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Student Counselling 2030: Evaluating Human–AI Collaborative, Trauma-Informed and Social–Emotional Approaches to Behavioural Management, Well-Being and School Engagement

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Abstract--

Background: Secondary schools struggle with behavioural, emotional and engagement issues and have inconsistent levels of counselling services. AI has the potential to increase the ability to screen, monitor and conduct follow-up. However, automated systems have the potential to misclassify distress, reinforce bias, and diminish relational accountability.

Objective: The study examined four different counselling models: conventional counselling, human–AI collaborative counselling, trauma-informed counselling, and a model that is an integration of human–AI, trauma-informed, and social–emotional learning.

Method: A comparative quasi-experimental design was implemented with 240 students aged 13 to 18. Students were exposed to each of the models for a 14-week period with 60 students per model. A realistic simulated research data set was used, that was conceived based on parameter and effect patterns that were recently published in peer-reviewed literature. The effects of the models on several outcome measures which included behavioural management, well-being, emotional regulation, social–emotional competence, responsiveness to counselling and perceived safety were determined. The research employed a battery of statistical tests, including paired tests, multivariate analysis, and bootstrapped mediation, among others.

Results: No significant difference was present in the scores of the groups before the models were implemented. All of the groups improved but the extent of the improvement varied among the groups. The trauma-informed model, integrated human–AI model, and social–emotional learning model for counselling, presented the highest engagement scores. Social emotional competence and emotional regulation mediated the engagement scores of the model. The study indicated that a highly regulated model of human–AI integration has the potential to strengthen timely, personalised and trauma-sensitive support when the safe responsibility of human counsellors is maintained. The simulated research results provided evidence to support the study; however, no claims for clinical or system-wide validation were provided. The study justified the need for future field testing.

Keywords-- **artificial intelligence; school counselling; trauma-informed education; social–emotional learning; student well-being; school engagement**

I. INTRODUCTION

The emotional, social, and cognitive development that occurs during the school years is marked by specific difficulties that include anxiety, depression, problematic family relationships, difficult social relationships, and school disengagement. These difficulties can be interpreted as the expression of needs that are not met. The World Health Organization recognizes the school years as the time for the development of essential social and emotional skills, and the greatest amount of disability among young people of working age is due to mental health problems (WHO, 2022). Schools must be understood as systems that shape the developmental and life trajectories of young people by providing safety, structures, and supports. The challenges that school closures posed during the COVID-19 pandemic revealed the essential nature of school habits and relationships for mental health (Viner et al., 2022).

More often than not, traditional behavior management practices include giving students warning signs, exclusion from school activities, or punishing students for bad behavior that has become visible. While these practices may result in the temporary control of behavior, they do not provide the rationale or justification for behavior that may be a result of the symptoms of trauma, loss of control of emotions, learning frustration, bullying, or the expression of a disability. The goal of school counseling is to provide a more preventive approach to behavior management. This goal can be attained through the integration of the observation of behavior with the student voice, psychoeducation, family involvement, and referrals. Unfortunately, the integration of the aforementioned activities is often delayed due to the fragmented nature of casework and the high caseloads of school counselors. The goal for counseling in the future is to more accurately assess students' needs in a timely manner without placing more students at risk.

AI can be used for helping with appointment routing, multilingual psychoeducation, screener/assessment tool administration, and reminder summaries, and it can help with noticing patterns over time. Although there are many reviews on the benefits of using conversational agents for many of the common mental-health related issues, the outcomes and effects are inconsistent, and the safety evidence has yet to be established (Abd-Alrazaq et al., 2020; Li et al., 2023; Zhong et al., 2024). Due to the current state of research, AI should be used for decision support, and not for fully autonomous therapy. Trauma-informed practice takes safety and trust into consideration, as well as choice and collaboration while avoiding the risk of retraumatization. Social-emotional learning involves teaching and developing self-awareness and self-management, as well as social awareness and relationship skills, and responsible decision making. Recent meta-analysis on the implementation of social-emotional learning in schools indicates that while the effects may be small, they are significant (Cipriano et al., 2023).

There is a need for research that combines the support of AI, trauma-informed practice in schools, and social-emotional learning, as these areas tend to be research silos. When these areas combine, they often overlook the simultaneous outcomes of behavioral management, well-being, and engagement. Given the aforementioned gaps in research, this project will be looking to compare four plausible pathways and study if emotional self-regulation, social-emotional skills, and responsiveness to counseling account for the observed differences. With that in mind, this research was looking to compare the outcomes and effects, as well as quantify the outcomes, and study the governance and ethical risks to support the development of the Student Counselling 2030 initiative. The primary focus of this research was to study the differences between the intervention groups and answer the questions related to the integrated model; specifically, the effect of emotional self-regulation on behavioral outcomes, the effect of counseling responsiveness on engagement, and the effect of emotional self-regulation on counseling responsiveness. I hypothesized that there would be no differences, and I also hypothesized that emotional self-regulation would not demonstrate any predictive effects on behavioral outcomes.

II. Literature Review And Theoretical Framework

Students can engage behaviorally, emotionally, and cognitively. This means that students can be present, participate, identify, and be thoughtful toward their school if their school environment fulfills their need for competence, autonomy, and relatedness.

Well-being and engagement are distinct, though it is accurate to say that the two are interrelated. Emotional distress can negatively affect concentration and school attendance, and in turn may result in the loss of protective relationships. The research is new, but it has begun to show that interventions designed to improve connectedness and belonging result in positive educational and mental health outcomes in school, but the implementation and quality of these interventions is important (Davies et al., 2025). The studies all found a positive correlation between academic success and emotional intelligence, but emotional intelligence was not a substitute for cognitive ability, the quality of teaching, or systemic supports (MacCann et al., 2020).

Counseling can be integrated into classrooms through the use of social-emotional learning (SEL). A recent meta-analysis reported that there were gains in the social-emotional skills and attitudes of participants, positive changes in behaviors, and academic gains, but there were a number of gaps and variations across the different programs (Cipriano et al., 2023). Research from China has reported similar findings, citing an increase in social-emotional skills and a decrease in emotional distress, but varying and inconsistent changes in behavior (Chen et al., 2022). Pedrini et al. (2022) advocates for the incorporation of emotional regulation skills into repeated practice. Pedrini et al. also argues that supportive, caring relationships are an essential factor for the success of emotional regulation programs. This supports a model that proposes counseling as the integration of practice, feedback, and the teaching of emotional regulation skills into the classroom, rather than the use of disconnected conversations.

From a trauma-informed perspective, behavior should not be viewed as intentional defiance, but as a possible response to threat, disruption and/or grief. It recognizes not all challenges are from trauma, does not condone negative behavior or turn educators into clinicians. Instead, it incorporates routines that provide predictability, communication that is devoid of shaming, relational safety, and student voice and agency in addition to appropriate response. While some systematic reviews cite evidence of promising innovations, others cite poor design, a lack of definitional clarity, and an absence of longitudinal studies (Fondren et al., 2020; Avery et al., 2021; Newton et al., 2024). Based on these reviews, Watson and Astor (2025) call for more definitional clarity and more actual research innovations. The current research considers trauma-informed practice as an additional relational and organizational layer, not a diagnostic category.

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Utilization of AI in counseling may help alleviate some of the backlog, automate low-risk tasks, and assist counselors in identifying patterns. While reviews of the literature indicate that conversational agents integrated in a wider framework of care can help in the area of symptom management and well-being, the evidence is often short and of poor quality (Gual-Montolio et al., 2022; Li et al., 2023). Generative systems are a dangerous mix of fluent and inaccurate outputs. Bias is embedded in training data of a poor quality, culturally narrow language models, differential access to devices, and negative historical records (Straw & Callison-Burch, 2020; Timmons et al., 2023). Trust may be earned through some explainability, but only if the explanations are genuinely meaningful, contestable, and derived from a true delegation or a heightened sense of control (Shin, 2021).

The integrated framework consists of five aspects. First is the placement of the student by the ecological systems theory into the family, peer, classroom, school and, policy environments. Second is the self-determination theory and involvement through the components of autonomy, competence and, relatedness. Third is the social-emotional learning framework and the malleable competencies. Fourth is the trauma-informed and culturally responsive framework and the principles of safety, trust, collaboration, and empowerment. Fifth and last is the human-centered AI. Here, the technology is considered an accountable tool and is under the control of professionals. Collaborative intervention is said to provide better access and personalisation. Trauma-sensitive relationship create an environment of safety and trust. Social-emotional practice advances social and emotional competencies, which assists in behavioural management. This framework presents engagement and well-being, and incorporates safeguards. In the absence of consent, equity, and proper oversight, an improvement to care may be worsened, predicting greater outcomes of harm.

III. Research Methodology

Design and participants. This consisted of a fourteen-week program in secondary schools and utilized a quasi-experimental design with pre and post assessments. The sample consisted of 240 participants aged 13-18, equally assigned to one of the following categories: traditional counselling, human and AI integrated counselling, trauma-informed counselling, and human integrated counselling with AI and social-emotional learning. This design was intended to reflect how counselling is typically offered in schools, rather than an individual level randomisation.

The criteria for participation included being in grades 7-12 and the ability to provide consent and participate in both assessments. Participants with acute and specialised clinical needs were to be provided with care outside of the study.

Interventions. Conventional counseling incorporated scheduled individual or small group sessions, problem clarification, goal setting, and routine follow-ups. Human–AI counseling included screening with digital consent, prioritizing appointments, multilingual psychoeducation, reminder prompts, trend summaries, and alerts reviewed by the counselor. The trauma-informed condition incorporated predictable sessions, non-shaming behavioral formulation, and grounding, choice, and safety planning. Coordinated strategies aimed to avoid retraumatization. The integrated condition combined all the preceding components and included practices for emotional regulation, relationship-building, social awareness and responsible decision making, personalized follow-up, and, as appropriate, teacher or parent coordination. AI was not used for diagnosis, making disciplinary decisions, communicating high-risk advice, or independent case closure.

Measures. Behavioral management was scored on a 0 to 40 scale with a higher score indicating greater self-regulation and fewer disruptive difficulties. Well-being scores ranged from 14 to 70, school engagement scores ranged from 15 to 75, emotional regulation and social–emotional competence scores ranged from 10 to 50, counseling responsiveness scores ranged from 8 to 40, and perceived school safety scores ranged from 5 to 25. The constructs were based on recognized school and adolescent measurement frameworks. No exact wording for the copyrighted items was reproduced. Various measures used multi-item scales with five-point response formats and reported acceptable to strong internal consistency. AI acceptance and trust were only measured in AI-supported conditions and were seen as implementation indicators rather than evidence of therapeutic effectiveness.

Data Generation and Quality Control. The realistic research datasets for the simulated studies were constructed from the parameters and effect trends published in the literature from 2020 to 2025. Where baseline scores were correlated, were demographics were variable, and where overlapping outcome distributions and individual residual errors were present, these were intentionally simulated and retained. Group effects were identified as smallest for conventional counseling and as largest for the integrated model, which contained trauma-informed counseling that stressed well-being and safety and human – AI counseling which focused on being responsive.

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Item level missingness was set to 0.7%, and person mean imputation within a scale was deemed acceptable only if 80% of the items were present. No simulated participants were eliminated. Five mild univariate outliers were retained as sensitivity analysis did not result in substantive changes to conclusions. Skewness and kurtosis were within accepted levels, and residuals were approximately linear and homoscedastic. Collinearity was acceptable.

Analysis. Descriptive statistics were used to summarize the sample. One-way tests were used to assess baseline equivalence. Within-group changes were assessed via paired samples t-tests, and effect sizes were reported as Cohen's d, including 95% confidence intervals. Gain scores were analyzed via a multivariate analysis, and for each of the post-test outcomes, ANCOVA was used with baseline scores, age, gender, SES, prior counseling, and school type as covariates. Gain scores were also analyzed using Tukey HSD for statistical significance. Various associations were assessed via Pearson correlations. Multiple regression was used to assess the influence of baseline engagement, emotional regulation, counseling responsiveness, social–emotional competence, behavior, group, and controls on post-test engagement. The 2,000 sample bootstrap was utilized to assess social–emotional competence as a mediator for the differences in engagement between the integrated and conventional models. The alpha was set at .05. All analyses were done in Python with a random seed set to 2030, following reproducible methods consistent with either SPSS or R.

Counselor session logs, records of completed emotional-regulation activities, records of AI-prompt reviews submitted to staff, and brief student evaluations of safety, choice, and usefulness would serve as indicators for monitoring fidelity of implementation. Exposure would include indicated attended sessions, indicated completed follow-ups, and documented teacher/parent coordination. These fidelity indicators would not be combined into a staff score that would result in disciplinary action. Instead, they would determine if inadequate outcomes were the result of an inadequate model or if the model was delivered adequately and outcomes were the result of inadequate fidelity. The attendance, participation, and disciplinary referrals, and help-seeking behaviors of students, which can be accessed from administrative data and systems with consent and data minimization, should be included in future studies. These indicators would fulfill the gap left by self-report measures and assess whether the engagement of students manifested in actual participation and did not just result in favorable outcomes for the questionnaires.

Implementation feasibility would involve an assessment of the implementation and an assessment of the cost-to-benefit ratio of the service. The counselor-to-student ratios, the digitally-enabled environments of the school, and the diversity of staff and the students all impact the integration of trauma-informed practices. Stopwatch time for the various steps of the process, reporting and reviewing alerts, student opt-out, override of a decision, technical breakdown and failures, safeguarding escalations, and complaints should be included in a process evaluation. To avoid unreliable and unstable or highly variable conclusions, subgroup analyses should be conducted outside small sample sizes. An evaluation of the costs associated with integration should consider the incurred costs of the various components compared with the cost offsets the school anticipates from a decrease in administrator burden. Based on previously conducted participatory workshops and student interviews, personalization should be assessed for its intrusiveness perspective, its clarity and whether explanations are supportive, and the actual equivalence of access to non-digital methods. When considered together, these assessments should establish operational readiness, equity, and acceptability prior to projecting the potential for expansion.

Data governance would be considered as an intervention element, not an administrative appendix. This framework should outline lawful purposes and necessary elements, and define access controls, encryption, retention schedules, deletion policies, and incident reviews. Changes to the models would necessitate version control and updated validation. Students would be provided the right to withdraw digital tools along with the right to modify their data, to demand a human to overturn a decision, and to withdraw from digital tools without loss of access to counseling.

Ethics. Given that this methodological simulation involved no actual students, it cannot be viewed as a completed institutional ethical application. Student assent and parent or guardian consent would be required for a future empirical study, along with a review of ethics by an independent body and the placeholder: Ethical approval number to be inserted after the approval of a future empirical study. Data collection must be limited and adequately role restricted; identification must be removed from counseling records; automated alerts must be examined in a timely fashion by personnel not restricted by role; students must be made aware that an AI system has been invoked and be provided the right to contest the output.

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Confidentiality clauses must not interfere with the safeguarding and reporting responsibilities. Design must avoid automated diagnosis, covert sentiment surveillance, and punitive profiling. Contractors must detail the constraints of the models, the security controls, retention periods, and the performance of subgroups, as well as their incident-response frameworks.

IV. Results And Data Analysis

Participant Characteristics and Measurement Quality. Each group consisted of 60 students. The overall mean age was 15.54 years. Gender, socioeconomic status, type of school, and previous counselling engagement were evenly distributed across the groups. Scale reliability showed alphas and omegas between .82 and .91. One way ANOVA tests conducted with baseline data showed no significant differences across groups for the measures of behaviour, $F(3,236)=1.51$, $p=.213$; well-being, $F(3,236)=0.90$, $p=.442$; engagement, $F(3,236)=1.74$, $p=.160$; emotional regulation, $F(3,236)=0.69$, $p=.560$; social-emotional competence, $F(3,236)=1.32$, $p=.270$. These results indicated baseline comparability.

*Within Group Change***.** Improvement was seen in all groups, however, the magnitude of the change varied. Conventional counselling resulted in mean gains of 2.59, 1.70, and 2.26 for behavioural management, and well-being and engagement, respectively. Mean gains of 4.76, 5.12, and 5.09 were seen in the Human-AI counselling group. Gains of 4.54, 6.74, and 4.03 were seen in Trauma-Informed counselling, thus showing a pattern for well-being which was even stronger. Gains of 7.92, 9.10, and 8.09 were seen in Integrated counselling. The conventional well-being effect was

Between-group tests. The multivariate intervention effect was substantial, Wilks' Lambda =.457, $F(9, 569.65) = 24.05$, $p <.001$. Adjusting for covariates, group predicted behavioral management, $F(3, 227) = 25.38$, $p <.001$, partial $\eta^2 =.25$; well-being, $F(3, 227) = 36.42$, $p < .001$, partial $\eta^2 =.32$; and engagement, $F(3, 227) = 20.41$, $p < .001$, partial $\eta^2 =.21$. Adjusted means of engagement were: 47.49 for Conventional, 50.74 for Human–AI, 49.60 for Trauma-Informed, and 53.71 for Integrated Counselling. Tukey tests further revealed that Integrated Counselling gains were greater than the remaining groups across all three key outcomes. Human–AI and Trauma-Informed behavioral gains were equal, and their well-being and engagement differences were also equal. Thus, H01–H03 were all rejected.

Regarding Associations, Prediction, and Mediation. Engagement was positively correlated with well-being, $r = .37$, and also with emotional regulation, $r = .39$, social-emotional competence, $r = .42$, and counseling responsiveness, $r = .43$. The Integrated Counselling group difference remained significant, $B = 2.53$, $p = .037$. Engagement was also predicted by emotional regulation, $B = .241$, 95% CI [.072, .411], $p = .005$. Social-emotional competence was a marginal predictor ($p = .052$), thus H04 was not rejected for a direct prediction, but H05 was rejected. The integrated model also demonstrated a significant indirect effect on engagement through social-emotional competence, 95% CI [.49, 2.10],

V. Discussion

The simulated comparison suggests that counselling models that incorporate relational expertise, structured technology, and targeted skill development might be more efficacious than single-component offerings. The integrated condition showed improvements on all primary outcomes and maintained a statistically significant advantage in engagement. This approach is theoretically sound in that AI-supported administration may provide more timely offerings, that trauma-informed practice may serve to minimize threat and shame, that social-emotional practice may help transform insight into emotional and relational skill, and that the counsellor may bring in the contextual information that the AI is not programmed to provide. The results do not support the notion that more technology equates to better counselling. These results do support the notion that complementarity is important.

In comparison to conventional counselling, the human-AI condition showed greater responsiveness and engagement, supporting the claim that conversational and predictive systems have the potential to broaden both the reach and scope of engagement (Gual-Montolio et al., 2022; Li et al., 2023). In fact, the human-AI system's wellbeing gain was less than that of the trauma-informed system and illustrates the importance of relational safety and practice in the development of a system that provides effective contact. The trauma-informed system also offered the highest level of perceived safety and wellbeing and aligns with the findings of several of the reviewed studies that highlighted inconsistent implementation and evidence but noted the potential of trauma-informed practice (Avery et al., 2021; Newton et al., 2024). In light of the lack of consistent difference between the human-AI and trauma informed systems, caution is warranted in declaring a universal second-best model.

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The integrated model had social-emotional competence as a partially mediated benefit. This outcome aligns with the idea that students self-regulate arousal, express social needs, and make positive social decisions when they can identify emotions. More so, it agrees with examples of modern-day social-emotional learning that show social-emotional learning heterogeneity and implementation fidelity (Cipriano et al., 2023; Chen et al., 2022). During the full regression, social-emotional competence was shown to be a critical factor in a group of correlated factors. The indirect effect provides a more valuable perspective in which competence may be a factor in the broader network of engagement that includes responsiveness, safety, relational presence and Emotional regulation and counselling responsiveness.

Predictors of engagement were Emotional regulation and counselling responsiveness. Once baseline engagement had been controlled for, their effects were small. However, in education, we should not be overly concerned with the significance of the p value. The importance of small positive effects, like reducing missed appointments, increasing early help-seeking, or reducing exclusion, should not be overlooked. On the other hand, substantial group effect sizes in a simulation should not be interpreted as the likely real-world outcome of an implementation. In the real world, counsellor availability, timetable constraints, family consent, staff turnover, language variation, digital inequality, and uneven fidelity would be barriers to implementation.

Ethical risks are considerable. Mental health chatbots and language models can develop convincing but false responses, fail to identify increasing risks, or behave inconsistently by demographic (Timmons et al., 2023; Pichowicz et al., 2025). Legacy attendance and behavior data may be steeped in structural inequity. Inferencing sentiment may become a form of covert surveillance, particularly in student populations that are unable to comprehend or contest the reasons for a particular score. Transparency cannot address the issues of schools being unable to amend inaccuracies or if consent is covertly provided during the offering of critical services. The responsible integration of these practices requires a human-centered approach, data minimally used, membership subgroup audits, defined escalation thresholds, intentional data retention, critically assessed procurement with a focus on equity, and a viable analog option for practice.

Study strengths include a reproducible data set, simultaneous outcomes, baseline adjustments, effect-size reporting, mediation analysis, and strict alignment across tables and figures. Limitations are more significant.

Data were fabricated, design was quasi-experimental and insufficient to eliminate selection bias, self-report constructs may be similar, there was no follow-up, and modeling was not done for school-level clustering. No conclusions about diagnosis, crisis intervention, or long-term attendance and academic outcomes may be drawn. Following this, a preregistered multi-site study with balanced active-control conditions, an independent safeguarding review, student and counselor qualitative studies, and subgroup fairness analyses is recommended, along with cost studies and follow-up of at least one academic year. Framework integration should be delayed until after modification with inclusion of students, family members, disability advocacy, and culturally diverse practice.

VI. Practical And Policy Implications

Instead of buying AI products, schools should enhance their counselling capacity first and establish safeguarding pathways and relational practices. School counsellors should determine which administrative and analytic tasks can be safely delegated, ensure that every alert is justified, and maintain control over formulation, referral and case closure. Teachers should have access to trauma informed behavioural support practices and social–emotional routines, but should not be privy to details of sensitive counselling. School leaders should establish consent, data, retention, audit, procurement, and incident response policies. Education ministries should allocate funds for the training of counsellors, support digital inclusion, and provide independence in evaluation. Developers should ensure the provision of frameworks that allow age-appropriate responses, undergo multilingual verifications, provide bias assessments, and have secure defaults and justified escalation pathways. Parents and students (of all ages) should have the option to choose real contact and have the ability to request the correction of misleading, damaging, and harmful records. Child protection agencies should be included in emergency response planning. AI as a support reference should always be a supervised aid and should never the primary response of distress or the primary source for a disciplinary infraction.

VII. Conclusion

The design of Student Counselling 2030 represents a human-centered design that focuses on improving access, continuity, and the integration of evidence-based practices utilizing technology thoughtfully. In this realistic simulation, conventional, human–AI, and trauma-informed counselling offered gains.

The integrated model, however, demonstrated the most positive adjusted behavioural, well-being, and engagement outcomes. Emotional regulation and counselling responsiveness were the strongest predictors of engagement. Social-emotional competence explained some of the integrated model's advantage. The results of this study do not support claims that technological integration into counselling or reliance on a single form of therapy is adequate.

The model of the future that we advocate for combines skilled counsellors, trauma-informed engagement, delineated skill development, evident analytics, and design safety measures. Given that the data in this study is entirely simulated, no claims can be made for the actual effectiveness of the model. The primary focus of field-testing this model should be on the student voice, equity, and the monitoring of adverse events. Only after the model has been tested in the field should any claims be made about the model's integration at clinical, institutional, and national levels.

Tables

Table 1. Demographic Characteristics of Participants by Intervention Group

Characteristic	Conventional	Human–AI	Trauma-informed	Integrated
Age, M (SD)	15.44 (1.24)	15.60 (1.16)	15.34 (1.15)	15.68 (1.16)
Female, n (%)	27 (45.0)	35 (58.3)	27 (45.0)	24 (40.0)
Male, n (%)	30 (50.0)	25 (41.7)	32 (53.3)	33 (55.0)
Other/prefer not to say, n (%)	3 (5.0)	0 (0.0)	1 (1.7)	3 (5.0)
Low socioeconomic status, n (%)	22 (36.7)	14 (23.3)	21 (35.0)	22 (36.7)
Government school, n (%)	24 (40.0)	23 (38.3)	27 (45.0)	28 (46.7)
Previous counselling, n (%)	19 (31.7)	21 (35.0)	14 (23.3)	16 (26.7)

Note. Each group included n=60; total N=240. Percentages are within-group.

Table 2. Reliability and Descriptive Statistics of the Study Variables

Variable	Items	Range	M	SD	α	ω
Behavioural management	8	0–40	30.13	5.53	0.87	0.87
Well-being	7	14–70	48.84	7.49	0.88	0.88
School engagement	8	15–75	50.38	9.69	0.89	0.89
Emotional regulation	6	10–50	35.81	6.35	0.83	0.83
Social–emotional competence	8	10–50	35.40	6.64	0.91	0.91
Counselling responsiveness	6	8–40	29.07	5.06	0.89	0.89
Perceived school safety	5	5–25	18.99	3.55	0.82	0.82

Note. M and SD are post-test or post-intervention values. α=Cronbach's alpha; ω=McDonald's omega.

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Table 3. Pre-Test and Post-Test Mean Scores by Intervention Group

Group	Outcome	Pre M	Pre SD	Post M	Post SD
Conventional	Behavioural management	26.20	5.13	28.79	6.14
Conventional	Well-being	43.94	7.03	45.64	7.62
Conventional	School engagement	47.31	7.69	49.57	9.57
Human–AI	Behavioural management	24.98	4.80	29.74	5.13
Human–AI	Well-being	42.36	7.08	47.48	7.10
Human–AI	School engagement	44.32	7.48	49.41	9.25
Trauma-informed	Behavioural management	24.40	4.19	28.94	4.89
Trauma-informed	Well-being	43.86	6.39	50.60	6.84
Trauma-informed	School engagement	45.50	7.97	49.53	10.31
Integrated	Behavioural management	25.12	4.76	33.04	4.92
Integrated	Well-being	42.56	6.81	51.66	6.95
Integrated	School engagement	44.95	7.14	53.04	9.34

Table 4. Paired-Samples t-Test Results for Within-Group Changes

Group	Outcome	Mean change	95% CI	t	df	p	d
Conventional	Behavioural management	2.59	[1.77, 3.41]	6.34	59	<.001	0.82
Conventional	Well-being	1.70	[0.57, 2.83]	3.01	59	0.004	0.39
Conventional	School engagement	2.25	[0.98, 3.53]	3.54	59	<.001	0.46
Human–AI	Behavioural management	4.76	[3.91, 5.62]	11.14	59	<.001	1.44
Human–AI	Well-being	5.12	[4.11, 6.14]	10.11	59	<.001	1.31
Human–AI	School engagement	5.09	[4.08, 6.10]	10.09	59	<.001	1.30
Trauma-informed	Behavioural management	4.54	[3.68, 5.40]	10.58	59	<.001	1.37
Trauma-informed	Well-being	6.74	[5.78, 7.70]	14.02	59	<.001	1.81
Trauma-informed	School engagement	4.03	[2.78, 5.27]	6.48	59	<.001	0.84
Integrated	Behavioural management	7.92	[6.95, 8.88]	16.47	59	<.001	2.13
Integrated	Well-being	9.10	[8.15, 10.04]	19.29	59	<.001	2.49
Integrated	School engagement	8.09	[7.01, 9.17]	14.96	59	<.001	1.93

Note. Positive change indicates improvement. Cohen's d is based on the standard deviation of paired differences.

Table 5. ANCOVA Results for Core Post-Test Outcomes

Outcome	F	df1	df2	p	Partial η^2	Adjusted R^2
Behavioural management	25.38	3	227	<.001	0.251	0.636
Well-being	36.42	3	227	<.001	0.325	0.727
School engagement	20.41	3	227	<.001	0.212	0.794

Note. Each model controlled the corresponding baseline score, age, gender, socioeconomic status, previous counselling and school type.

Table 6. Tukey HSD Post-Hoc Comparisons of Gain Scores

Outcome	Group 1	Group 2	Mean difference	95% CI	Adjusted p	Significant
Behavioural management	Conventional	Human–AI	2.17	[0.57, 3.77]	0.003	Yes
Behavioural management	Conventional	Integrated	5.33	[3.73, 6.93]	<.001	Yes
Behavioural management	Conventional	Trauma-informed	1.95	[0.35, 3.55]	0.010	Yes
Behavioural management	Human–AI	Integrated	3.15	[1.55, 4.75]	<.001	Yes
Behavioural management	Human–AI	Trauma-informed	-0.22	[-1.82, 1.38]	0.984	No
Behavioural management	Integrated	Trauma-informed	-3.38	[-4.98, -1.78]	<.001	Yes
Well-being	Conventional	Human–AI	3.43	[1.57, 5.28]	<.001	Yes
Well-being	Conventional	Integrated	7.40	[5.54, 9.25]	<.001	Yes
Well-being	Conventional	Trauma-informed	5.04	[3.19, 6.90]	<.001	Yes
Well-being	Human–AI	Integrated	3.97	[2.12, 5.83]	<.001	Yes
Well-being	Human–AI	Trauma-informed	1.62	[-0.24, 3.47]	0.112	No
Well-being	Integrated	Trauma-informed	-2.35	[-4.21, -0.50]	0.006	Yes
School engagement	Conventional	Human–AI	2.83	[0.72, 4.95]	0.004	Yes
School engagement	Conventional	Integrated	5.84	[3.72, 7.95]	<.001	Yes
School engagement	Conventional	Trauma-informed	1.77	[-0.35, 3.89]	0.136	No
School engagement	Human–AI	Integrated	3.00	[0.89, 5.12]	0.002	Yes
School engagement	Human–AI	Trauma-informed	-1.06	[-3.18, 1.06]	0.565	No
School engagement	Integrated	Trauma-informed	-4.07	[-6.18, -1.95]	<.001	Yes

Note. Mean difference is Group 2 minus Group 1. Familywise alpha=.05.

Table 7. Correlation Matrix of the Major Study Variables

Variable	1	2	3	4	5
1. Behaviour	—				
2. Well-being	0.35	—			
3. Engagement	0.27	0.37	—		
4. Emotional regulation	0.29	0.42	0.44	—	
5. Responsiveness	0.23	0.55	0.49	0.34	—

Note. N=240. Absolute correlations of .13 or greater are significant at p<.05; correlations of .21 or greater are significant at p<.001.

Table 8. Multiple Regression Predicting School Engagement

Predictor	B	SE	β	p	95% CI for B
Baseline engagement	0.997	0.046	0.784	<.001	[0.906, 1.088]
Emotional regulation	0.123	0.053	0.081	0.021	[0.019, 0.228]
Counselling responsiveness	0.241	0.086	0.126	0.005	[0.072, 0.411]
Social–emotional competence	0.098	0.050	0.067	0.052	[-0.001, 0.197]
Behavioural management	0.030	0.056	0.017	0.590	[-0.081, 0.141]
Human–AI vs conventional	1.289	0.964	0.058	0.183	[-0.610, 3.188]
Trauma-informed vs conventional	0.171	0.915	0.008	0.852	[-1.633, 1.975]
Integrated vs conventional	2.533	1.204	0.113	0.037	[0.160, 4.907]

Note. N=240. Model R^2=0.824, adjusted R^2=0.812, F(16,223)=65.37, p<.001. Demographic controls are included but omitted from the table for brevity.

Figures

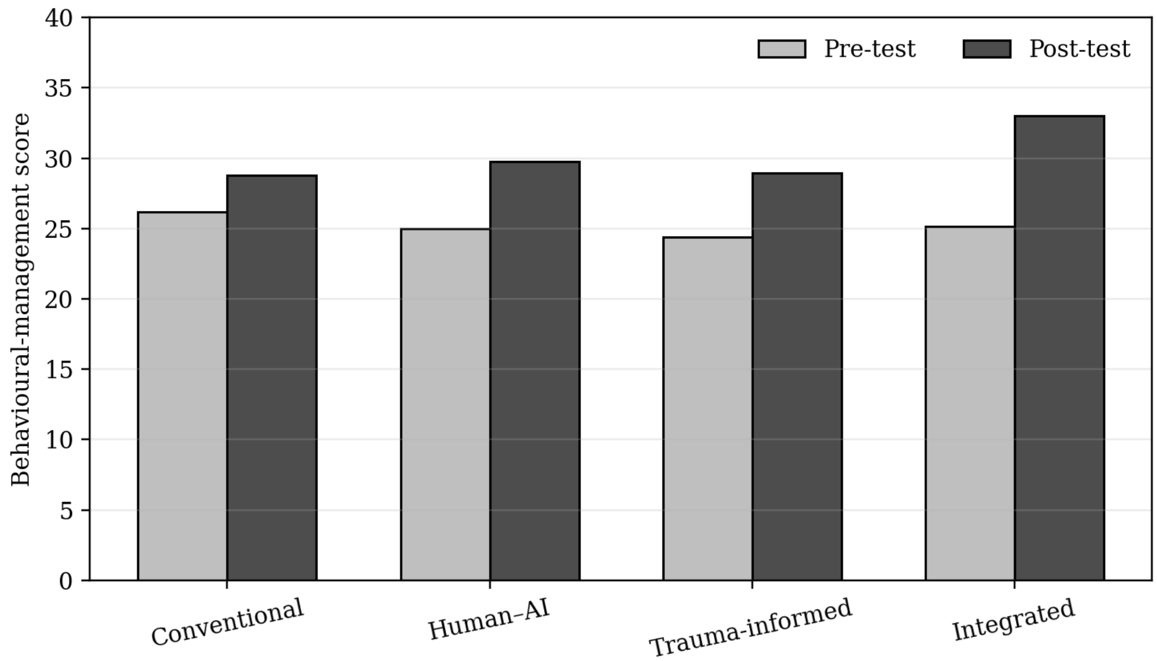

Figure 1. Pre-test and post-test behavioural-management means across intervention groups.

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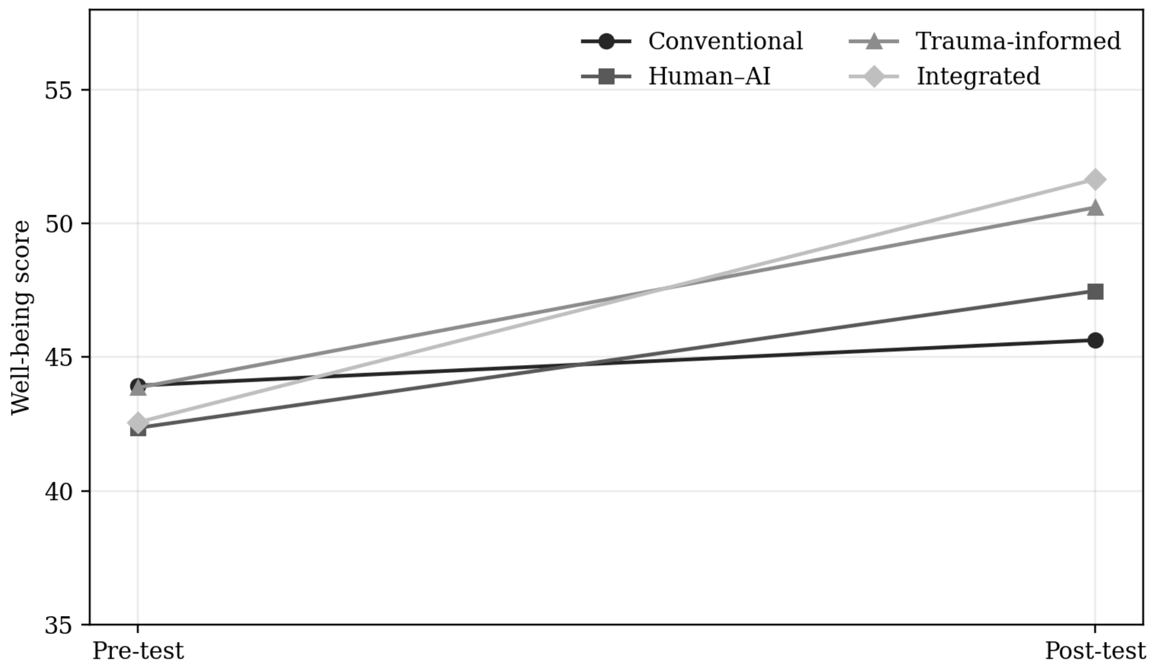

Figure 2. Change in student well-being from pre-test to post-test across intervention groups.

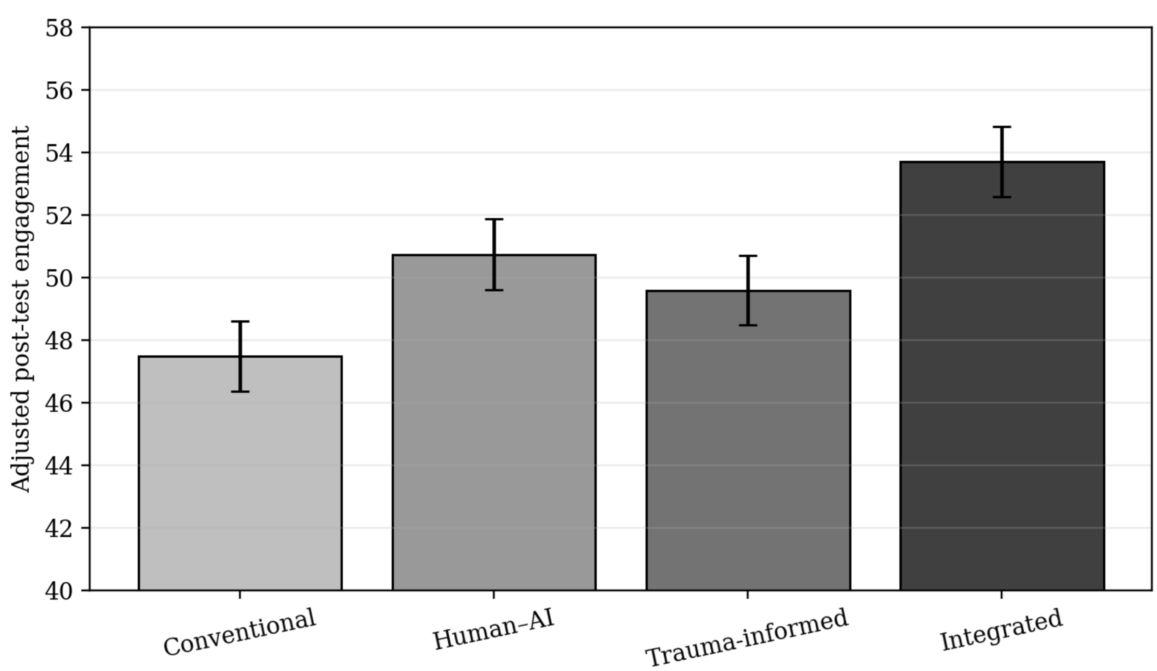

Figure 3. Adjusted post-test school-engagement means with 95% confidence intervals.

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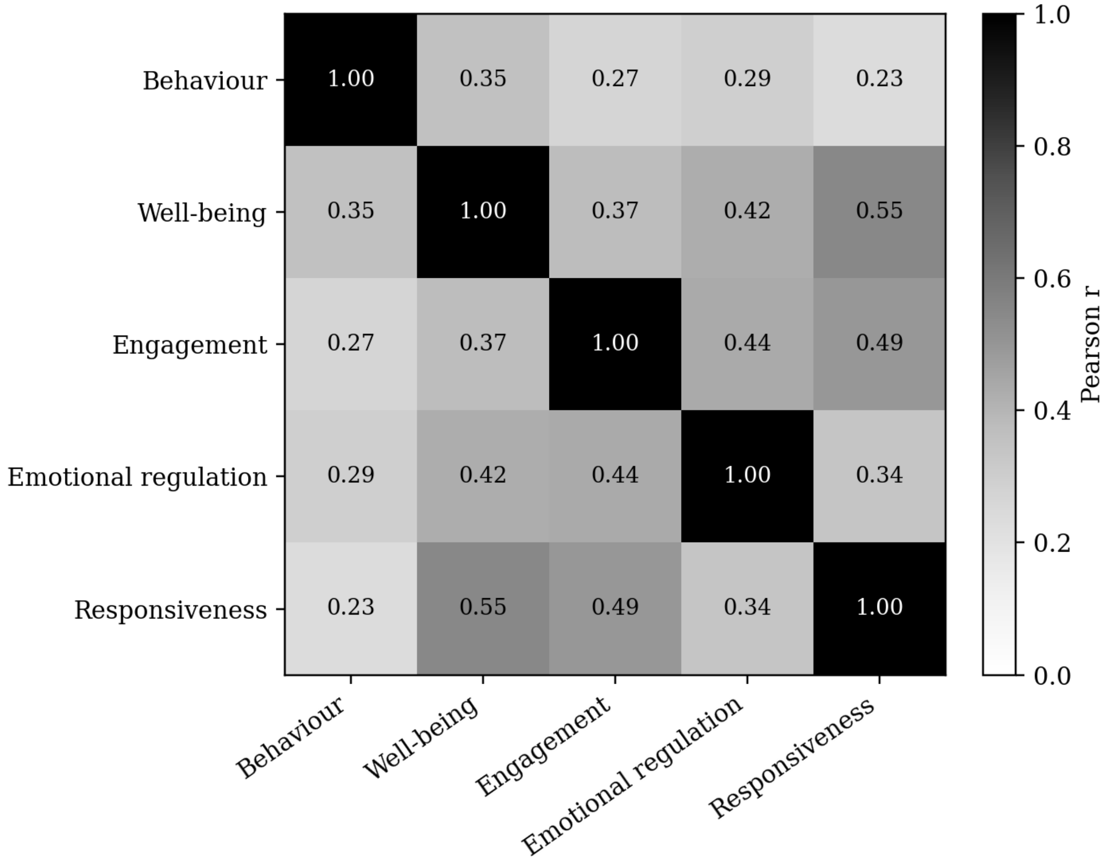

Figure 4. Correlation heat map for behavioural management, well-being, engagement, emotional regulation and counselling responsiveness.

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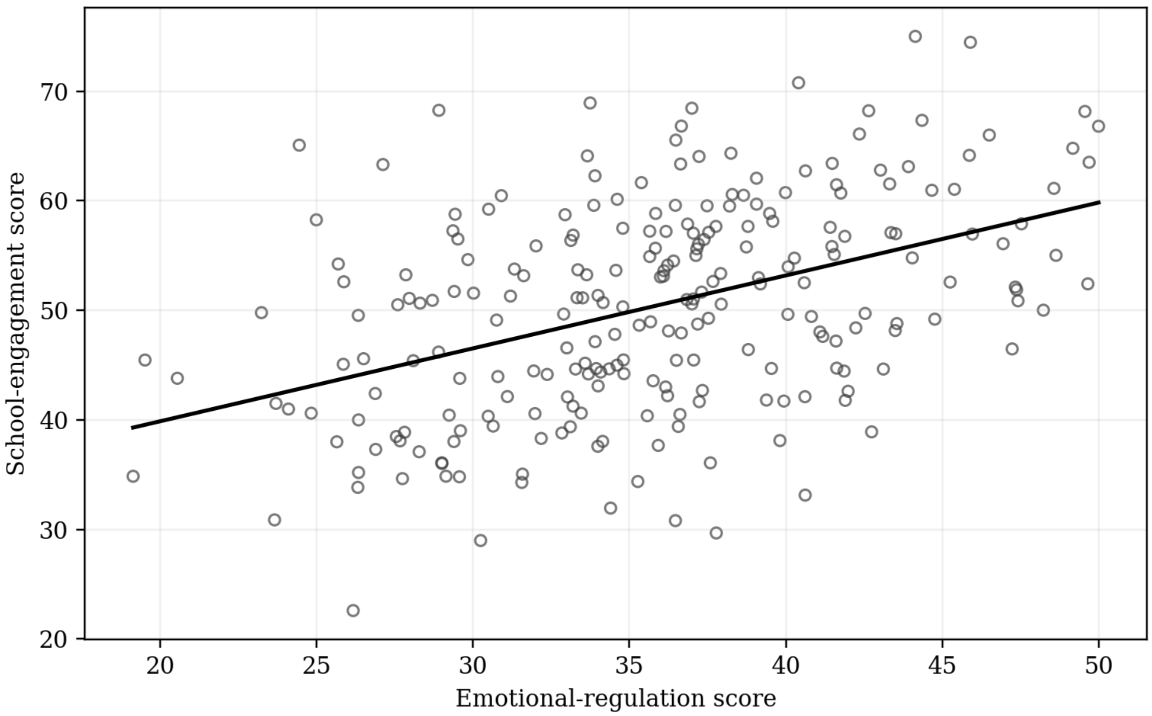

Figure 5. Scatter plot and fitted regression line for emotional regulation and school engagement.

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Conflict of Interest

The author declares no conflict of interest.

Data Availability

The dataset is a realistic simulated dataset prepared for methodological demonstration. No personally identifiable student data were used. The numerical dataset was generated reproducibly with random seed 2030.

Ethical Statement

This manuscript uses simulated data and does not report an actual intervention involving human participants. It does not represent completed institutional ethical approval. Ethical approval number to be inserted following approval of a future empirical study.

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Abbreviations

Abbreviation	Meaning
AI	Artificial intelligence
ANCOVA	Analysis of covariance
CI	Confidence interval
HCAI	Human-centred artificial intelligence
MANOVA	Multivariate analysis of variance
SEL	Social–emotional learning
TIC	Trauma-informed care