Journal of Educational Foundations [Special Edition], 2025 - Volume 14, Issue 3:026-034
https://jef.unn.edu.ng/

PERCEPTION AND SELF-EFFICACY AS PREDICTORS OF INTENTION TO USE LARGE LANGUAGE MODELS AMONG SPECIAL EDUCATION TEACHERS TO PROMOTE INCLUSIVITY

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Abstract

This study targeted teachers of learners with special needs and determined the proportion of their intention to used LLMs to promote inclusivity that can be predicted by their perception of LLMs and self-efficacy. The study was guided by three research questions and three null hypotheses. The study adopted correlational survey design. The population of the study was all 51 special education teachers at the Kaduna State Special Education School (KASSES) and Danbo Special Needs School (DSENS). All 51 special education teachers were purposively sampled to take part in the study as the population was deemed small. Data was collected using a teacher perception of LLMs scale, a self-efficacy scale and an intention to use LLM scale. The instruments were duly validated and their reliability determined suing Cronbach's Alpha. Collected data was analysed using regression and Hayes process moderation analyses. Findings revealed that teachers' perception of LLMs ($r^2 = 0.719$) and self-efficacy ($r^2 = 0.146$) are positive and significant predictors of intention to use LLMs to promote inclusivity among special need learners. Also, both variables jointly predict 11.08% of teachers' intention to use LLMs for inclusivity. The study recommended that although LLMs were useful for promoting inclusivity in education, they remain emerging technologies and so teachers should cross-reference all information obtained from them with reliable sources. Teachers should also not allow their use of LLMs to limit their cognitive development.

Keywords: Large language models, perception, self-efficacy, special education

Introduction

The landscape of educational technology is constantly evolving, with new tools and resources emerging to reshape teaching and learning. Large language models (LLMs) represent a particularly intriguing emerging technology, offering vast potential to support teachers in a multitude of ways, including helping them promote inclusivity in the classroom. Inclusivity in education refers to the practice of creating learning environments that accommodate and support the diverse needs of all students, regardless of their abilities, backgrounds, or learning styles (Ainscow, 2020). It involves removing barriers to learning by implementing flexible teaching methods, accessible materials, and supportive interventions that enable every student to participate fully in the educational process. Inclusive education fosters equity, ensuring that students with disabilities, neurodivergent learners, and those from marginalized communities receive the same opportunities for academic and social development as their peers (UNESCO, 2021).

Large language models (LLMs) are generally a type of artificial intelligence (AI) that excel at processing and generating human-like text. Kerner (2023) defines it as a type of artificial intelligence algorithm that uses deep learning techniques and massively large data sets to understand, summarize, generate and predict new content. IBM (2023) describe LLMs as artificial intelligence (AI) systems capable of understanding and generating human language by processing vast amounts of text data. The top ten LLMs in use globally are categorized by Kerner (2023: 2) are: "Bidirectional Encoder Representations from Transformers, commonly referred to as Bert; Claude; Cohere; Enhanced Representation through Knowledge Integration, or Ernie; Falcon 40B; Galactica; Generative Pre-trained Transformer 3, commonly known as GPT-3; GPT-3.5; GPT-4; and Language Model for Dialogue Applications, or Lamda." These AI-powered systems can generate text, translate languages, write different kinds of creative content, and answer questions in an informative way. The most commonly used of these LLMs in education is Chat GPT (Mogavi, et al., 2024; Meyer, et al., 2023).

Large language models (LLMs) can serve as powerful tools for teachers in promoting inclusivity among learners with special needs by providing personalized and adaptive learning experiences. These models can assist in generating simplified explanations, text-to-speech conversions, and real-time translations to support students with learning disabilities, visual impairments, and language barriers (Sharma & Bansal, 2023). Teachers can leverage LLMs to create customized instructional materials tailored to individual learning preferences, thereby enhancing engagement and comprehension. Additionally, AI-powered chatbots and virtual assistants can provide real-time academic support, allowing students with special needs to access immediate feedback and clarification on learning concepts (Lai et al., 2022). Although large language models (LLMs) have the potential to promote inclusivity in education, several challenges may hinder their effective implementation. One major concern is bias and fairness, as LLMs are trained on vast datasets that may contain inherent biases, potentially leading to inaccurate or discriminatory outputs that could disadvantage marginalized learners (Bender et al., 2021). Additionally, accessibility and digital literacy remain significant barriers, as not all schools—especially those in low-resource settings—have the necessary infrastructure, such as reliable internet, updated devices, and trained personnel, to integrate LLMs effectively (Selwyn, 2022). Furthermore, data privacy and security issues arise when sensitive student information is processed through AI systems, raising ethical concerns about data protection and informed consent (Floridi & Cowls, 2019). Another key challenge is teacher perception of LLMs and self-efficacy, as many educators may lack the confidence or professional training required to incorporate LLMs into inclusive teaching practices effectively (Zhou & Parmigiani, 2022).

The potential use of LLMs, as is with any new technology, hinges primarily on user perception (Mökander, et al., 2023) and self-efficacy (Russo, 2024). Perception in the context of this study refers to teachers' general beliefs and understanding of LLMs, encompassing their perceived usefulness, and ease of use. Teachers' willingness to integrate LLMs into their learning is significantly influenced by their perception of their usefulness (Bernabei, et al., 2023). If teachers view LLMs as valuable tools that can enhance their learning experience, streamline tasks, and improve their understanding of complex scientific concepts, they will be more likely to embrace them (Tu, et al., 2024). Conversely, if teachers perceive LLMs as unreliable sources of information or tools that could hinder their critical thinking skills, they will be less inclined to use them. A positive perception of user-friendliness is another key factor driving LLM adoption. If teachers perceive LLMs as complex or difficult to navigate, they will be less likely to invest the time and effort required to learn how to use them effectively.

Furthermore, teachers' academic self-efficacy, their confidence in their ability to succeed in science, also plays a role. Academic self-efficacy, on the other hand, reflects teachers' confidence in their ability to successfully navigate academic challenges (Hayat, et al., 2020). Academic self-efficacy plays a critical role in shaping teachers' willingness to integrate LLMs into their learning experiences. Teachers who feel confident in their understanding of scientific concepts may be more open to using LLMs as supplementary tools, whereas those struggling with the material might view LLMs as a crutch or a shortcut (Prasad, et al., 2023). Despite the potential of LLMs in fostering inclusivity, limited research has explored the perceptions and self-efficacy of special education teachers regarding their use in classrooms. Self-efficacy, which reflects teachers' confidence in their ability to integrate LLMs effectively, plays a crucial role in adoption and implementation (Bandura, 1997). However, existing studies primarily focus on general education settings, neglecting the unique challenges and opportunities in special education (Zhou & Parmigiani, 2022). Furthermore, research on teachers' intentions to use LLMs in inclusive settings remains scarce, making it necessary to examine how perception and self-efficacy influence their willingness to adopt these technologies. Majority of extant studies were also carried out overseas where technology acceptance and use is far more advanced than in Northern Nigeria. These findings from those studies thus leave a gap in research which the present study attempted to fill by determining the proportion of teachers' intention to use LLMs to promote inclusivity that can be attributed to perception and academic self-efficacy.

Research Question

The following questions were posed to guide the study:

1. What proportion of special education teachers' intention to use LLMs to promote inclusivity can be attributed to their perception?
2. What proportion of special education teachers' intention to use LLMs to promote inclusivity can be attributed to their self-efficacy?
3. What proportion of special education teachers' intention to use LLMs can be jointly attributed to their perception and self-efficacy?

Hypotheses

The following null hypotheses were tested at 0.05 level of significance to guide the study.

Ho_1: The proportion of special education teachers' intention to use LLMs to promote inclusivity can be attributed to their perception is not significant.

Ho_2: The proportion of special education teachers' intention to use LLMs to promote inclusivity can be attributed to their self-efficacy is not significant.

Ho_3: The proportion of special education teachers' intention to use LLMs can be jointly attributed to their perception and self-efficacy is not significant.

Methods

The study adopted correlational survey design. A correlational survey design is a non-experimental approach that measures relationships between variables without manipulating them (Price, 2015). This design was ideal for the study because it aims to understand how special education teachers' perceptions of LLMs and their self-efficacy predicts their willingness to use these tools to promote inclusivity, rather than manipulating any of these factors directly. The study was carried out in Kaduna State, Nigeria. The state is home to two renewed special education schools – Kaduna State Special Education School (KASSES) and Danbo Special Needs School (DSENS). The population of the study comprised of all first year teachers of the Department of science

Education who took the course SED 101 (Introductory Science Education), in the 2022/2023 academic session. This population included 89 teachers across five units in the Department; 41 in Biology unit, 30 in Chemistry unit, 9 in Physics, 5 in Mathematics Unit and 4 in integrated Science Unit (Source: Department of Science Education, UNN, 2023). The sample size of the study was 51 special education teachers for the 2023/2024 academic session. The population of the study was deemed manageable and so all the teachers were purposively included in the study. Data for this study was collected using three instruments: teachers' perception of LLMs questionnaire, a self-efficacy scale and an intention to use LLMs questionnaire. The teacher perception questionnaire is a 15-item instrument developed by the researchers on a 4-point Likert response option of SA, A, D, and SD. This instrument is designed with items to elicit responses on teachers' perceived usefulness and ease of use of LLMs with items like "I find LLMs to be an intuitive and hassle-free tool for learning science." The self-efficacy question was also developed by the researchers and consists of 15 items on the likert scale response options of SA, A, D, and SD. The instrument is designed to determine the confidence level teachers have in using LLMs to promote inclusivity with items like "I am confident in my ability to use LLMs to generate lessons plans for learners with special needs." The intention to use LLMs questionnaire is a researcher-developed instrument consisting of 14 items on a 4-point response option of HL (highly likely), L (likely), U (unlikely) and HU (highly unlikely). The instrument sought to elicit data on teachers' likelihood to adopt LLMs for promoting inclusivity.

Face and content validities were established for the three instruments by three experts in the Faculty of Education, Ahmadu Bello University, Zaria. The measure of internal consistency of the instruments was also determined using Cronbach Alpha analysis. The instruments were trial-tested on a random sample of 20 teachers of the Ahmadu Bello University Staff School. This population was used because the teachers teach mainstreamed classrooms where students with special needs are also found. The analysis yielded reliability indices of 0.81, 0.78 and 0.88 for the teachers' perception of LLMs questionnaire, self-efficacy scale and intention to use LLMs questionnaire respectively. The direct delivery and retrieval method of data collection was adopted to collect data for this study. Teachers were given the instrument in their respective classrooms, with the instruments retrieved the following day. Data collected were analysed using regression and moderation analysis. All hypotheses were tested at 0.05 level of significance.

Results

Findings from the study are organized in tables in line with the research questions and hypotheses that guided the study.

Table 1: Regression analysis for the proportion of special education teachers' intention to use LLMs to promote inclusivity that can be attributed to their perception.

Model	N	β (Reg. Weight)	r	r^2	SE
1	51	12.961	0.722	0.521	2.748

The result shows that teachers' perception is a predictor of their intention to use, with positive regression weight (β = 12.961; r = 0.722). This implies that for every 1-unit increase in teachers' perception, the outcome variable (intention to use LLMs to promote inclusivity) will increase by 0.722. The coefficient of determination r^2 is 0.521. This implies that the proportion of science teachers' intention to use LLMs that can be predicted by their perception of LLMs is 52.1%. The linear regression model thus is Y = 12.961 + 2.748x, where x is teachers' intention to use LLMs.

Table 2: Regression ANOVA of special education teachers' intention to use LLMs attributed to their perception.

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	4886.403	1	4886.403	94.685	.000
	Residual	4489.799	49	51.607		
	Total	9376.202	50			

Result on table 2 shows that the probability associated with the calculated value of F (94.685) is 0.000. Since the probability value of 0.000 is less than 0.05 level of significance, the null hypothesis is rejected. Therefore, the proportion of special education teachers' intention to use LLMs to promote inclusivity attributed to their self-efficacy is significant.

Table 3: Regression analysis for the proportion of special education teachers' intention to use LLMs to promote inclusivity that can be attributed to their self-efficacy.

Model	N	β (Reg. Weight)	r	r^2	SE
1	51	8.557	0.644	0.415	3.925

The result shows that teachers' self-efficacy is a predictor of their intention to use, with positive regression weight (β = 8.557; r = 0.415). This implies that for every 1-unit increase in teachers' academic self-efficacy, the outcome variable (intention to use LLMs to promote inclusivity) will increase by 0.644. The coefficient of determination r^2 is 0.415. This implies that the proportion of science teachers' intention to use LLMs to promote inclusivity that can be predicted by their academic self-efficacy is 41.5%. The linear regression model thus is Y = 8.557 + 3.925x, where x is teachers' intention to use LLMs to promote inclusivity.

Table 4: Regression ANOVA of proportion of special education teachers' intention to use LLMs to promote inclusivity attributed to their self-efficacy.

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	3887.867	1	3887.867	61.630	.000
	Residual	5488.335	49	63.084		
	Total	9376.202	50			

Result on table 4 shows that the probability associated with the calculated value of F (61.630) is 0.000. Since the probability value of 0.000 is less than 0.05 level of significance, the null hypothesis is rejected. Therefore, proportion of undergraduate science teachers' intention to use LLMs that can be attributed to their academic self-efficacy is significant.

Table 5: Regression analysis for the proportion of special education teachers' intention to use LLMs jointly attributed to their perception and self-efficacy.

Model	N	β (Reg. Weight)	r	r^2	SE
1	51	2.771	0.786	0.617	3.306

The result shows that teachers' perception and academic self-efficacy are joint predictor of their intention to use, with positive regression weight (β = 2.771; r = 0.786). This implies that for every 1-unit combined increase in teachers' perception and self-efficacy, the outcome variable (intention to use LLMs to promote inclusivity) will increase by 0.786. The coefficient of determination r^2 is 0.617. This implies that the proportion of special education teachers' intention to use LLMs that can jointly be predicted by their perception and self-efficacy is 61.7%. The linear regression model thus is Y = 2.771 + 3.306x, where x is teachers' intention to use LLMs.

Table 6: Regression ANOVA of proportion of special education teachers' intention to use LLMs jointly attributed to their perception and self-efficacy.

Model		**Sum of Squares**	**Df**	**Mean Square**	**F**	**Sig.**
1	Regression	5785.287	2	2892.643	69.277	.000
	Residual	3590.916	48	41.755		
	Total	9376.202	50			

Result on table 6 shows that the probability associated with the calculated value of F (69.227) is 0.000. Since the probability value of 0.000 is less than 0.05 level of significance, the null hypothesis is rejected. Therefore, proportion of undergraduate science teachers' intention to use LLMs to promote inclusivity that can jointly be attributed to their perception and academic self-efficacy is significant.

Discussion

The study revealed that over half (52.1%) of the variation in special education intention to use LLMs to promote inclusivity can be explained by their perception of these tools. This suggests a strong link between how special education teachers view LLMs and their willingness to integrate them into their learning. Teachers who perceive LLMs as valuable resources for enhancing understanding, improving writing, and summarizing complex information are more likely to see them as beneficial additions to their learning toolkit. Conversely, teachers with concerns about the accuracy, potential for plagiarism, or ability to hinder critical thinking might be hesitant to embrace LLMs. A positive perception of user-friendliness can play a role. Special education teachers who find LLMs easy to navigate and feel comfortable using them are more likely to adopt them compared to those who perceive them as complex or requiring significant technical expertise. This finding corroborates those of Bonsu and Baffour-Koduah (2023) and Farhi et al. (2023), who reported that perception of LLMs strongly predicts actual intention to use. Strzelecki (2024) however reported that LLMs acceptance was a stronger predictor of intention to use than perception.

The study also revealed that 41.5% of the variation in special education teachers' intention to use LLMs can be significantly predicted by their self-efficacy. This suggests that special education teachers who feel confident in their understanding and abilities related to science are more likely to embrace LLMs as learning tools. There are two key reasons for this observation. First, special education teachers with high academic self-efficacy likely view themselves as capable learners who can navigate new challenges. They may perceive LLMs as supplementary resources that can enhance their existing scientific knowledge and skills, without undermining their own competence. Conversely, teachers with lower self-efficacy might be apprehensive about using LLMs, fearing they might not be able to critically evaluate the information generated or integrate it effectively into their learning. Secondly, self-efficacy can influence teachers' willingness to experiment with new learning strategies. Special education teachers who are confident in their abilities might be more open to exploring the functionalities of LLMs and discovering how they can benefit their studies. They may see LLMs as opportunities to expand their learning horizons and deepen their understanding, fostering a more positive perception of these tools.

Finally, the study showed that 61.7% of the variation in special education teachers' intention to use LLMs can be jointly explained by their perception of these tools and their self-efficacy. This highlights the crucial role these two factors play in shaping teachers' willingness to integrate LLMs into their learning. Special education teachers with a positive perception of LLMs, viewing them as valuable, user-friendly, and reliable sources of information, are more likely to be interested in using them. Furthermore, teachers with high academic self-efficacy, those confident in their scientific abilities, are more likely to see LLMs as complementary tools that can enhance their learning rather than a crutch. This interplay between perception and self-efficacy suggests that interventions aimed at improving teachers' understanding of LLMs and fostering their confidence in using them alongside their existing knowledge could significantly increase LLM adoption in science education.

Conclusion

This study revealed that teachers' perception of LLMs and their self-efficacy are key factors influencing their willingness to use these tools in special education. The of this study highlights the importance of addressing teachers' perceptions and self-efficacy, and ensuring they understand the strengths and limitations of LLMs to promote their effective use in science education. As emerging technologies, LLMs have come to stay and will continue to evolve. So, it will be almost impossible to stop teachers from using them, especially ChatGPT. So, efforts have to turn towards promoting effective LLMs integration and use in science education in ways that minimizes the negative associated with its use by teachers.

Recommendations

To this end, the study recommends that:

1. Workshops or modules that clarify LLM functionalities, strengths, and limitations of LLMs should be organized for teachers in Universities to foster positive perceptions of LLMs and raise awareness to the risk associated with its use.
2. Teachers should be encouraged to always cross-reference all information obtained from LLMs like ChatGPT with reliable sources before using them.
3. Teachers should also be encouraged to not allow their use of LLMs to limit their cognitive development but educated on ways to use them as guide rather than allow it replace their ability to think.

REFERENCES

Akor, P. U., Maxwell, C., Oladokun, B. D., & Akor, S. O. (2023). Teachers' Perception towards the Use of ChatGPT for Reference Services in a Nigerian University. *25th National Association of Library and Information Science Educators (NALISE) Conference/Annual General Meeting*.

Bernabei, M., Colabianchi, S., Falegnami, A., & Costantino, F. (2023). Teachers' use of large language models in engineering education: A case study on technology acceptance, perceptions, efficacy, and detection chances. *Computers and Education: Artificial Intelligence*, *5*, 100172. https://doi.org/10.1016/j.caeai.2023.100172

Bonsu, E., & Baffour-Koduah, D. (2023, March 7). *From the Consumers' Side: Determining Teachers' Perception and Intention to Use ChatGPTin Ghanaian Higher Education*. Papers.ssrn.com. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4387107

Farhi, F., Jeljeli, R., Aburezeq, I. M., Dweikat, F. F., Al–shami, S. A., & Slamene, R. (2023). Analyzing the teachers' views, concerns, and perceived ethics about chat GPT usage. *Computers & Education: Artificial Intelligence*, *5*, 100180–100180. https://doi.org/10.1016/j.caeai.2023.100180

Hayat, A. A., Shateri, K., Amini, M., & Shokrpour, N. (2020). Relationships between academic self-efficacy, learning-related emotions, and metacognitive learning strategies with academic performance in medical teachers: a structural equation model. *BMC Medical Education*, *20*(1). https://doi.org/10.1186/s12909-020-01995-9

IBM. (2023). *What Are Large Language models? | IBM*. Www.ibm.com. https://www.ibm.com/topics/large-language-models

Kerner, S. M. (2023, September). *What is a large language model (LLM)? – TechTarget Definition*. WhatIs.com. https://www.techtarget.com/whatis/definition/large-language-model-LLM

Liu, Y., Han, T., Ma, S., Zhang, J., Yang, Y., Tian, J., He, H., Li, A., He, M., Liu, Z., Wu, Z., Zhu, D., Li, X., Niu, Q., Shen, D., Liu, T., & Ge, B. (2023). Summary of ChatGPT-Related Research and Perspective Towards the Future of Large Language Models. *Meta-Radiology*, *1*(2). https://doi.org/10.1016/j.metrad.2023.100017

Meyer, J. G., Urbanowicz, R. J., Martin, P., O'Connor, K., Li, R., Peng, P.-C., Bright, T. J., Tatonetti, N., Kyoung Jae Won, Gonzalez-Hernandez, G., & Moore, J. H. (2023). ChatGPT and large language models in academia: opportunities and challenges. *BioData Mining*, *16*(1). https://doi.org/10.1186/s13040-023-00339-9

Mogavi, R. H., Deng, C., Kim, J. J., Zhou, P., Kwon, Y. D., Metwally, A. H. S., Tlili, A., Bassanelli, S., Bucchiarone, A., Gujar, S., Nacke, L. E., & Hui, P. (2023). ChatGPT in education: A blessing or a curse? A qualitative study exploring early adopters' utilization and perceptions. *Computers in Human Behavior: Artificial Humans*, *2*(1), 100027. https://doi.org/10.1016/j.chbah.2023.100027

Mökander, J., Schuett, J., Kirk, H. R., & Floridi, L. (2023). Auditing large language models: a three-layered approach. *AI Ethics*, *2*. https://doi.org/10.1007/s43681-023-00289-2

Nordmann, E. (2023, July 21). *ChatGPT: Student guidance for mulitple-choice assessments*. Dr. Emily Nordmann. https://www.emilynordmann.com/post/chatgpt-student-guidance-for-mulitple-choice-assessments/

Pan, X. (2020). Technology Acceptance, Technological Self-Efficacy, and Attitude Toward Technology-Based Self-Directed Learning: Learning Motivation as a Mediator. *Frontiers in Psychology*, *11*. https://doi.org/10.3389/fpsyg.2020.564294

Prasad, S., Greenman, B., Nelson, T., & Krishnamurthi, S. (2023). Generating Programs Trivially: Student Use of Large Language Models. *Proceedings of the ACM Conference on Global Computing Education Vol 1*. https://doi.org/10.1145/3576882.3617921

Price, P. (2015). *Correlational Research – Research Methods in Psychology*. Opentextbc.ca. https://opentextbc.ca/researchmethods/chapter/correlational-research/

Russo, D. (2024). *Navigating the Complexity of Generative AI Adoption in Software Engineering*. Arxiv.org. https://arxiv.org/html/2307.06081v2

Tu, X., Zou, J., Su, W., & Zhang, L. (2024). What Should Data Science Education Do With Large Language Models? *Harvard Data Science Review*, *6*(1). https://doi.org/10.1162/99608f92.bff007ab