Exploring the Impact of Artificial Intelligence on Communication Effectiveness among Business Education Lecturers

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Abstract
The rapid advancement of Artificial Intelligence (AI) is reshaping business education by enhancing communication effectiveness. This mixed-methods study examined AI's impact on communication effectiveness among business education lecturers in Kwara State tertiary institutions. Data were collected from 219 respondents via questionnaire and analysed using PLS-SEM; 29 lecturers were interviewed and thematically analysed using NVivo. Findings revealed strong correlations between AI Adaptive and Personalised Learning Systems and communication effectiveness, though path coefficients were non-significant, indicating early-stage adoption. Lecturers primarily use AI for content creation, course development, and classroom instruction. Institutions should invest in AI infrastructure, training, and feedback mechanisms.
Keywords: ***Artificial Intelligence; Communication Effectiveness; Business Education***

1. Introduction

Innovation, as Henry Ford once highlighted, is not about adhering to traditional methods but about transcending conventions to devise entirely new solutions. This mindset forms the cornerstone of modern technological advancements across various fields, including education. Before the advent of computers, teaching and learning were entirely manual processes, heavily reliant on human effort and limited resources. The emergence of microcomputers in the 1970s marked a revolutionary period that democratised access to computing power, initiating widespread adoption of electronic computers (Flamm, 1988). Campbell-Kelly (2018) further emphasised that personal computers empowered individuals and organisations to own and utilise technology for diverse purposes, catalysing the integration of computers into numerous sectors, including education.

Advancing upon earlier research in programmed instruction, the rise of computing technology facilitated the development of Computer-Aided Instruction and Learning (CAI/L) systems, fundamentally altering classroom interactions (Cairns & Malloch, 2017). These breakthroughs laid the groundwork for Artificial Intelligence (AI). Coppin (2004) defined AI as machines' ability to adapt, solve problems, and perform functions typically requiring human intelligence; Whitby (2009) similarly described AI as the study and engineering of intelligent behaviour in humans, animals, and machines. AI thus represents the convergence of advanced computing and information communication technologies, enabling machines to execute tasks with human-like intelligence.

AI technologies have the potential to transform instructional delivery by providing personalised and adaptive learning experiences tailored to individual student needs (Afo et al., 2024). The application of AI in the educational field has opened new avenues for the design and development of more effective technology-enhanced learning systems (Hwang et al., 2020; Moreno-Guerrero et al., 2020; Papamitsiou et al., 2018). Through data-driven analytics, natural language processing, and adaptive learning technologies, AI facilitates more interactive and responsive teaching methodologies, supports efficient assessment processes, and enhances collaboration between educators and students (Chassignol et al., 2018).

Business education in tertiary institutions plays a critical role in preparing students for the challenges of a globalised and dynamic business environment. Afolabi (2024) viewed business education as training that equips individuals with knowledge and skills to enter the world of work. AI offers numerous opportunities to enhance these objectives through virtual assistants, adaptive learning systems, and data-driven analytics; however, such advancements also carry challenges, including over-reliance on automation, risks of miscommunication, and the potential erosion of traditional interpersonal teaching methods (Luckin & Holmes, 2016; Zawacki-Richter et al., 2019). This study examines business education lecturers' perceptions of integrating AI into instructional delivery and its impact on communication effectiveness in Kwara State, Nigeria.

1.1 Review of Related Literature

The integration of AI in education represents a transformative approach to enhancing communication, learning outcomes, and overall teaching effectiveness. Zhang and Aslan (2021) emphasised AI's ability to tailor tasks based on individual competencies, provide timely feedback, and create adaptive digital environments. AI-driven platforms enrich learning by fostering intellectual growth, creativity, critical thinking, and problem-solving skills (Southworth et al., 2023). AI also fosters collaborative communication environments, enhancing accessibility to information and promoting meaningful learner networks (Li & Wang, 2024).

Ouyang and Jiao (2021) identified three paradigms of AI adoption in education: AI-direct, AI-supported, and AI-empowered, with Cope et al. (2021) cautioning against over-reliance that reduces education to mechanistic processes. Kabudi et al. (2021) opined that AI Adaptive Learning Systems are personalised platforms that adapt to students' learning strategies, task sequence, difficulty, and feedback timing. Lee et al. (2018) described the Personalised Learning System as a student-centred approach that creates tailored strategies and instructional content for students with distinct qualities and interests. Chaipidech et al. (2022) further noted that teachers in the digital era must integrate content, pedagogical, and technological knowledge within the TPACK framework. In business education, Getchell et al. (2022) discussed AI's implications for business communication, emphasising the need to understand both capabilities and limitations of these technologies for effective instructional use.

1.2 Statement of the Problem

The integration of AI into instructional delivery in business education offers significant potential for enhancing communication effectiveness between lecturers and students. However, in Nigeria, AI technologies in teaching remain underemphasised, with inadequate technological infrastructure, limited lecturer awareness and training, cultural resistance to change, and ethical concerns regarding student data security posing significant barriers. It is therefore imperative to explore lecturers' perspectives on AI-driven communication tools in business education, particularly in the Kwara State context.

1.3 Purpose of the Study

The main objective of this study is to investigate the relationship between artificial intelligence and communication effectiveness in business education. Specifically, the study sought to:

1. Examine the perception of business education lecturers towards AI.
2. Find out the level of utilisation of AI by business education lecturers.
3. Establish the relationship between artificial intelligence and communication effectiveness in business education.

1.4 Research Questions

The following research questions guided the study:

1. What is the perception of business education lecturers towards AI?
2. What purposes do business education lecturers use AI for?
3. Is there any relationship between artificial intelligence and communication effectiveness among business education lecturers in tertiary institutions?

1.5 Research Hypotheses

The following null hypotheses were formulated and tested at a 0.05 level of significance:

H_0: There is no significant relationship between artificial intelligence and communication effectiveness among business education lecturers in Kwara State.

H_0^1: There is no significant relationship between the AI Adaptive Learning System and communication effectiveness among business education lecturers.

H_0^2: There is no significant relationship between the AI Personalised Learning System and communication effectiveness among business education lecturers.

H_0^3: There is no significant relationship between the AI Intelligent Tutoring System and communication effectiveness among business education lecturers.

2. Methodology

2.1 Research Design

The study adopted an explanatory sequential mixed-methods research design to examine the impact of AI on communication effectiveness among business education lecturers in tertiary institutions in Kwara State, Nigeria. In this design, quantitative data were collected and analysed first, followed by qualitative data collection to explain and contextualise the quantitative findings (Creswell & Plano Clark, 2018). This approach was chosen because it enabled both statistical testing of hypothesised relationships and in-depth exploration of the meanings behind the observed patterns.

2.2 Population and Sampling

The target population comprised business education lecturers in tertiary institutions in Kwara State, Nigeria. A pro forma was used to obtain the total population from the Kwara State Ministry of Education, yielding 600 academics across all higher education institutions in the state. Of these, 234 were selected purposively based on their experience with AI-driven communication technologies, ensuring diverse and appropriate representation. For the qualitative strand, following the principle of theoretical saturation, 33 lecturers were approached for semi-structured interviews; 29 completed the interview process.

2.3 Research Instrument and Data Collection

Quantitative data were collected using a structured pro forma questionnaire developed and adapted from validated instruments in prior AI-education research. The instrument comprised items measuring four constructs: Artificial Intelligence (general), AI Adaptive Learning System (ALS), AI Personalised Learning System (PLS), and Communication Effectiveness (CE), all rated on a five-point Likert scale. Content validity was established through expert review by academics in educational technology and business education. Reliability was assessed using Cronbach's alpha, with all constructs yielding coefficients above 0.70 (Hair et al., 2017). Of the 234 questionnaires distributed, 225 were returned and 219 were valid for analysis, yielding a response validity rate of 93.6%. Qualitative data were collected through semi-structured interviews, transcribed verbatim, and analysed thematically in NVivo 14 following Braun and Clarke's (2006) six-phase framework.

2.4 Data Analysis

Quantitative data were analysed using descriptive statistics (mean, median, and standard deviation) to answer the research questions, and Partial Least Squares Structural Equation Modelling (PLS-SEM) using SmartPLS 4 to test the hypotheses. The measurement model was assessed for reliability (Cronbach's alpha and composite reliability), convergent validity (Average Variance Extracted), and discriminant validity (Fornell-Larcker criterion). The structural model was evaluated using bootstrapping with 5,000 resamples to determine the significance of path coefficients.

2.5 Measurement Model Assessment and AVE Justification

A key consideration in the measurement model is the Average Variance Extracted (AVE) values recorded for the AI Adaptive Learning System (AVE = 0.300) and the AI Personalised Learning System (AVE = 0.284), both of which fall below the conventional threshold of 0.50 recommended by Fornell and Larcker (1981). The study acknowledges this limitation transparently. However, several considerations justify the retention and interpretation of these constructs within the analysis.

First, both constructs achieved composite reliability (ϱ_c) values of 0.767 and 0.736, respectively, both exceeding the 0.70 threshold, indicating acceptable internal consistency (Hair et al., 2017). Composite reliability is considered a more robust indicator of construct reliability than Cronbach's alpha, particularly in exploratory PLS-SEM studies (Hair et al., 2019). Second, consistent with the recommendation of Henseler et al. (2015), discriminant validity was further assessed using the Heterotrait-Monotrait (HTMT) ratio criterion, which is recognised as a more sensitive and accurate measure of discriminant validity than the Fornell-Larcker criterion alone. Third, this study is explicitly exploratory and contextual in nature, targeting a population in a developing-country setting where AI adoption is nascent. In such contexts, lower AVE values are not uncommon and may reflect genuine variability in how respondents understand and experience AI constructs, rather than measurement error per se (Hair et al., 2019). These considerations support the retention of all constructs, with the limitation explicitly acknowledged in Section 7.

3. Results

3.1 Discriminant Validity (Fornell-Larcker Criterion)

Table 1 presents the Fornell-Larcker discriminant correlations. The correlation between the AI Adaptive Learning System and the AI Personalised Learning System is robustly positive (r = 0.921). The AI Adaptive Learning System shows a strong positive relationship with Communication Effectiveness (r = 0.831), as does the AI Personalised Learning System (r = 0.818). Overall AI and Communication Effectiveness reflect a moderate positive relationship (r = 0.484), suggesting that targeted AI subsystems explain communication outcomes better than general AI use alone.

Table 1: Fornell-Larcker Discriminant Correlations of the Constructs

Construct	AI Adaptive Learning System	AI Personalized Learning System	Artificial Intelligence	Communication Effectiveness
AI Adaptive Learning System	0.548			
AI Personalized Learning System	0.921	0.533		
Artificial Intelligence	0.537	0.541	0.650	
Communication Effectiveness	0.831	0.818	0.484	0.652

3.2 Convergent Validity

Table 2 presents the convergent validity indices. Cronbach's alpha ranged from 0.706 to 0.845 and composite reliability (ϱ_c) from 0.736 to 0.876, all meeting the recommended threshold of 0.70 (Hair et al., 2017). As discussed in Section 2.5, the AVE values for the AI Adaptive Learning System (0.300) and AI Personalised Learning System (0.284) fall below the 0.50 threshold; however, given satisfactory composite reliability and the exploratory nature of this study in a developing-country context, these constructs are retained with the limitation explicitly noted. The AVE values for Artificial Intelligence (0.423) and Communication Effectiveness (0.425) approach the threshold and are considered acceptable (Hair et al., 2019).

Table 2: Convergent Validity (Cronbach's α, Composite Reliability, and AVE)

Construct	Cronbach's α	CR (ρ_a)	CR (ρ_c)	AVE
AI Adaptive Learning System	0.706	0.806	0.767	0.300
AI Personalized Learning System	0.731	0.819	0.736	0.284
Artificial Intelligence	0.845	0.868	0.876	0.423
Communication Effectiveness	0.825	0.900	0.862	0.425

3.3 Structural Model: Path Coefficient Analysis

Table 3 and Figure 1 present the structural model results. Artificial Intelligence usage (β = 0.030, p = 0.171), AI Adaptive Learning System (β = 0.502, p = 0.106), and AI Personalised Learning System (β = 0.339, p = 0.236) all showed positive but statistically non-significant relationships with communication effectiveness, leading to the retention of all three null hypotheses. The R^2 value of 0.710 indicates that the model explains 71.0% of the variance in communication effectiveness, affirming strong overall model fit. The substantive magnitude of the ALS path coefficient (β = 0.502, f^2 = 0.131) approaches the medium effect size threshold of 0.15 defined by Cohen (1988), suggesting meaningful practical relevance despite non-significance.

Table 3: PLS-SEM Path Coefficient Analysis

Path Relationship	β	Std. Dev.	R^2	f^2	p-value	T-Value	Decision
Artificial Intelligence → Communication Effectiveness	0.030	0.178	0.710	0.002	0.171	0.864	H_0^1 Retained
AI Adaptive Learning System →Communication Effectiveness	0.502	0.311	—	0.131	0.106	1.615	H_0^2 Retained
AI Personalized Learning System →Communication Effectiveness	0.339	0.287	—	0.059	0.236	1.184	H_0^3 Retained

Note: p-values based on bootstrapping with 5,000 resamples. All hypotheses retained at α = 0.05. R^2 = 0.710.

Figure 1: Path Coefficient Analysis (SmartPLS Structural Model Output)

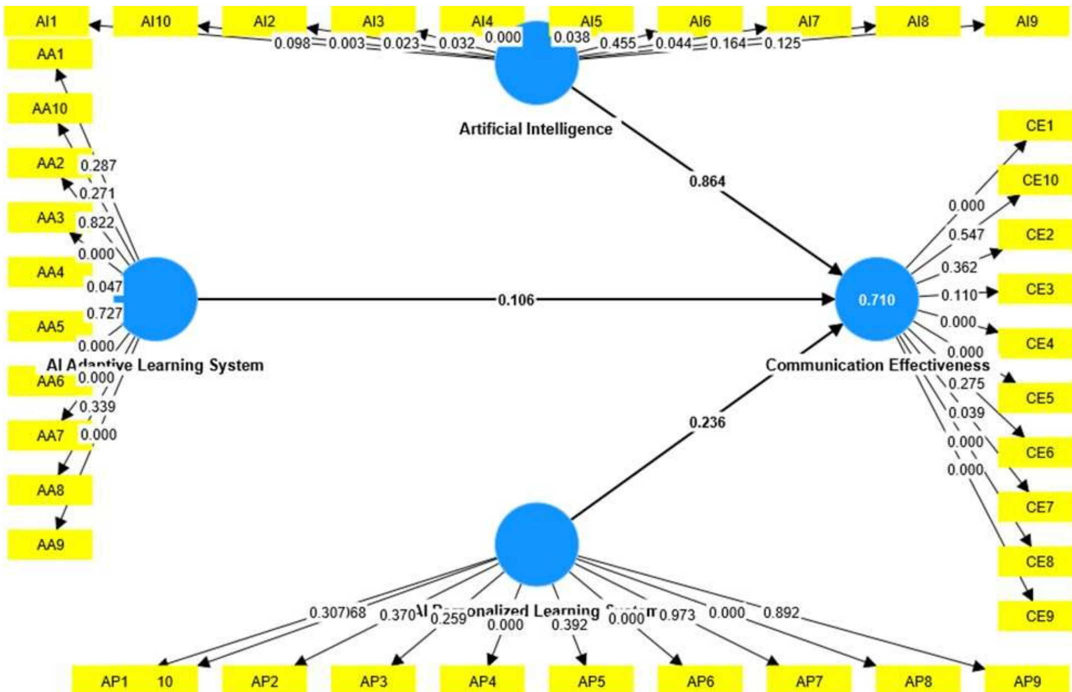

Fig. 1. Path coefficient analysis showing relationships between AI constructs and Communication Effectiveness (R^2 = 0.710).

3.4 Research Question 1: Lecturers' Perceptions of AI

The thematic analysis of interview data revealed that business education lecturers perceive AI in education through two primary lenses: (1) the development of online educational platforms, and (2) the development of AI chatbot technologies, as visualised in Figure 2.

Figure 2: NVivo Framework — Business Education Lecturers' Perceptions Towards AI

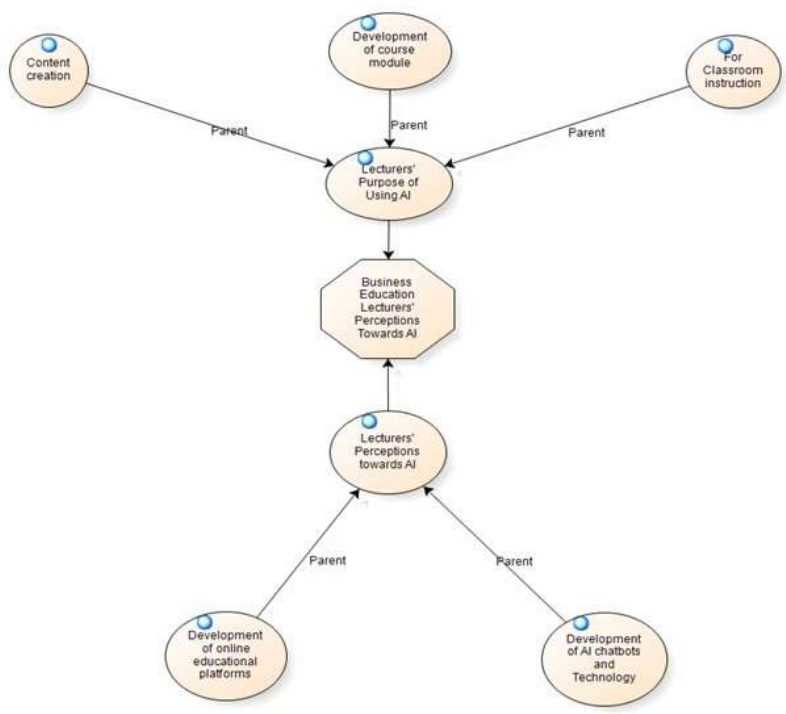

Fig. 2. NVivo thematic framework explaining lecturers' purposes for using AI and perceptions towards AI in business education.

3.4.1 Development of Online Educational Platforms

Most lecturers perceived AI in education as embodied in online educational platforms:

Respondent 1: *"It is known as educational platforms like video conferencing, chatbots, and Zoom."*

3.4.2 Development of AI Chatbots and Technology

Many lecturers associated AI in education with AI chatbot technologies such as ChatGPT:

Respondent 11: *"I believe AI in education deals with the development of technologies like ChatGPT."*

3.5 Research Question 2: Purposes for Which Lecturers Use AI

The interview data revealed that lecturers primarily use AI for three purposes: content creation, course module development, and classroom instruction, as reflected in the upper tier of Figure 2.

3.5.1 Development of Course Modules

Respondent 3: *"Amplifies our work and makes it effective."*

Respondent 6: *"AI enlightens us in writing the right composition and in terms of any communication."*

3.5.2 Content Creation

Respondent 2: *"Yes, I mostly used AI for my M.Ed. programme."*

Respondent 4: *"AI helps me to prepare more for and produce extensive course notes."*

Respondent 14: *"Usage of AI through the WhatsApp platform."*

3.5.3 Classroom Instruction

Respondent 6: *"Usage of AI tools like ChatGPT, chatbots, video conferencing, and Meta AI for classroom teachings."*

4. Discussion of Findings

The discriminant validity analysis revealed that the AI Adaptive Learning System had a strong correlation with the AI Personalised Learning System (r = 0.921) and a strong positive relationship with Communication Effectiveness (r = 0.831). The AI Personalised Learning System similarly showed a strong positive relationship with Communication Effectiveness (r = 0.818). These findings align with Kabudi et al.'s (2021) submission that adaptive learning systems are personalised platforms that adjust to students' learning tactics, task sequence, complexity, and feedback timing, and with Lee et al.'s (2018) characterisation of personalised learning as a student-centred system that accommodates diverse needs and promotes skill development.

The structural model results (Table 3; Figure 1) indicate that none of the path coefficients reached statistical significance at $\alpha = 0.05$, leading to the retention of all null hypotheses. Nonetheless, the R^2 value of 0.710 demonstrates that the model explains a substantial proportion of the variance in communication effectiveness, affirming the overall model's explanatory power. The ALS path coefficient of $\beta = 0.502$ is particularly noteworthy; while it does not reach significance, its effect size ($f^2 = 0.131$) approaches the medium threshold defined by Cohen (1988), suggesting meaningful practical relevance that may manifest statistically in a larger or more AI-experienced sample. The negligible coefficient for general AI ($\beta = 0.030$) reinforces that broad AI exposure, without purposeful deployment of specific systems, does not meaningfully alter communication outcomes.

The qualitative findings, as visualised in Figure 2, contextualise the quantitative results effectively. Lecturers' perceptions were oriented towards visible and accessible AI manifestations: online platforms and chatbots reflecting early-stage, tool-level AI conceptualisation rather than pedagogically integrated understanding. Their reported uses reflect Ouyang and Jiao's (2021) AI-direct paradigm, resonating with Afo et al.'s (2024) observation that AI's transformative communicative potential is only realised when purposefully and systematically integrated. Crompton et al.'s (2024) emphasis on professional development programmes and Getchell et al.'s (2022) call for educators to understand AI's capabilities and limitations both point to the same institutional imperative evident in this study.

5. Conclusion

This study examined the influence of artificial intelligence on communication effectiveness as perceived by business education lecturers in tertiary institutions in Kwara State, Nigeria. Using a mixed-methods design combining PLS-SEM analysis of 219 valid questionnaire responses with NVivo-assisted thematic analysis of 29 interviews, the study found that neither AI in general nor its specialised implementations via adaptive and personalised learning systems exerted a statistically significant impact on communication effectiveness at the 0.05 level. Nonetheless, the strong model fit ($R^2 = 0.710$), positive path directions, and strong discriminant correlations suggest substantial latent potential that has yet to be fully realised. The NVivo framework confirms that lecturers' engagement with AI remains at the level of productivity tools and technology recognition rather than deep communicative integration. Meaningful improvement in communication effectiveness through AI will require deliberate institutional investment in training, infrastructure, and strategic AI integration.

6. Recommendations

Based on the findings of this study, the following recommendations are offered:

4. Tertiary institutions should integrate AI-driven communication tools into both online and traditional classroom settings to foster better interaction and engagement.
5. School authorities should invest in reliable digital infrastructure including stable internet connectivity and uninterrupted power supply as a foundational prerequisite for meaningful AI adoption.
6. Regular structured training programmes should be provided to equip lecturers with skills to use AI tools purposefully for content creation, adaptive feedback, and classroom communication.
7. Institutions should develop more comprehensive measures of communication effectiveness to capture the nuanced impacts of AI systems.
8. Accessible, user-friendly AI tools should be developed and promoted to align with lecturers' existing purposes and positively shape their perceptions.
9. Continuous feedback mechanisms involving both lecturers and students should be established to monitor AI tool impact and guide iterative improvements.

7. Limitations and Directions for Future Research

This study has several limitations that should be acknowledged. First, the AVE values for the AI Adaptive Learning System (0.300) and AI Personalised Learning System (0.284) fall below the 0.50 threshold, indicating that measurement instruments for these constructs may require refinement. Future studies should increase the number of reflective indicators or conduct item-level analysis to identify and remove poorly performing items. Second, the study was conducted in a single state (Kwara State), which limits generalisability; future research should extend the sample across multiple states or include comparative multi-institutional analyses. Third, the cross-sectional design precludes causal inference; a longitudinal design would better capture how AI adoption evolves and whether communicative effects strengthen as lecturers gain experience. Fourth, the study focused exclusively on lecturers' perspectives; future research should incorporate students' perceptions to provide a more complete picture of AI's communicative impact in business education.

Declaration of Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors. The study was conducted independently, and no external organisation had any role in the study design, data collection, analysis, interpretation, or the decision to submit the manuscript for publication.

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Authors Contribution
Felicia Kikelomo Oluwalola: Conceptualisation, Methodology, Data Collection, Formal Analysis, Qualitative Analysis, Writing Original Draft, Writing Review & Editing, Supervision, Final Approval. Bajeh Methodology, Formal Analysis (PLS-SEM), writing review & editing, and final approval. Ayanwole: Qualitative Analysis, Writing Review & Editing, Final Approval.

Ethical Approval Statement

This study was conducted in accordance with the ethical principles governing research involving human participants. Ethical approval was obtained from the Ethical Review Committee at the University of Ilorin before data collection (ethics approval number). All participants were fully informed of the study's purpose and voluntarily consented to participate. No participant was coerced. To protect participant confidentiality and anonymity, all qualitative respondents are identified solely by self-chosen pseudonyms throughout this manuscript. No personally identifiable information was collected or reported.

Data Availability Statement

The data that support the findings of this study are not publicly available due to ethical restrictions related to the privacy and confidentiality of research participants. The data were collected under informed consent agreements that do not permit public sharing. The quantitative summary data and analytical outputs presented in the tables and figures of this manuscript are available within the article. Requests for further information may be directed to the corresponding author.

Generative AI Use Statement

During the preparation of this work, the author(s) used Grammarly to enhance the clarity of the writing. After using Grammarly, the author(s) review(s) and edit(s) the content as needed and take(s) full responsibility for the content of the publication.

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