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AI-Enabled School Management Dashboards for the Early Identification of Student Mental-Health Risks in Secondary Schools in the Federal Capital Territory, Abuja

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ABSTRACT

Adolescent mental health is a growing concern in secondary schools worldwide. In Nigerian schools, systematic mechanisms for the early detection of psychological risk remain limited, with most institutions continuing to rely on informal observation and crisis-driven referrals. This study examined the influence of artificial intelligence (AI)-enabled school management dashboards on the early identification of student mental health risks in selected private secondary schools in the Federal Capital Territory (FCT), Abuja, Nigeria. A descriptive survey research design was adopted. A researcher-developed AISMMH questionnaire, validated by subject experts, was used to generate responses from 472 respondents. Multiple linear regressions revealed that AI-driven data indicators significantly predicted early mental health risk identification.

Keywords: artificial intelligence in education, early identification, Nigeria, school management dashboards, secondary schools, student mental health

INTRODUCTION

Adolescence is a period of rapid change. Biologically, socially, and emotionally, young people in secondary school navigate transitions that carry real psychological weight, and for a significant proportion, the strain becomes clinically meaningful. The World Health Organization (2021) estimates that approximately 50% of lifetime mental health conditions begin before age 14 and that approximately 75% are manifested by the mid-twenties. Globally, depression and anxiety are among the leading causes of illness and disability among adolescents (UNICEF, 2022). Recent educational research has further emphasized the importance of school environments in promoting emotional wellness and psychological resilience among students, reinforcing the need for proactive school-based mental health monitoring and support systems (Dhandapani & Kaur, 2026). These are not minor statistics. They point to a population-level challenge in which schools, whether they acknowledge it or not, are positioned at the center of.

Secondary schools occupy a unique position in adolescent development. Students spend the majority of their waking hours within school environments, making schools one of the few institutional settings where behavioral change, the kind that often signals emerging psychological difficulty, can be observed consistently over time. Attendance records fluctuate. Grades shift. Disciplinary incidents accumulate. These signals, taken individually, may mean little. Taken together and tracked systematically over weeks, they can indicate a student in distress (Kroenke et al., 2024). The problem, as Suresh et al. (2024) note, is that most schools have no systematic mechanism for connecting these signals in time to matter.

Nigeria is not unique in this regard, although its challenges are specific. Mental health literacy in Nigerian schools has improved over the past decade, yet the structural foundations for early identification remain thin (Akintoye & Odei, 2026). In the Federal Capital Territory (FCT), Abuja, home to a growing number of well-resourced private secondary schools, guidance counselors are present in most institutions but are often overwhelmed by administrative responsibilities and career guidance functions. Referrals to counselors tend to occur after a problem has escalated, not before (Akintoye & Odei, 2026). The warning signs that precede a crisis, such as sustained absenteeism, declining performance, and escalating peer

conflict, are gathered in school records but rarely analyzed. The data exist; the analytical infrastructure to use them does not.

Recent years have seen the emergence of AI-enabled school management dashboards, digital platforms that aggregate student data from multiple sources and surface patterns in visual form, which are accessible to administrators and counselors without the need for technical expertise (Ifenthaler & Yau, 2020). Attendance records, assessment scores, behavioral logs, and digital activity can be combined to produce risk scores or color-coded alerts, providing school staff with a structured mechanism for proactive attention. Commercial platforms, including 360School (2025) and SchoolRex (2020), have been adopted in private Abuja schools, primarily for administrative and academic purposes. Whether these tools can be meaningfully extended to mental health risk identification remains, at present, an open empirical question, at least in the Nigerian context. Internationally, evidence is accumulating.

Wong et al. (2024) demonstrated that digital trace monitoring can identify self-harm risk earlier than conventional teacher referrals can. Suresh et al. (2024) reported that multi-indicator early warning systems in K-12 settings meaningfully reduced intervention delays. The United Nations Educational, Scientific and Cultural Organization (2023) has called for contextually grounded, ethically governed applications of AI in education. These findings are promising. They do not, however, tell us what happens when similar approaches are attempted in Abuja's secondary schools, where the sociocultural context, institutional structures, and data governance frameworks differ significantly from those studied elsewhere.

This study therefore set out to fill that gap. The central question was whether AI-enabled school management dashboards influence the early identification of student mental health risks in private secondary schools in the FCT, Abuja. Three subsidiary questions guided the empirical work: First, do AI-driven data indicators, attendance, academic performance, and behavioral records, significantly predict early mental health identification outcomes; second, to what extent do these dashboards support guidance counselors in their decision-making; and third, do school administrators and counselors differ in how they perceive these tools? The findings are intended to support evidence-based policy and practice development in Nigerian school mental health systems.

LITERATURE REVIEW

Conceptual Framework

What exactly is an AI-enabled school management dashboard? This question matters because the term is used loosely in both commercial and academic contexts. For the purposes of this study, an AI-enabled school management dashboard is defined as a digital platform that aggregates structured student data

from multiple administrative sources, attendance, assessment scores, disciplinary records, and digital engagement logs and presents these data in a visualized form intended to support decision-making by nontechnical school personnel (Ifenthaler & Yau, 2020). The "AI-enabled" dimension typically involves predictive algorithms that generate risk scores or flags on the basis of observed patterns in the data rather than simple descriptive reporting.

Commercial FCT platforms such as 360School (2025) and SchoolRex (2020) represent the most widely adopted tools of this kind. Both systems emphasize administrative efficiency and academic performance tracking. Neither platform has been formally evaluated for its capacity to support mental health identification. This is not unusual globally; Luckin et al. (2016) reported that even sophisticated educational AI systems are rarely designed with psychological well-being as a primary output. The conceptual move from an *administrative dashboard* to *a well-being surveillance system* requires deliberate design choices: incorporating clinically anchored indicators, calibrating alert thresholds to local population norms, and embedding the system within a responsive counseling infrastructure (Kroenke et al., 2024).

There is a certain irony in the term "wellbeing surveillance". It suggests that monitoring and monitoring carry connotations of control. Scholars reasonably argue that the same data systems used to identify students at risk can also be misused to discipline, track, or stigmatize them (Worsley et al., 2024). This tension is not resolved by technology alone. It requires institutional governance, ethical frameworks, and, critically, human judgment embedded in the loop between data output and response. The present study treats the dashboard as a decision-support tool, not a diagnostic tool.

The application of any such model to schools in Abuja also demands contextual adaptation. Variable digital infrastructure across schools, cultural norms that stigmatize mental health disclosure and the historically reactive orientation of Nigerian school counseling practices all condition what these tools can and cannot do (Atilola & Ola, 2016; Akintoye & Odei, 2026). Dashboard models designed for schools in the United Kingdom or the United States cannot be imported wholesale. They require localization, a process that, as yet, has not been formally documented in the FCT.

Theoretical Framework

Four interrelated theoretical frameworks inform the conceptual architecture of this study. They are not used as ornaments. Each addresses a specific dimension of the problem, population-level risk detection, individual risk dynamics, data-to-action translation, and the ethical governance of AI systems in institutional contexts.

Public Health Model of School Mental Health.

Borrowing from epidemiology, this model organizes school mental health support into three tiers: universal (preventive support for all students), selective (targeted support for at-risk groups), and indicated (intensive individual intervention) (Wong et al., 2024). In this framework, AI-enabled dashboards function as surveillance mechanisms at the Universal and Selective levels. They generate the longitudinal, population-wide data necessary for identifying students who warrant more targeted attention before their difficulties require intensive individual responses. For schools in Abuja, where counselor-to-student ratios are unfavorable, such tools offer the possibility of extending the effective reach of counseling without proportionally expanding staffing.

Risk and Resilience Theory.

Unger (2019) and Ager et al. (2023) emphasize that adolescent mental health is not determined by risk factors alone. It is shaped by the interplay between those risks and the protective factors, teacher relationships, community ties, and peer networks that buffer their impact. For AI predictive models to carry validity in the Nigerian context, they must be calibrated to reflect both Nigeria-specific stressors (high-stakes examination pressure, family economic precarity, rapid urbanization) and locally relevant protective factors. A model trained on data from North American schools may generate misleading risk scores when applied to Abuja students whose risk and resilience profiles differ. This is a design challenge, not simply a statistical one.

Learning analytics and educational data mining.

Ifenthaler and Yau (2020) describe learning analytics as an iterative cycle: data are collected, processed, visualized, and then translated into pedagogical or institutional action. Educational data mining extends this by applying machine-learning methods to large educational datasets to surface patterns that are not apparent from descriptive statistics. Both frameworks establish the theoretical legitimacy of using routine school data, attendance, grades, and behavior as inputs for well-being-oriented predictive models, provided that appropriate validation is conducted. The critical word is "validation." It is argued here that the application of learning analytics to mental health identification in Nigerian schools cannot rely on validation data from other contexts alone.

Ethical AI and Socio-Technical Systems Theory.

Perhaps the most important framework for contextualizing this study. UNESCO (2023) articulates the position that AI systems in education are not neutral technical artifacts; they carry assumptions, encode values, and produce effects shaped by the institutional and cultural environments in which they operate. In Abuja, this means that the Nigeria Data Protection Act (2023) establishes a legal

foundation for student data processing, but school-level awareness of and compliance with these provisions is inconsistent. In the cultural context of mental health stigma in Nigeria, a student flagged by a dashboard as "at risk" faces potential harm if that information is handled carelessly. The principle of the "human-in-the-loop" is not merely a design preference; it is an ethical requirement. AI outputs must be filtered through professional judgment, cultural sensitivity, and institutional accountability (Nguyen, 2026).

Empirical Review

Evidence from the Nigerian Context

Empirical research on AI use in Nigerian secondary schools is growing but uneven. Ogundokun and Okoye (2023) surveyed international private secondary schools in Abuja and reported moderate adoption of AI tools, concentrated primarily in academic engagement monitoring and assessment analytics. Their data suggest that technical infrastructure exists. The institutional will to apply it to mental health is another matter. Neither the schools surveyed nor the platforms they used had incorporated psychological risk detection into their data systems.

National platform providers tell a similar story. SchoolRex (2020) and comparable Nigerian school management systems report administrative gains, faster attendance tracking, streamlined reporting, and more efficient fee management. What is consistently absent is any reference to student well-being data or counseling integration. Akintoye & Odei (2026) offer perhaps the most direct empirical account of counseling conditions in FCT schools: a reactive orientation, a career-guidance emphasis, a high caseload, and very limited data infrastructure. More recently, Olowe et al. (2025) reported that the majority of in-school adolescents in Nigerian secondary schools demonstrated poor knowledge and poor attitudes toward mental health, with more than one-third at risk of conduct problems indicating the urgency of systematic, technology-supported identification systems. It is against this backdrop that the present study's question about AI-enabled dashboards must be understood. This gap is not merely technical, as ICT dashboards in Nigerian schools have improved efficiency but remain underutilized for monitoring well-being (Adeyemi & Oladimeji, 2026; Chukwuemeka et al., 2026).

International Evidence

Internationally, the evidence base is considerably richer, although not without its own complications. Suresh et al. (2024) conducted a systematic review of early warning systems in K-12 education and reported consistent evidence that multi-indicator systems, combining attendance, grade trajectories, and behavioral incident data, outperform single-indicator approaches in identifying students at

elevated risk. Their analysis also revealed that the timeliness of intervention is the key mediating variable: identification that precedes crisis is associated with markedly better student outcomes than identification that follows it.

Wong et al. (2024) extended this work to the domain of digital monitoring, demonstrating that compared with conventional teacher referrals, self-harm risk signals can be detected earlier when anonymized digital trace data, search patterns, platform query frequencies, and messaging activity are used. The data tentatively indicate that the passive monitoring of digital behavior, even without active screening, may offer a low-burden, scalable approach to early identification. This is a genuinely promising finding. It is also a source of legitimate concern. Worsley et al. (2024) reported that secondary school students held deeply ambivalent views about dashboard monitoring: many acknowledged its protective potential while simultaneously expressing unease about continuous surveillance, loss of privacy, and the permanence of digital records.

Kroenke et al. (2024) provide clinical grounding for the administrative indicators most commonly used in these systems. Their longitudinal analysis revealed statistically significant associations between specific school-administrative markers, sudden attendance deterioration, grade trajectory reversals, escalating incident records, and validated measures of depression and anxiety in adolescent populations. This is an important finding for the present study because it provides evidence-based justification for the specific predictor variables included in the regression model.

Research Gap

Three distinct gaps emerge from this synthesis. The contextual gap is the most pressing: all empirical work on AI-based student monitoring in Nigerian schools has focused on academic performance, leaving mental health identification entirely unaddressed. The methodological gap is closely related: no published study has validated AI-generated indicators against mental health identification outcomes using data from the FCT secondary school population. The perceptual gap is perhaps the most underappreciated: Nigerian administrators, counselors, and students have not been asked how they understand or evaluate these tools, and their perspectives may be quite different from those of stakeholders in high-income settings where most of the literature originates.

The present study addresses all three gaps directly through a quantitative investigation of the influence of the dashboard on mental health identification in private secondary schools in Abuja, incorporating both predictive modeling and a comparison of stakeholder perceptions.

MATERIALS AND METHODS

Research Design

A descriptive survey research design was adopted for this study. Survey designs are appropriate when the research aim is to describe the attitudes, perceptions, or experiences of a defined population at a given point in time, without experimental manipulation (Creswell & Creswell, 2023). Here, the aim was to obtain quantitative evidence about how school administrators and guidance counselors in Abuja perceive and experience AI-enabled school management dashboards in relation to mental health risk identification. Cross-sectional data collection was deemed sufficient for this purpose, although it has the inferential limitations discussed later.

Population and Sampling

The target population comprised principals, vice-principals, senior administrators, and guidance counselors from private secondary schools registered with the FCT Secondary Education Board in the Abuja Municipal Area Council (AMAC) and Bwari Area Council. These two councils were selected because they contain the highest concentration of private secondary schools in the FCT and because documented evidence suggests that their schools are more likely to operate digital management platforms (FCT Education Secretariat records, as cited in Ogundokun & Okoye, 2023).

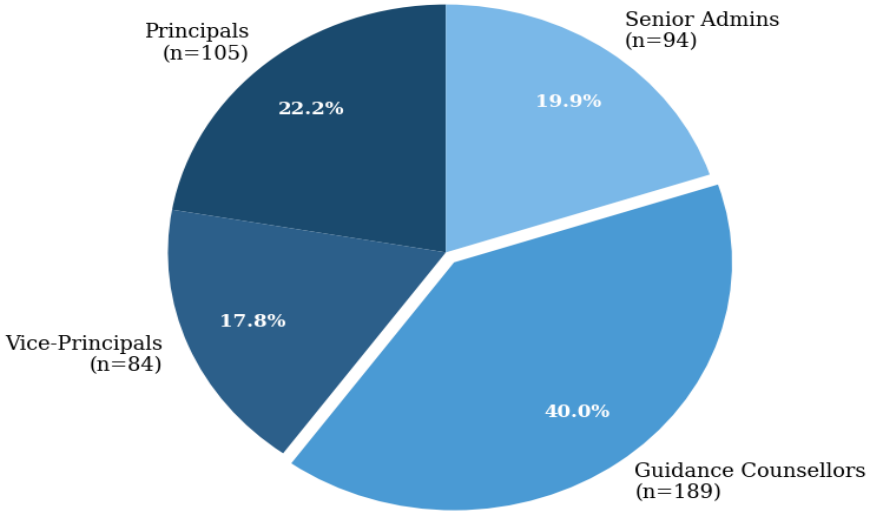

Figure 1. *Sample composition by respondent role (N = 472).*

221 schools met the inclusion criterion of operating a digital school management information system. Purposive sampling was used to ensure that the respondents had direct experience with the technology under study. Within each school, proportionate stratified sampling was applied to draw respondents from across all four role categories, with role type (principals, vice-principals, guidance counselors, and senior administrators) serving as the stratification variable. A total of 496 questionnaires were distributed in person by the researcher and trained research assistants, who visited each school on a scheduled date. Of these, 472 were returned in usable condition, representing a response rate of 95.2%. This high response rate was facilitated by in-person administration, whereby questionnaires were distributed and collected on the same visit to each school. The composition of the final sample by role is shown in Figure 1, with guidance counselors constituting the largest group at 40.0%, reflecting their centrality to the study's research questions.

Table 1: Demographic profile of the respondents (N = 472)

Category	Frequency	Percentage (%)
Principals	105	22.2
Vice-Principals	84	17.8
Guidance Counselors	189	40.0
Senior Administrators	94	19.9
Total	**472**	**100.0**

Note. The respondents were drawn from 221 private secondary schools in the Abuja Municipal Area Council and Bwari Area Council of the FCT.

Research instrument

Data were collected using the AI-Enabled School Management and Mental Health Monitoring Questionnaire (AISMMHQ), a 16-item researcher-developed instrument organized into four subscales: (a) *Influence on Early Identification* (4 items); (b) *AI-Driven Data Indicators* (4 items); (c) *Support for Counselor Decision-Making* (4 items); and (d) *Perceptions of Administrators and Counselors* (4 items). Items were rated on a four-point Likert scale (1 = strongly disagree to 4 = strongly agree). A mean score of $M >= 2.50$ was adopted as the criterion for agreement, which is consistent with the four-point format and in line with standard practice in Nigerian educational survey research.

Validity and Reliability

Content validity was established through review by three subject-matter experts in educational technology, guidance and counseling, and educational management. Each expert independently assessed the clarity, relevance, and

coverage of the items against the corresponding subscale construct. Items identified as ambiguous or poorly aligned were revised or removed before the instrument was finalized. Facial validity was assessed separately through a small panel of school administrators, who reviewed the questionnaire for comprehensibility.

A pilot study involving 30 respondents from schools outside the main sample was conducted prior to full administration. Internal consistency reliability was assessed via Cronbach's alpha, yielding alpha = .80 for the full instrument. This exceeds the widely applied alpha threshold of .70 in social science research (Taber, 2018), indicating satisfactory internal consistency across all four subscales.

Data Analysis

Descriptive statistics, means and standard deviations were calculated for each subscale and for the overall instrument. Multiple linear regression analysis was then conducted to examine the joint and individual predictive effects of three AI-driven data indicators (attendance records, academic performance, and behavioral records) on early identification of mental health risk. Before running the regression, the standard assumptions were checked: linearity was examined via residual plots; multicollinearity was assessed using variance inflation factors (all VIF values were below 3.0); homoscedasticity was confirmed visually; and the normality of the residuals was verified using a normal probability plot. All the assumptions were judged to be adequately met.

An independent samples t-test was used to assess whether administrators and counselors differed significantly in their perceptions of the dashboards. All inferential tests were conducted at a two-tailed significance level of alpha = .05.

RESULTS

Descriptive Statistics

The respondents agreed with the items across all four AISMMHQ subscales, with all the mean scores exceeding the criterion value of $M = 2.50$. The highest mean was recorded for *support for counselor decision-making* ($M = 3.19$, standard deviation, and $SD = 0.49$), *whereas perceptions of administrators and counselors* produced the lowest mean ($M = 3.05$, and SD = 0.57). The overall scale mean was $M = 3.11$ ($SD = 0.55$). These descriptive results are presented in Table 2 and Figure 2.

Table 2: Descriptive Statistics by AISMMHQ Subscale (N = 472)

Subscale	Mean (M)	*SD*
Influence on Early Identification	3.12	0.54
AI-Driven Data Indicators	3.08	0.61
Support for Counselor Decision-Making	3.19	0.49
Perceptions of Administrators and Counselors	3.05	0.57
Overall Scale	3.11	0.55

Note. All subscale means exceeded the agreement criterion of $M \geq 2.50$. SD = standard deviation.

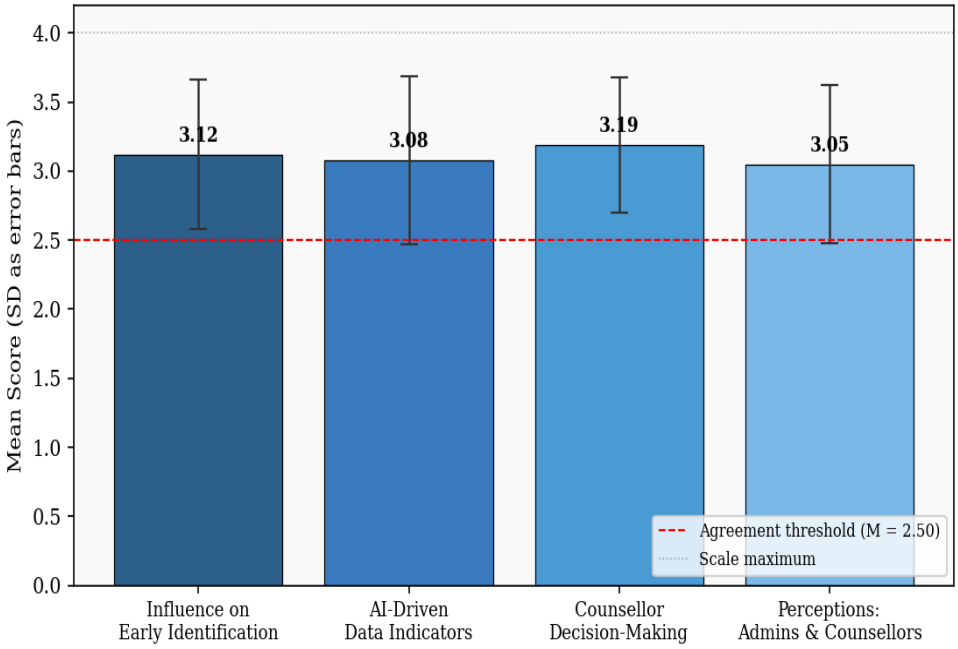

Figure 2. *Mean scores with standard deviation error bars across the four AISMMHQ subscales (N = 472).* The dashed reference line indicates the agreement threshold ($M = 2.50$). All the subscales exceeded this criterion.

Regression Analysis: Predicting early mental health risk identification

Multiple linear regressions were conducted to assess the predictive influence of AI-driven data indicators on the early identification of student mental health risks. Attendance records, academic performance, and behavioral records were entered simultaneously as predictor variables. The model was statistically significant, $F(3, 468) = 108.42$, $p < .001$, and accounted for 41% of the variance in the outcome variable ($R^2 = .41$). All three predictors were independently significant. Attendance records carried the strongest standardized effect (β = .38, p < .001), followed by academic performance (β = .29, p = .003) and behavioral records (β = .22, p = .012). The full regression results are presented in Table 3 and Figure 3.

Table 3: Multiple Linear Regression: AI-Driven Indicators as Predictors of Early Mental Health Risk Identification

Predictor	B	SE B	β	*t*	*p*
Attendance records	0.41	0.07	.38	5.86	.001
Academic performance	0.35	0.08	.29	4.37	.003
Behavioral records	0.28	0.09	.22	3.11	.012
Model: $R^2 = .41$, $F(3, 468) = 108.42$, $p < .001$					

Note. B = unstandardized coefficient; SE B = standard error of B; *β* = standardized coefficient. = .41. The overall model was significant at p < .001.

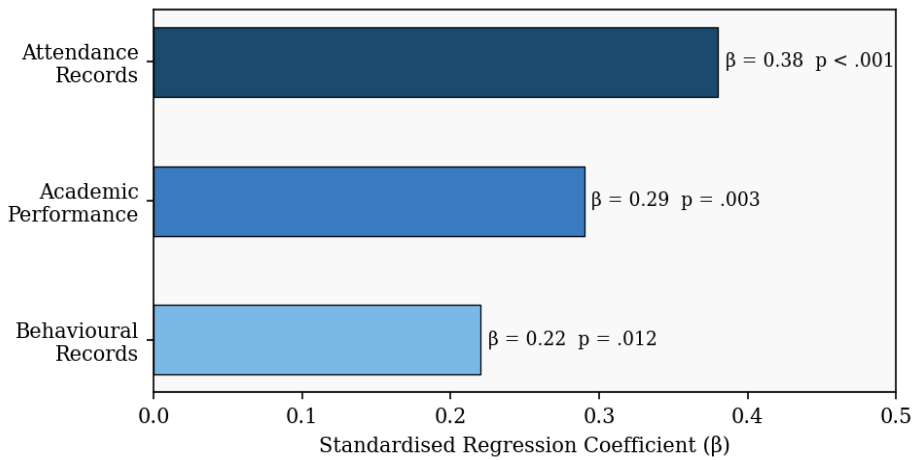

Figure 3. *Standardized regression coefficients (β) for the three AI-driven predictors.* Attendance records demonstrated the strongest predictive effect (β = .38), followed by academic performance (β = .29) and behavioral records (β = .22). All the predictors were statistically significant (p < .05).

T-Test: Perceptual Differences between Administrators and Counselors

An independent samples t-test was conducted to determine whether the perceptions of school administrators (n = 283; M = 3.09; SD = 0.56) differed significantly from those of guidance counselors (n = 189; M = 3.14; SD = 0.53). The result was not statistically significant, $t(470) = 1.47$, $p = .143$. The null hypothesis of no perceptual difference was retained. The complete results are presented in Table 4 and Figure 4.

Table 4: Independent Samples T-Test: Perceptions of Administrators and Guidance Counselors

Group	*n*	*M*	*SD*	*t*	**df**	*p*
Administrators	283	3.09	0.56	1.47	470	.143
Guidance Counselors	189	3.14	0.53			

Note. A two-tailed test was conducted at α = .05. The result was not statistically significant.

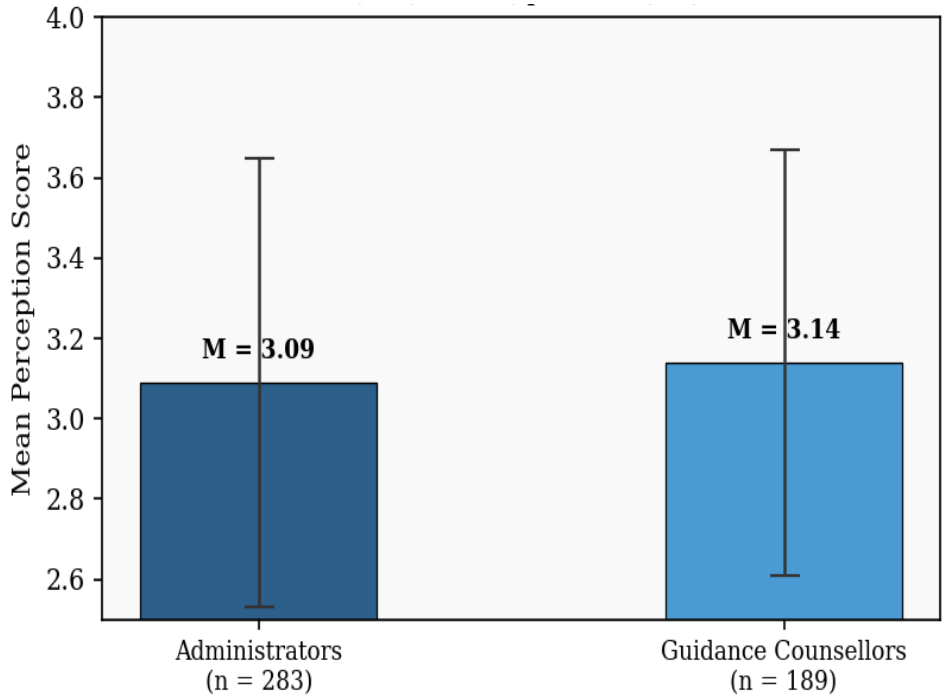

Figure 4. *Mean perception scores for administrators and guidance counselors with standard deviation error bars.* No statistically significant difference was found between groups, $t(470) = 1.47$, $p = .143$.

DISCUSSION

Predictive Power of AI-Driven Indicators

The regression model accounted for 41% of the variance in early mental health risk identification ($R^2 = .41$, $p < .001$). That is a meaningful result in a field context. This suggests that what schools routinely collect, attendance data, grades, and behavioral incident records, contains real signals for psychological risk. These findings are consistent with the learning analytics framework proposed by Ifenthaler and Yau (2020), who argue that iterative cycles of educational data collection and algorithmic visualization can surface patterns that informal observation misses.

Attendance records were the strongest single predictor ($\beta = .38$). This is not surprising. Absenteeism is among the earliest and most consistent behavioral correlates of adolescent emotional distress (Kroenke et al., 2024). Students who experience depression or anxiety often stop coming to school before they tell anyone why. Academic performance ($\beta = .29$) was the second strongest predictor, which is consistent with the well-documented association between declining grades and internalizing disorders in secondary school populations (UNICEF, 2022). Wang (2025) similarly demonstrated that AI-enabled student management systems that monitor academic performance trajectories in real time substantially improve the timeliness and targeting of institutional interventions. The contribution of behavioral records, although more modest ($\beta = .22$), accords with the proposition of risk and resilience theory that risk indicators carry greater weight in combination than any single marker alone does (Unger, 2019; Ager et al., 2023).

The 59% unexplained variance is also worth taking seriously. It points to risk dimensions that these three administrative indicators do not capture, peer relationship quality, family dynamics, economic stress, and psychological factors that do not manifest as visible school behavior until considerably later in their trajectory. This is not a criticism of the model as much as an honest characterization of what administrative data can and cannot do. Schools that adopt AI-enabled dashboards are therefore advised to treat any risk flag as a prompt for further counselor inquiry rather than as a diagnosis. This distinction is consistent with the "human-in-the-loop" principle articulated by UNESCO (2023) and supported by recent evidence that administrators sometimes misinterpret algorithmic alerts as definitive diagnoses, a form of automation bias that can lead to the premature labeling of students (Nguyen, 2026).

These findings align with those of Suresh et al. (2024), whose systematic review of K-12 early warning systems revealed consistent evidence that multi-indicator models outperform single-indicator approaches in identifying at-risk students. These findings are further corroborated by recent computational studies: Shi et al. (2025) demonstrated that a multimodal AI model combining graph convolutional networks and temporal behavioral data achieved high accuracy in

early student mental health risk detection, whereas Fu et al. (2025) reported that the Apriori algorithm applied to institutional data streams reliably identified mental health risk patterns among college students. The present study extends this evidence to a private secondary school context in sub-Saharan Africa for the first time (although this estimate has inherent limitations given the cross-sectional, single-site design).

Decision-Making Support for Counselors

The respondents most strongly agreed with items in the *support for counselor decision-making* subscale (M = 3.19, SD = 0.49). Field observations during data collection suggested that counselors who had experience using dashboard outputs found them useful for prioritizing student contact, a function that is difficult to perform systematically when working with large numbers of students and limited time. This is theoretically consistent with the public health tiered model (Wong et al., 2024): In this reading, dashboards serve as the analytical infrastructure needed to distinguish between students who may benefit from universal-level support and those who warrant selective or indicated intervention.

High perceived utility does not, however, guarantee effective practice. Worsley et al. (2024) caution that dashboard adoption among practitioners depends on digital literacy, algorithmic confidence, and trust in the data governance environment. Similar concerns have been reported within educational settings where users' AI literacy significantly influences their understanding and engagement with emerging AI technologies (Threadgill et al., 2026). In Abuja's private schools, where formal training on AI tools is limited, the transition from perceived utility to competent and ethically informed use will require sustained investment. Perceived value is a starting point. It is not the endpoint.

It is argued here that counseling infrastructure is the binding constraint. An AI-generated risk flag that is not connected to a clear, responsive referral pathway does very little for the student it identifies. Renta-Davids et al. (2025), in a scoping review of AI in educational leadership, similarly cautioned that effective dashboard adoption requires school leaders to develop digital literacy and AI competence and that the absence of such competencies constitutes a structural barrier to realizing the tools' potential. UNESCO (2023) frames this in terms of sociotechnical systems: the value of AI tools is coproduced by the technology and the institutional structures, protocols, relationships, and leadership support that surround it. Dashboard adoption, in other words, is a systems-change process, not a software installation.

Convergence between Administrators and Counselors

The absence of a significant difference in perception between administrators and counselors ($t(470) = 1.47$, $p = .143$) was among the more practically useful findings of this study. This suggests that the two professional

groups most central to any dashboard adoption process share a broadly aligned view of the utility of these tools. This contrasts with patterns documented in higher-income countries, where tensions between administratively oriented and clinically oriented staff have sometimes impeded the adoption of integrated well-being technology (Worsley et al., 2024).

Why might this alignment exist in the Abuja context? Several explanations are plausible. Both groups appear to share an awareness of the inadequacy of current mental health identification systems, a common problem recognition that may create shared openness to new tools. It is also possible that the relatively early stage of AI adoption in these schools means that strong professional identity conflicts around the technology have not yet crystallized. As dashboards become more embedded in school practice, these distinctions may emerge. The data tentatively indicate institutional readiness at the perceptual level; what remains to be established is whether that readiness translates into coordinated, ethically grounded practice.

Ethical Dimensions and Contextual Constraints

The Nigeria Data Protection Act (2023) established a legal framework for processing student data, but school-level compliance capacity is variable, and enforcement remains uneven. The risk of data misuse in this context is real: student mental health information, if handled carelessly, can lead to stigmatization, unauthorized disclosure, or discriminatory treatment. These are not hypothetical concerns (Federal Government of Nigeria, 2023; Atilola, 2015).

Cultural context matters here in ways that the international literature does not fully address. Mental health disclosure in Nigeria is associated with significant social stigma at the family level, within peer networks, and within communities (Atilola & Ola, 2016). A student identified as “at risk” through a dashboard system may face social consequences that the system’s designers did not anticipate. This means that the architecture of dashboard implementation must include not only technical safeguards but also institutional protocols for how risk information is communicated, who has access to it, and how counselors are trained to respond in culturally sensitive ways.

Scholars maintain that the “human-in-the-loop” principle is not a design preference but an ethical necessity in educational AI (UNESCO, 2023). In the context of Abuja's secondary schools, this principle is doubly important. Counselors must be equipped not only to interpret algorithmic outputs but also to contextualize them to ask whether a flagged student's declining attendance reflects depression or whether it reflects economic precarity, family crisis, or something else entirely. The dashboard narrows the search space. It does not replace the search.

Limitations and Future Research

This study is not without limitations. First, the research employed a cross-sectional descriptive survey design, which limits causal inference. The associations identified between AI-enabled dashboard indicators and early mental health identification are correlational; longitudinal designs are needed to establish directionality. Second, the study was confined to private secondary schools in two area councils of the FCT, namely, the Abuja Municipal Area Council and Bwari Area Council. Private schools in the FCT may be atypical in their levels of digital infrastructure relative to public schools and schools in other geopolitical zones of Nigeria, which constrains the generalizability of the findings. Third, the study relied entirely on self-reported perceptual data from school staff. The respondents' assessments of the effectiveness of the dashboard may not correspond to objectively verified identification rates or intervention outcomes. Social desirability bias cannot be ruled out.

Fourth, the study did not examine student perspectives. Adolescents' perceptions of AI-mediated monitoring, including privacy concerns and trust, constitute a critical and largely unmeasured dimension of this research problem (Worsley et al., 2024). Fifth, the AISMMHQ was developed specifically for this study, while its reliability was satisfactory ($\alpha = .80$), its use beyond the FCT context would require revalidation with other populations.

Future research should address these limitations in several ways. Longitudinal cohort designs tracking mental health identification outcomes in schools with and without AI-enabled dashboards over at least two academic sessions would substantially strengthen causal evidence. Comparative studies extending to public secondary schools and to schools in other Nigerian states, particularly in the Southeast, Northwest, and South–South geopolitical zones, are needed to establish whether the present findings are generalizable beyond FCT. Researchers should also triangulate self-report data with objective school records such as counselor referral logs, disciplinary incident data, and academic performance trajectories to validate perceptual measures against behavioral outcomes. Studies incorporating student and parental perspectives would provide a more complete and ethically grounded evidence base. Finally, intervention studies evaluating the effectiveness of structured AI literacy training programs for school counselors and administrators would address the critical implementation gap identified by the present findings. Internationally, comparative research within the West African subregion would help to contextualize the FCT findings and identify the institutional conditions under which AI-enabled dashboards most effectively support early mental health identification (Olowe et al., 2025; Fu et al., 2025).

CONCLUSION

This study examined whether AI-enabled school management dashboards influence the early identification of student mental health risks in private secondary schools in the FCT, Abuja. Three AI-driven data indicators, attendance records, academic performance, and behavioral logs, collectively predicted early identification outcomes, accounting for 41% of the outcome variance ($R^2 = .41$, $F(3, 468) = 108.42$, $p < .001$). The respondents across all the subscales reported general agreement with the dashboard utility. No significant difference in perception was found between administrators and counselors, suggesting baseline institutional alignment for technology adoption.

To the authors' knowledge, this study is the first to provide quantitative empirical evidence linking AI-enabled dashboard features to mental health risk identification outcomes in secondary schools in FCT. It extends the learning analytics and early warning systems literature to a sub-Saharan African context, where empirical work has been lacking. It also establishes, through t-tests, that stakeholder perceptual alignment, a necessary precondition for coordinated adoption, appears to exist within the Abuja private school sector.

REFERENCES

360School. (2025). *School management and analytics platform*. https://www.360school.ng

Adeyemi, O. V., Atoyebi, B. I., & Oladimeji, A. H. (2026). Leveraging information communication technology for innovative educational management practices in Nigeria. *FUOYE International Journal of Educational Management, 3*(1), 55–70.

Ager, A., Akesson, B., Stark, L., & Boothby, N. (2023). School-based mental health and psychosocial support. *Journal of Child & Adolescent Mental Health, 35*(2), 85–98. https://doi.org/10.1080/17450128.2023.2186490

Akintoye, V. O., & Odei, M. A. (2026). Digital tools and the modernization of counselling practices in the Nigerian educational sector. *Impact International Journals and Publications*. https://impactinternationaljournals.com/publications/index.php/ojs/article/view/339

Atilola, O. (2015). Mental health service utilization in sub-Saharan Africa: Is public mental health literacy the problem? *Global Health Promotion, 22*(1), 30–37. https://doi.org/10.1177/1757975914527514

Atilola, O., & Ola, B. (2016). Towards school mental health programmes in Nigeria: Systematic review revealed the need for contextualized and culturally-nuanced research. *Journal of Child & Adolescent Mental Health, 28*(1), 47–70. https://doi.org/10.2989/17280583.2016.1144607

Chukwuemeka, A. C., Sanni, O. F., Akyala, A. I., Jaggu, A. R., Amuta, E. U., Agbeshie, G. D., & Otieno, J. (2026). Perceptions and determinants of mental health awareness among adolescent students in the Federal Capital Territory (FCT), Abuja, Nigeria. *MGM Journal of Medical Sciences, 13*(1), 22–32. https://doi.org/10.4103/mgmj.mgmj_16_26

Creswell, J. W., & Creswell, J. D. (2023). *Research design: Qualitative, quantitative, and mixed methods approaches* (6th ed.). SAGE Publications.

Dhandapani, S., & Kaur, K. . (2026). Examining the Role of School Climate in Promoting Cross-Cultural Emotional Wellness and Psychological Resilience Among Students in Army Schools. *Journal of Interdisciplinary Studies in Education*, *15*(2), 1-16. https://doi.org/10.32674/r4h84g39

Federal Government of Nigeria. (2023). *Nigeria Data Protection Act 2023*. Nigeria Data Protection Commission. https://ndpc.gov.ng/download/nigeria-data-protection-act-2023/

Fu, Y., Ren, F., & Lin, J. (2025). Apriori algorithm based prediction of students' mental health risks in the context of artificial intelligence. *Frontiers in Public Health, 13*, Article 1533934. https://doi.org/10.3389/fpubh.2025.1533934

Ifenthaler, D., & Yau, J. Y.-K. (2020). Utilizing learning analytics to support study success in higher education: A systematic review. *Educational Technology Research and Development, 68*(4), 1961–1990. https://doi.org/10.1007/s11423-020-09788-z

Kroenke, K., Strine, T. W., Spitzer, R. L., Williams, J. B. W., Berry, J. T., & Mokdad, A. H. (2024). Adolescent behavioral indicators and psychological risk in school settings: Evidence from longitudinal surveillance. *Journal of Adolescent Health, 74*(3), 412–421. https://doi.org/10.1016/j.jadohealth.2023.09.014

Luckin, R., Holmes, W., Griffiths, M., & Forcier, L. B. (2016). *Intelligence unleashed: An argument for AI in education*. Pearson.

Nguyen, M. G. (2026). Artificial intelligence ethics in education: A systematic review of challenges, policy governance frameworks, and pedagogical integration directions. *Journal of Artificial Intelligence Technological Development, 2*(2), 123–130. https://doi.org/10.59324/jaitd.2026.2(2).09

Nguyen, M. T. (2026). Artificial intelligence in educational management: A conceptual review of leadership and governance implications. *Journal of Applied Research in Higher Education*. Advance online publication. https://doi.org/10.1108/JARHE-01-2026-0092

Ogundokun, R. O., & Okoye, C. (2023). Artificial intelligence adoption in Abuja private secondary schools: Patterns, outcomes, and gaps. *Nigerian Journal of Educational Technology, 5*(2), 78–96.

Olowe, A. O., Tshabalala, A. M., & Bruce, J. C. (2025). Self-reported knowledge, attitude and mental health status of in-school adolescents in Nigeria. *African Journal of Primary Health Care & Family Medicine, 17*(1), Article 4858. https://doi.org/10.4102/phcfm.v17i1.4858

Renta-Davids, A. I., Jiménez-González, J. M., Fandos-Garrido, M., & González-Soto, Á. P. (2025). Navigating the challenges and opportunities of artificial intelligence in educational leadership: A scoping review. *Review of Education, 13*, Article e70101. https://doi.org/10.1002/rev3.70101

SchoolRex. (2020). *School management information system: Platform overview*. SchoolRex Technologies. https://www.schoolrex.com

Shi, X., Pan, J., Yuan, D., Li, M., & Pan, Y. (2025). Advanced data analysis and prediction model for student mental health risk assessment. *Frontiers in Psychology, 16*, Article 1682083. https://doi.org/10.3389/fpsyg.2025.1682083

Suresh, A., Lee, J., & Kizilcec, R. F. (2024). Early-warning systems in K-12 education: A systematic review of design, predictors, and outcomes. *Computers & Education: Artificial Intelligence, 5*, 100178. https://doi.org/10.1016/j.caeai.2023.100178

Taber, K. S. (2018). The use of Cronbach's alpha when developing and reporting research instruments in science education. *Research in Science Education, 48*(6), 1273–1296. https://doi.org/10.1007/s11165-016-9602-2

Threadgill, B., Paudel, S., Bista , K., Gaulee, U., Prime , G., Momoh, V., Anderson, P. C., Gole , R., Sharma , S., Mandal , U., Rajput , M., Garbuja, S., Tiwari, K., & Pandey, V. (2026). Understanding AI Literacy Among College Students: Voices from a Historically Black College and University. *Journal of Interdisciplinary Studies in Education*, *15*(2), 169-194. https://doi.org/10.32674/w76bnk04

United Nations Children's Fund. (2022). *Adolescent mental health: Promoting mental health in adolescence*. https://www.unicef.org/health/adolescent-mental-health

United Nations Educational, Scientific and Cultural Organization. (2023). *AI and education: Guidance for policy-makers*. https://doi.org/10.54675/PCSP7350

Unger, M. (2019). Designing resilience research: Using multiple methods to investigate risk exposure, promotive and protective processes, and contextually relevant outcomes for children and youth. *Child Abuse & Neglect, 96*, 104098. https://doi.org/10.1016/j.chiabu.2019.104098

Wang, Y. (2025). Artificial intelligence in student management systems to enhance academic performance monitoring and intervention. *Scientific Reports, 15*, Article 35122. https://doi.org/10.1038/s41598-025-19159-4

Wong, C. A., Merchant, R. M., & Moreno, M. A. (2024). Digital trace monitoring for adolescent self-harm risk identification in K-12 settings. *JAMA Pediatrics, 178*(2), 134–142. https://doi.org/10.1001/jamapediatrics.2023.4810

World Health Organization. (2021). *Adolescent mental health*. https://www.who.int/news-room/fact-sheets/detail/adolescent-mental-health

Worsley, J. D., Harrison, P., & Corcoran, R. (2024). Student perspectives on AI-mediated wellbeing monitoring in secondary schools: Utility, privacy, and trust. *British Journal of Educational Technology, 55*(1), 58–74. https://doi.org/10.1111/bjet.13340

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