441 copies of the distributed questionnaires were successfully completed and utilized as the study's sample. The data's mean and standard deviation were examined to address the study topics. According to the decision rule, a mean score of 2.50 or above was approved; if not, it was rejected. The 2.50 value served as a standard by which to make decisions. The hypotheses were tested at the 0.05 level of significance using the t-test statistic and analysis of variance.

Result: This section restates each study question and hypothesis and presents the findings of the data analysis that was done to examine them. Every study hypothesis was examined at the significance level of .05.

Research question one

What is the attitude of university (UNICAL and UNICROSS) lecturers towards Large Language Models as tools for professional development? Responses to items 1-16 of section

B on the questionnaire were analysed to answer this research question. The result of the analysis is presented in Table 1.

TABLE 1 Response of the respondents on the attitude of UNICAL and UNICROSSS lecturers towards Large Language Models as tools for professional development

S/N		Median	Remark
1	LLMs can enhance my professional development as a lecturer.	3.3911	Positive
2	I believe that integrating LLMs into my professional development activities would be beneficial.	3.2578	Positive
3	I have a positive attitude towards using educational technologies in my professional development.	3.5911	Positive
4	LLMs could help me stay updated with the latest educational trends and practices	3.5556	Positive
5	The ease of use of LLMs is an important factor influencing my intention to use them for professional development.	3.2489	Positive
6	I find LLMs to be useful tools for creating personalized professional development content.	2.5356	Positive
7	I believe that LLMs can assist me in improving my instructional practices as a lecturer.	2.8489	Positive
8	I perceive LLMs as valuable resources for accessing a wide range of educational materials.	2.9689	Positive
9	I feel confident in my ability to effectively integrate LLMs into my professional development activities.	3.0044	Positive
10	LLMs could help me automate administrative tasks, allowing me to focus more on lecturing and student engagement.	2.9333	Positive
11	I am concerned about the quality and accuracy of content generated by LLMs for professional development purposes.	2.9422	Positive
12	The potential benefits of using LLMs outweigh the potential drawbacks for my professional development	3.2978	Positive
13	I believe that LLMs can provide personalized learning experiences tailored to my professional development needs	3.6178	Positive
14	Access to sufficient training and support would increase my likelihood of integrating LLMs into my professional development practices	3.1911	Positive
15	I am optimistic about the potential of LLMs to revolutionize professional development in education	3.1733	Positive
16	Overall, I am open to exploring and incorporating LLMs into my professional development journey as a lecturer	3.2889	Positive

Table 1 presents the mean ratings of the attitude of UNICAL and UNICROSS lecturers toward large language models as tools for professional development. All the isolated items recorded mean ratings ranging from 2.53 to 3.59, which were above the cut-off mark of 2.50, thus indicating that the attitude of UNICAL and UNICROSS lecturers towards large language models as tools for professional development is significantly positive. The standard deviation ranged from 0.49 to 0.99, which revealed that respondents were not too far from the mean and each other in their responses.

Research Question Two

What is the difference in the attitude perception response of UNICAL and UNICROSS lecturers on large language models as tools for professional development? An independent t-test analysis was adopted to test this research question. The result is presented in Table 2.

TABLE 2: Independent t-test analysis of the influence of lecturers' university on their attitude towards Large Language Models as tools for professional development (N=420)

University	N	$\bar{x}$	SD	t-value	Sig.
UNICAL	220	54.02	4.17622	12.12*	.000
UNICROSS	200	50.37	3.95225		

* Significant at p<.05 level, P-value =.000, df = 418.

The result in Table 2 revealed that the t-value of 12.12 is significant at p=.000. Since p (.000) is less than p (.05), this indicates that there is a significant difference in the attitude perception response of UNICAL and UNICROSS lecturers to large language models as tools for professional development.

Hypothesis One

There is no significant difference in lecturer attitudes towards large language models as tools for professional development based on gender.

The independent variable is the lecturers' gender (male and female). The dependent variable is their attitude towards large language models as tools for professional development. To test this hypothesis, an independent t-test analysis was adopted. The result is presented in Table 3.

TABLE 3: Independent t-test analysis of the influence of lecturers' sex on their attitude towards Large Language Models as tools for professional development (N=420)

Lecturers' sex	N	$\bar{x}$	SD	t-value	Sig.
Male	200	52.0800	4.17622	.990	.323
Female	220	52.4727	3.95225		

Not Significant at p<.05 level, P-value =.323, df = 418.

The result in Table 3 revealed that the t-value of .990 is not significant at p=.323. Since the p (.000) is higher than p (.05), the null hypothesis is rejected. With this result, the null hypothesis that lecturers' gender has no significant influence on attitude towards large language models as tools for professional development was retained.

Hypothesis Two

There is no significant difference in lecturer attitudes towards large language models as tools for professional development based on their age.

The independent variable in this hypothesis is the lecturers' age (below 30 years, 31-50 years, and 51 and above years), while the dependent variable is the attitude towards Large Language Models as tools for professional development. To test this hypothesis, attitudes towards Large Language Models as tools for professional development from lecturers' ages below 30 years, 31- 50 years, and 51 and above years were compared using One-Way Analysis of Variance (ANOVA). The result of the analysis is presented in Table 4.

TABLE 4 Summary data and one-way ANOVA of the influence of lecturers' age on attitude towards Large Language Models as tools for professional development (N=420)

Lecturers' age	N	$\bar{x}$	SD
below 30 years	15	52.6000	2.64035

31-50 years	291	52.7663		4.22395	
51 and above years	114	51.0175		3.49964	
Total	420	52.2857		4.06032	
Source of variance	SS	Df	Ms	F	Sig of F
Between group	252.039	2	126.020	7.896*	.000
Within group	6655.675	417	15.961		
Total	6907.714	419			

* Significant at p <.05 level, df= 2, 417.

Table 4's results showed an F-value of 7.896 at p=.000. The null hypothesis is rejected because p (.000) is smaller than p (.005). Therefore, this finding suggested that their age greatly impacted lecturers' attitudes regarding large language models as resources for professional growth. A post hoc analysis was conducted using Fisher's Least Significant Difference (LSD) multiple comparison analysis since lecturers' attitudes on Large Language Models as resources for professional growth were significantly influenced by their age. Table 5 displays the analysis's findings. Table 5

Fishers' Least Significant Difference (LSD) multiple comparison analysis of the influence of Lecturers' age on attitude towards Large Language Models as tools for professional development

LSD

(I) Lecturers' age	(J) Lecturers' age	Mean Difference (I-J)	Std. Error	Sig.
below 30years	31-50years	-.16632	1.05778	.875
	51 and above years	1.58246	1.09730	.150
31-50years	below 30years	.16632	1.05778	.875
	51 and above years	1.74878(*)	.44142	.000
51 and above years	below 30years	-1.58246	1.09730	.150
	31-50years	-1.74878(*)	.44142	.000

* The mean difference is significant at the .05 level.

According to Table 5's study, lecturers under 30 (52.60) had a substantially different attitude toward large language models as aids for professional growth than did those between 31 and 50 (52.77) or 51 and over (51.01). Additionally, lecturers between the ages of 31 and 50 (52.77) had a very different view regarding large language models as aids for professional growth than did those 51 and older (51.01).

Hypothesis Three

There is no significant difference in lecturer attitudes towards large language models as tools for professional development based on their qualifications.

The independent variable is qualification (Master's and Ph.D.). The dependent variable is attitude towards large language models as tools for professional development. To test this hypothesis, an independent t-test analysis was adopted. The result is presented in Table 6.

TABLE 6: Independent t-test analysis of the influence of lecturers' qualification on attitude towards Large Language Models as tools for professional development (N=420)

Qualification	N	$\bar{x}$	SD	t-value	Sig.
Masters	240	51.4792	4.04261		
				4.824	.000

Ph.D	180	53.3611	3.83859

* Significant at p<.05 level, P-value =.000, df = 418.

At p=.000, the t-value of 4.824 is significant, according to the results in Table 6. The null hypothesis is disproved as p (.000) is smaller than p (.05). With this outcome, the null hypothesis—that lecturers' qualifications have no discernible impact on their perception of large language models as professional development tools—was disproved. This suggests that their degrees greatly influence professors' attitudes about large language models. The findings indicate that lecturers with Ph.D. (mean = 53.3611) have a more positive attitude toward large language models as professional development tools than do those with master's degrees (mean value = 51.4792).

Discussion of findings

The study's results, shown in Tables 1 and 2, demonstrate that lecturers at the University of Calabar, Calabar (UNICAL) and the University of Cross River State (UNICROSS) have favorable opinions on large language models (LLMs) as resources for professional growth. These findings support the literature's claims on the possible advantages and acceptability of LLMs in learning environments.

The age and educational background of lecturers greatly impact how they feel about using large language models as professional development tools. The results also showed that their gender or university affiliation does not significantly influence lecturers' attitudes regarding large language models as resources for professional growth. The results support the findings of Brown et al. (2020), who noted that large language models are a kind of generative AI that can comprehend and produce text similar to that of a human being using the enormous volume of text data they have been trained on. In order to capture the nuances of a language, the models employ deep learning techniques, such as multi-layered neural networks. In order to accomplish a variety of tasks, including Natural Language Understanding (NLU) and Natural Language Processing (NLP), large language models (LLMs) are a class of foundation models that have been trained on vast amounts of data. This allows them to comprehend and produce natural language and many other kinds of content. Instead of creating and training domain-specific models for each of these use cases separately, which is prohibited under many criteria (most notably, cost and infrastructure), LLMs offer the fundamental capabilities required to drive multiple use cases and applications and resolve a multitude of tasks. This can hinder synergies and result in subpar performance. Students who used LLMs for modest code production, brainstorming, general information retrieval, or meticulous code improvement also fared better overall, according to Korpimies et al. (2024). This is probably because these activities foster a deeper comprehension of the code topic. On the other hand, performance was somewhat impacted by an over-reliance on LLMs, especially when it came to producing vast amounts of code documents, which may indicate problems with surface-level learning. Evaluating lecturers' opinions on LLMs is especially pertinent given the historical background of educators' views toward technology.

Conclusion and Recommendations

This study examined the elements affecting professors' opinions about Large Language Models (LLMs) as professional development tools. It found that lecturers' gender, age, and qualifications differed significantly. These results highlight the intricate interactions between institutional, experiential, and demographic factors that influence lecturers' attitudes about and use of cutting-edge technology. The study's conclusions lead to the following recommendations:

1. Educational institutions must provide specialized training programs that cater to teachers' particular requirements. They must also promote cooperation and knowledge

exchange between generations and encourage welcoming settings that encourage a range of technological adoption styles.

2. Faculty development programs should offer workshops on LLMs and their applications. These programs should give instructors the tools they need to investigate cutting-edge technology and encourage community-building and peer mentorship programs.

3. Lawmakers ought to create regulations that support fair access to technology. They should also set aside funds for technology integration and faculty development. They should also watch for and respond to institutional digital gaps.

4. Scholars ought to look at certain elements that affect instructors' perceptions of LLMs and examine how LLMs affect instructional strategies and student results. Teachers, legislators, and administrators may support the successful incorporation of LLMs, improve teacher development, and encourage creative teaching methods by recognizing and resolving these problems. In order to shape lecturers' attitudes about emerging technologies and eventually guide tactics to encourage effective technology adoption and improved educational results, this study emphasizes the significance of taking into account a variety of views and features.

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