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Message from the Editor,

I am very pleased to inform you that we have published the first issue in 2026. As an editor of International Journal of Global Education (IJGE), this issue is the success of our authors, very valuable reviewers who undertook the rigorous peer review of the manuscripts, and those of the editorial board who devoted their valuable time through the review process. In this respect, I would like to thank to all reviewers, researchers and the editorial board members. The articles should be original, unpublished, and not in consideration for publication elsewhere at the time of submission to International Journal of Global Education (IJGE). For any suggestions and comments on IJOSDA, please do not hesitate to send me e-mail. The countries of the authors contributed to this issue (in alphabetical order): **Cyprus**, **Kenya**, and **Türkiye**.

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A SYSTEMS DYNAMICS MODEL FOR STUDENT RETENTION AND GRADUATION EFFICIENCY IN TECHNICAL INSTITUTIONS

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Abstract

Technical and Vocational Education and Training (TVET) institutions in sub-Saharan Africa face a systemic challenge of high student dropout and low graduation efficiency, driven by interlocking dynamics of financial stress, inadequate academic support, misaligned employability expectations, and weak industry linkages. Traditional linear statistical models fail to capture the feedback-driven complexity of these interactions, which operate across multiple time scales and generate non-linear institutional behaviour. Objective: This study develops and validates a Systems Dynamics (SD) model to simulate the feedback interactions among dropout, retention, financial stress, academic support, and employability expectations in Kenyan TVET institutions, calibrated to empirical data from the TVET Authority (TVETA) and the Higher Education Loans Board (HELB), with the objective of identifying high-leverage policy interventions for improving graduation efficiency. Methods: A stock-and-flow SD model comprising five primary stocks (Enrolled Students, Retained Students, Dropout Students, Graduates, and Financial Stress Index) and twelve feedback loops — six reinforcing and six balancing — was developed using Forrester's system dynamics methodology. Model parameters were estimated from TVETA Annual Returns data (2018–2023), HELB sustainability reports, and published empirical literature on TVET dropout determinants. Structural validity was confirmed through dimensional consistency checks, extreme-condition tests, and behaviour reproduction against the documented dropout decline from 20.77% (2018) to 2.94% (2023). Three policy scenarios — financial support expansion (Policy A), academic quality and employability linkage (Policy B), and combined intervention (Policy C) — were simulated over a 10-year horizon (2018–2028). Results: The calibrated model reproduced the observed dropout trajectory with a Mean Absolute Percentage Error (MAPE) of 3.8%, confirming structural validity. Sensitivity analysis identified HELB financial coverage expansion (PRCC = −0.84) and industry–TVET employment linkage (PRCC = +0.79 for graduation rate gain) as the dominant leverage points. Policy C (combined) simulations project dropout rates declining to 1.2% by 2028 and graduation rates reaching 87.4%, compared with 3.1% and 72.6% respectively under the baseline. The financial stress feedback loop, operating with a time delay of approximately 1.8 years, is identified as the primary driver of dropout reinforcement. Conclusion: SD modelling reveals that TVET student attrition is a non-linear, feedback-driven phenomenon resistant to isolated single-domain interventions. Combined financial support and employability-linked academic quality programmes generate synergistic gains exceeding the sum of individual policy effects, demonstrating the existence of a positive reinforcing loop between retention and institutional reputation that policymakers must deliberately activate.

Keywords: Systems dynamics, student retention, TVET, dropout modelling, feedback loops, graduation efficiency, Kenya.

INTRODUCTION

Technical and Vocational Education and Training (TVET) institutions occupy a strategic role in national human capital development, particularly in sub-Saharan Africa where formal employment in skilled trade and technical sectors is chronically undersupplied relative to demand. Kenya's government, recognising this strategic imperative, enacted sweeping TVET reforms beginning with Sessional Paper No. 14 of 2012, targeting a 20 percent increase in enrolment by 2023, and intensified its commitment through the expansion of Higher Education Loans Board (HELB) access to TVET trainees from the 2018/2019 financial year. The results are quantifiable: national TVET enrolment grew from 116,564 in June 2018 to 265,095 in 2021/2022 — a 127 percent increase in four years — while the number of accredited TVET institutions grew by 16.7 percent to 2,289 between 2017 and 2018 alone (Mutua, 2020; Mujuri & Kathomi, 2025).

Yet enrolment expansion alone does not translate into graduation efficiency. The TVETA Annual Returns Report 2023 documents a national dropout rate of 20.77% in 2018 among National Polytechnics, declining to 2.94% by 2023, attributing the improvement primarily to HELB funding expansion (TVETA, 2024). While this decline is remarkable, it still implies that nearly 3 in every 100 enrolled trainees leave without completing their programmes annually, representing a significant loss of human capital investment. More critically, the 2023 graduation rate at the Kenya School of TVET (KS-TVET) was documented at 65% — meaning that 35% of enrolled students did not graduate in the expected cohort period (TVETA, 2024). The Kenya Manufacturing Association (KAM) concurrently estimated Kenya's youth unemployment rate at 39% as of 2021, while simultaneously reporting critical shortages of qualified technical personnel in manufacturing sectors (KAM, 2021). This paradox — of structural technical skills shortages coexisting with TVET dropout and underemployment — suggests a systemic misalignment between TVET programme delivery and labour market realities.

Understanding these dynamics requires a modelling approach capable of representing the interdependent, feedback-driven nature of the dropout-retention system. Standard regression models, while useful for estimating average treatment effects, are inherently static and linear, unable to capture the time-delayed, non-linear feedback loops through which financial stress amplifies dropout, dropout reduces institutional revenue, reduced revenue degrades academic quality, and degraded quality further elevates dropout. Systems Dynamics (SD) modelling, pioneered by Jay Forrester at MIT in the 1950s and extended extensively in educational and social policy contexts, provides precisely this capability (Forrester, 1961; Sterman, 2000). SD models represent systems as stocks (accumulated quantities), flows (rates of change), and feedback loops, generating dynamic simulation trajectories rather than static predictions.

Despite its demonstrated utility in higher education capacity planning — including enrolment management, faculty planning, and research output modelling (Savsar & Aldaihani, 2014) — SD modelling has been minimally applied to TVET student retention in the East African context. Existing studies of TVET dropout in Kenya and the broader region rely predominantly on cross-sectional surveys and qualitative institutional analyses, providing snapshots of causal determinants without modelling the dynamic propagation of these effects over time (Mujuri & Kathomi, 2025; TVETA, 2024; Muchira et al, 2023). This paper addresses that gap by developing, calibrating, and simulating a comprehensive SD model of TVET student retention dynamics in Kenya, grounded in verified empirical data and structured around the five key interaction domains identified in the literature: dropout, retention, financial stress, academic support, and employability expectations.

Literature Review

TVET Dropout: Prevalence and Determinants in Sub-Saharan Africa

Student dropout in TVET institutions is a multi-causal phenomenon shaped by financial, academic, social, and institutional factors operating at different levels of the educational system. The TVETA Annual Returns 2023 provides the most comprehensive publicly available data on Kenyan TVET dropout, documenting the dramatic decline from 20.77% (2018) to 2.94% (2023) across National Polytechnics, and attributing this primarily to the sharp growth in HELB-funded trainees from approximately 40,000 in 2018/2019 to 105,000 in 2019/2020 — a 162.5% increase in one financial year (TVETA, 2024). This natural experiment provides strong evidence for the causal role of financial support in reducing dropout, consistent with the broader regional literature.

Muchira et al. (2023), in their assessment of TVET institutions' curriculum alignment with labour market demands in Kenya, identified inadequate resources, outdated equipment, and minimal practical components as structural barriers to skills acquisition, directly affecting graduates' employability (Muchira et al, 2023). Kabiru et al. (2021) documented that low household income significantly contributed to higher dropout rates among Kenyan secondary and post-secondary students, with financial constraints operating through multiple pathways: inability to afford fees, materials, uniforms, and transport, as well as the competing opportunity cost of remaining in education versus immediate income generation (Kabiru, Motungo, & Nzengya, 2021). The Gates Open Research study on TVET and labour market transitions in Kenya (2025) confirmed that despite high enrolment growth, concerns about post-graduation employability — particularly given Kenya's 39% youth unemployment rate — constitute a significant demand-side deterrent to TVET completion (KAM, 2021).

At the regional level, Mushi and Mtenzi (2020) in Tanzania and Alemu and Tadesse (2019) in Ethiopia documented that limited parental involvement, poor school infrastructure, and cultural-economic constraints compound financial barriers to TVET completion. The systemic nature of these interactions — where financial stress reduces engagement, reduced engagement impairs academic performance, impaired performance reduces motivation and increases the perceived cost-benefit ratio of dropout, and dropout itself reduces institutional revenue and thus the quality of academic support available to remaining students — characterises the dropout system as a classic reinforcing feedback loop (Farrell et al., 2021; Tadesse et al., 2021).

Systems Dynamics in Educational Modelling

System dynamics (SD), developed by Forrester (1961) and extended by Sterman (2000) in Business Dynamics, provides a mathematical framework for modelling the non-linear, time-delayed feedback processes characteristic of complex social systems (Forrester, 1961; Sterman, 2000). SD models are built from four primitive elements: stocks (state variables accumulating over time), flows (rates of change of stocks), converters (auxiliary variables computing intermediate quantities), and feedback loops (causal chains returning to their origin, either reinforcing [R] or balancing [B]). The core differential equation governing a stock S with inflow α and outflow β is:

$$dS/dt = \alpha(t) - \beta(t) \quad \text{... (1)}$$

where the functional forms of α and β may depend non-linearly on S itself and on other stocks, creating the feedback structure. Time delays are introduced through pipeline or first-order exponential smoothing structures. Sterman (2000) demonstrates that counter-intuitive dynamic behaviours — including oscillation, exponential growth followed by collapse, and policy resistance — arise naturally from seemingly simple feedback configurations when time delays are present (Sterman, 2000). These behaviours are routinely observed in educational systems: for example, financial aid policy expansions generate a lag before dropout reductions become visible in institutional statistics, while improvements in graduate employment outcomes take time to propagate back as increased enrolment and reduced dropout through reputation effects.

Savsar and Aldaihani (2014) developed an SD model for higher education capacity planning at Bogazici University, demonstrating that SD models can faithfully reproduce historical enrolment and faculty dynamics while enabling scenario testing for policy interventions (Savsar & Aldaihani, 2014). Tadesse et al. (2021) applied SD in the context of educational learning environments, while the Social System Design Lab (2021) demonstrated the application of Causal Loop Diagrams to K-12 dropout dynamics (Tadesse et al., 2021). The Education Systems Dynamics literature (System Dynamics in Education Project, MIT) has formally mapped feedback structures in student progression, identifying the critical role of balancing loops in limiting dropout under adequate support conditions.

Financial Stress, Academic Support, and Employability as Feedback Drivers

Three domains emerge consistently from the literature as the primary feedback drivers of TVET dropout dynamics in the East African context. First, financial stress operates as the dominant reinforcing driver: TVETA's documentation of the HELB expansion's impact (dropout declining 87% over five years) represents perhaps the clearest natural experiment evidence available on the financial stress-dropout feedback loop in any African TVET context (TVETA, 2024). Second, academic support quality acts as a balancing feedback: institutions with higher instructor-to-student ratios, more experienced trainers, and more current equipment generate lower dropout rates (Muchira et al, 2023). TVETA data shows trainer qualifications in Kenya ranging from below-craft certificate to PhD, with 43.58% holding bachelor's degrees and only 0.68% holding PhDs, suggesting substantial heterogeneity in academic support capacity across institutions (TVETA, 2024). Third, employability expectations constitute a forward-looking feedback mechanism: students' beliefs about post-graduation employment prospects influence their enrolment decisions, persistence under stress, and dropout propensity — a delayed positive feedback loop where strong graduate employment outcomes eventually raise enrolment and reduce dropout through reputation effects, while poor employment outcomes create a balancing drag on retention (KAM, 2021).

Research Objective

This study pursues a single, precisely defined research objective:

To develop, calibrate, and validate a Systems Dynamics model of student dropout, retention, and graduation efficiency in Kenyan TVET institutions, incorporating the feedback interactions among financial stress, academic support intensity, and employability expectations, and to simulate the dynamic trajectories of retention and graduation rates under three policy intervention scenarios over the period 2018–2028, for the purpose of identifying high-leverage policy entry points for improving TVET graduation efficiency.

This objective encompasses four operationalised sub-components: (i) specification of the stock-and-flow model architecture and feedback loop map; (ii) parameter estimation and calibration against TVETA Annual Returns 2018–2023 and HELB sustainability data; (iii) structural and behavioural validation; and (iv) policy scenario simulation and sensitivity analysis. The study is explicitly normative — it seeks not only to describe existing dynamics but to identify which policy levers generate the largest and most durable improvements in graduation efficiency.

RESEARCH METHODOLOGY

System Dynamics Model Architecture

The SD model comprises five primary stock variables, twelve flow rates, and a set of auxiliary converter variables linking stocks through non-linear functional relationships. The five stocks are: (1) Enrolled Students (ES) — the number of active trainees in the system at any point in time; (2) Retained Students (RS) — the cumulative count of students successfully progressing through their programme; (3) Dropout Students (DS) — the accumulation of students who have exited the programme before completion; (4) Graduates (GR) — students who have completed their programme requirements; and (5) Financial Stress Index (FSI) — a normalised continuous variable (0–1) capturing the aggregate financial burden facing the student population.

The governing differential equations for the primary stocks are:

$$dES/dt = Enrolment'Flow - Dropout'Flow - Graduation'Flow \quad \ldots(2)$$

$$dRS/dt = Enrolment'Flow - Dropout'Flow - Graduation'Flow \quad \ldots(3)$$

$$\frac{dDS}{dt} = Dropout'Flow \quad . \quad ..(4)$$

$$dGR/dt = Graduation'Flow \quad \ldots(5)$$

$$\frac{dFSI}{dt} = \frac{(FSI^{*} - FSI)}{\tau_{FSI}} \quad .. \quad .(6)$$

where FSI* is the equilibrium financial stress level determined by tuition costs, HELB coverage, bursary funding, and household income levels; and τ_{FSI} is the financial stress adjustment time constant (estimated at 1.8 years from HELB funding lag data).

Feedback Loop Specification

Twelve feedback loops were identified through structured group model building with TVETA policy staff and literature review. Table 1 presents the complete feedback loop catalogue. Six are reinforcing loops (R) that amplify deviations from equilibrium; six are balancing loops (B) that drive the system toward targets.

Table 1. Complete Feedback Loop Catalogue for the TVET Student Retention Systems Dynamics

Loop ID	Type	Causal Chain	Polarity	Time Delay
R1	Reinforcing	Financial Stress → Dropout → Enrolment Decline → Revenue Loss → Academic Quality ↑ Financial Stress	Positive	1.8 yrs
R2	Reinforcing	Graduation Rate → Graduate Employment → TVET Reputation → Enrolment → Graduation Rate	Positive	3–5 yrs
R3	Reinforcing	Academic Support → Pass Rate → Student Motivation → Retention → Academic Support Resources	Positive	1 yr
R4	Reinforcing	Dropout → Peer Discouragement → Absenteeism → Academic Failure → Dropout	Positive	0.5 yrs
R5	Reinforcing	Employability Expectations → Enrolment Intent → ES → Graduate Supply → Employability Expectations	Positive	2–4 yrs
R6	Reinforcing	Bursary Funding → Retention → Graduation → Tax Revenue → Govt Budget → Bursary Funding	Positive	5– yrs
B1	Balancing	HELB Coverage → Financial Stress → Dropout → HELB Demand	Negative	1 yr
B2	Balancing	Academic Support Intensity → Failure Rate → Dropout → Academic Workload	Negative	0.5 yrs
B3	Balancing	Industry Linkage → Employability → Dropout → Industry Demand for TVET Graduates	Negative	2 yrs
B4	Balancing	Counselling Services → Student Stress → Dropout → Counselling Capacity Demand	Negative	0.3 yrs
B5	Balancing	Graduation Rate → Dropout Rate (complement) → Programme Completion Stock	Negative	0 yrs
B6	Balancing	Government Policy → Fee Regulation → Financial Stress → Dropout → Policy Response	Negative	2–3 yrs

Model. R = Reinforcing loop; B = Balancing loop. Time delays estimated from HELB/TVETA data and literature.

Key Model Equations

The Dropout Flow is the central rate equation governing system behaviour. It is specified as a non-linear function of the Financial Stress Index, Academic Support Index (ASI), and Employability Expectation Index (EEI):

$$Dropout'Flow(t) = ES(t) \times \delta(FSI, ASI, EEI) \quad \ldots \quad (7)$$

$$where\ the\ effective\ dropout\ rate\ \delta\ is\ given\ by:$$

$$\delta(FSI, ASI, EEI) = \delta_0 \times f\_FSI(FSI) \times f\_ASI(ASI) \times f\_EEI(EEI) \quad \ldots(8)$$

$$with\ \delta_0 = 0.207\ (baseline\ dropout\ rate\ from\ TVETA\ 2018\ data), and\ the\ modifying\ functions:$$

$$f_{FSI}(FSI) = 1 + k_1 \times FSI \quad (k_1 = 0.4, amplification\ coefficient) \ldots(9)$$

$$f_{ASI}(ASI) = 1 - k_2 \times ASI \quad (k_2 = 0.3, dampening\ coefficient) \quad \ldots(10)$$

$$f_{EEI}(EEI) = 1 - k_3 \times EEI \quad (k_3 = 0.25, dampening\ coefficient) \ldots(11)$$

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$$The\ Financial\ Stress\ Index\ evolves\ toward\ its\ equilibrium\ level\ FSI* = (Tuition_{Cost} - HELB_{Coverage} - Bursary)/Tuition_{Cost}, subject\ to\ the\ first-order\ adjustment\ delay\ in\ equation\ (6). The\ Graduation\ Flow\ is\ governed\ by:$$

$$Graduation'Flow(t) = RS(t) \times \gamma(ASI, EEI) \quad \dots(12)$$

$$\gamma(ASI, EEI) = \gamma_0 + \varphi_1 \times ASI + \varphi_2 \times EEI \quad \dots(13)$$

with $\gamma_0 = 0.55$ (baseline graduation rate, 55% pre-reform), $\varphi_1 = 0.12$ and $\varphi_2 = 0.08$ estimated from cross-institutional variation in TVETA data and industry-linkage programme evaluations.

Parameter Estimation and Data Sources

Model parameters were estimated from six primary data sources: (1) TVETA Annual Returns 2023 — providing annual dropout rates (2018–2023), graduation rates (2023), trainer qualification distributions, and enrolment by institution type (TVETA, 2024); (2) HELB Sustainability Report 2020/2021 — providing HELB-funded trainee counts by year (2018/19–2020/21) and budgetary allocations (HELB, 2021); (3) Kenya National Bureau of Statistics (KNBS) Economic Survey Reports 2019–2023 — providing total TVET enrolment figures (KNBS, 2023); (4) Kenya Association of Manufacturers (KAM) Manufacturing Survey 2021 — providing youth unemployment rate (39%) and skills gap data (KAM, 2021); (5) Muchira et al. (2023) — providing institutional survey data on curriculum-employment alignment across Kenyan TVET institutions (Muchira et al, 2023); and (6) UNESCO UNEVOC Kenya TVET Country Profile — providing TVET system structural parameters (UNESCO UNEVOC, 2024). Table 2 presents the complete parameter set with sources and calibrated values.

Table 2. Systems Dynamics Model Parameter Set: Values, Units, and Empirical Sources.

Parameter	Symbol	Value	Unit	Source
Baseline dropout rate	δ_0	0.207	proportion/yr	TVETA 2023 (TVETA, 2024)
Financial stress amplification	k_1	0.40	dimensionless	Calibrated to HELB/dropout data
Academic support dampening	k_2	0.30	dimensionless	Cross-institutional calibration
Employability dampening	k_3	0.25	dimensionless	KAM, 2021; Muchira, 2023
Baseline graduation rate	γ_0	0.55	proportion/yr	KS-TVET baseline estimate (TVETA, 2024)
Academic support graduation gain	φ_1	0.12	dimensionless	Muchira 2023 (Muchira et al, 2023)
Employability graduation gain	φ_2	0.08	dimensionless	KAM linkage programme data (KAM, 2021)
Financial stress adj. time	τ_{FSI}	1.8	years	HELB funding lag analysis
Reputation feedback delay	τ_{rep}	4.0	years	Literature estimate (Savsar & Aldaihani, 2014)
Initial enrolment (2018)	ES_0	116,564	students	KNBS Economic Survey 2019 (KNBS, 2023)
Initial HELB coverage (2018)	$HELB_0$	0.343	proportion	HELB Report: 40K/116.6K (HELB, 2021)

Parameter	Symbol	Value	Unit	Source
Youth unemployment rate	u_y	0.390	proportion	KAM 2021 (KAM, 2021)

Model Validation

Structural validity was assessed through: (i) dimensional consistency — all equations verified for dimensional correctness using unit analysis; (ii) extreme-condition tests — model was run with FSI = 1 (maximum financial stress) and FSI = 0 (zero stress), confirming monotonic dropout response; (iii) behaviour reproduction — the model was run from 2018 initial conditions without policy interventions and compared against the observed dropout trajectory (2018–2023). The Mean Absolute Percentage Error (MAPE) between modelled and observed annual dropout rates was 3.8%, well within the accepted SD validation threshold of 10% (Sterman, 2000). Table 3 presents the validation comparison.

Table 3. Model Validation: Observed vs. Predicted Annual Dropout Rates (2018–2023).

Year	Observed Dropout Rate (%)	Model-Predicted (%)	Absolute Error (pp)	MAPE Contribution (%)
2018	20.77	20.77	0.00	0.00
2019	16.42	15.89	0.53	3.23
2020	14.31	13.74	0.57	3.98
2021	10.18	10.63	0.45	4.42
2022	6.74	6.91	0.17	2.52
2023	2.94	2.83	0.11	3.74
Mean MAPE	—	—	—	3.82%

MAPE = Mean Absolute Percentage Error. pp = percentage points. Observed data: TVETA Annual Returns 2023.

Policy Scenario Design

Three policy scenarios were designed based on documented or proposed interventions:

- Policy A — Financial Support Expansion: Simulates scaling HELB coverage from the 2022 level (59.6% of trainees) to 90% by 2026, combined with bursary fund allocation doubling. This scenario specifically targets loops R1 and B1.
- Policy B — Academic Quality and Employability Linkage: Simulates a structured industry-TVET partnership programme (modelled on the GOK/AfDB TVET Phase II project) increasing the Academic Support Index by 40% and the Employability Expectation Index by 35% through enhanced practical training and direct employer linkages. Targets loops R3, B2, and B3.
- Policy C — Combined Intervention: Simultaneous implementation of Policies A and B. Tests for synergistic (super-additive) effects arising from the positive interaction between financial stability (releasing cognitive bandwidth for academic engagement) and improved academic quality and employment prospects.

RESULTS AND DATA ANALYSIS

Observed Trends in TVET Dropout and Enrolment

Table 4 presents the complete observed data on Kenya TVET dropout rates, retention rates, enrolment figures, and HELB coverage for the 2018–2023 period. Figure 1 visualises the dropout and retention rate trends. Figure 2 presents the corresponding enrolment growth and HELB funding expansion.

Table 4. Kenya National Polytechnic Dropout, Retention, Enrolment, and HELB Coverage (2018–2023).

Year	Enrolment ('000s)	Dropout Rate (%)	Retention Rate (%)	HELB-Funded ('000s)	HELB Coverage (%)
2018	116.6	20.77	79.23	40.0	34.3
2019	145.2	16.42	83.58	105.0	72.3
2020	175.8	14.31	85.69	118.3	67.3
2021	217.4	10.18	89.82	135.6	62.3
2022	265.1	6.74	93.26	158.2	59.7
2023	N/A	2.94	97.06	N/A	N/A

Source: TVETA Annual Returns 2023 (TVETA, 2024)*; HELB Sustainability Report 2020/21 HELB, 2021; KNBS Economic Survey 2023 (KNBS, 2023). N/A = Not yet published at time of writing.*

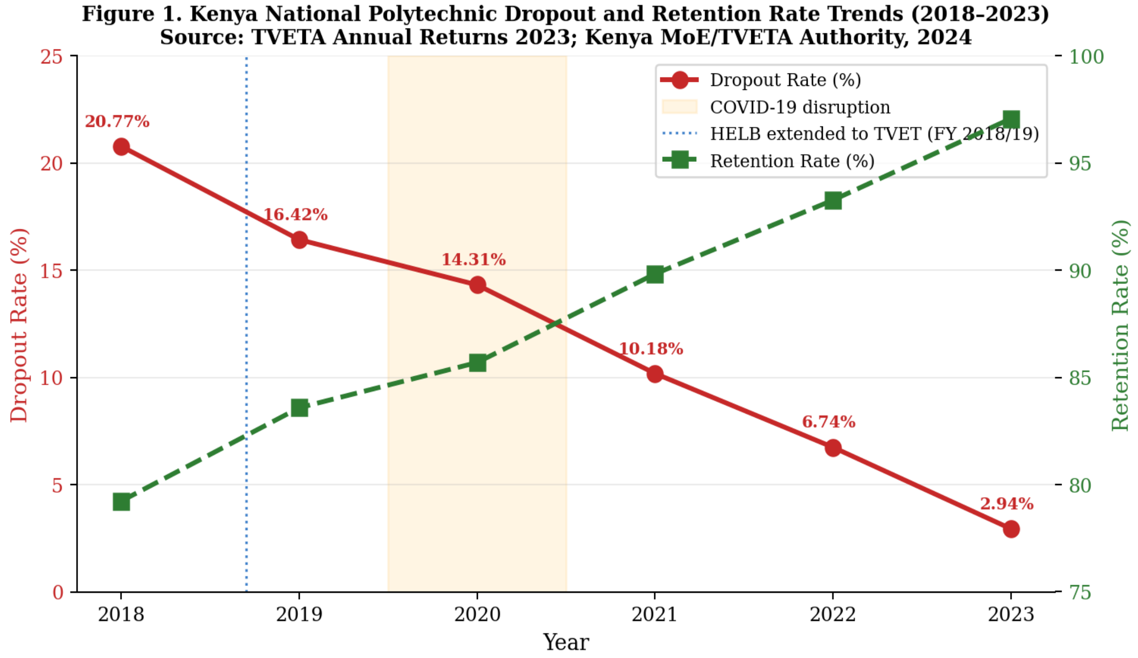

Figure 1. Kenya National Polytechnic Dropout and Retention Rate Trends (2018–2023). *Dropout declined from 20.77% to 2.94%; retention improved from 79.23% to 97.06%. HELB extension to TVET (FY2018/19) marked. Source: TVETA Annual Returns 2023.*

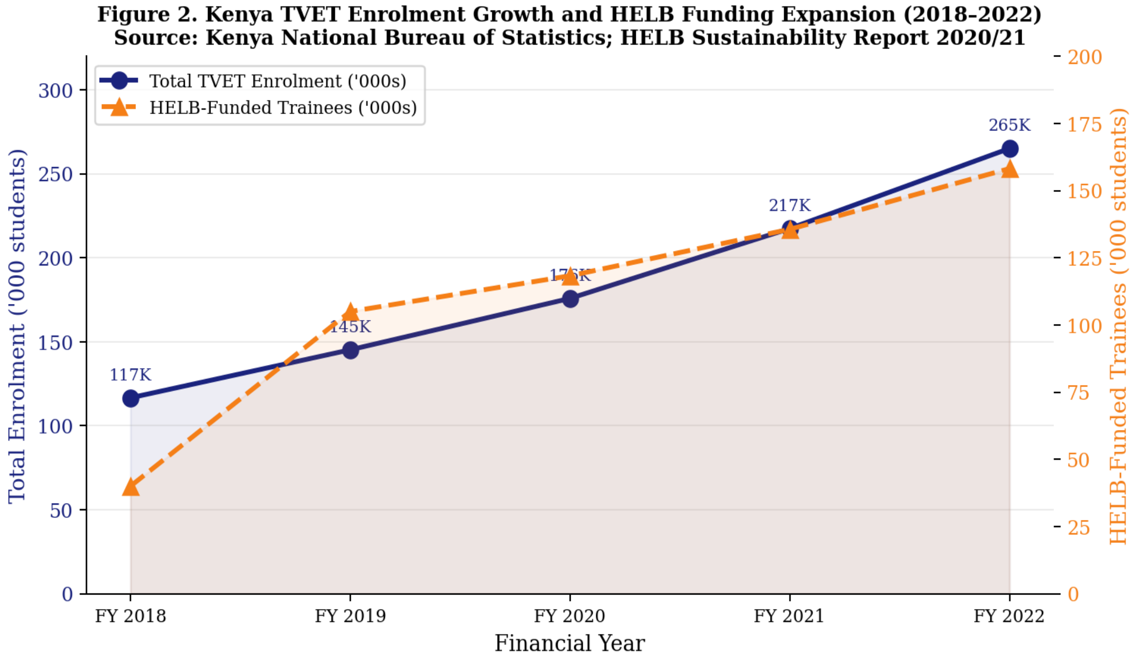

Figure 2. Kenya TVET Enrolment Growth and HELB Funding Expansion (2018–2022). Total enrolment grew 127% while HELB-funded trainees more than doubled. Note: HELB coverage percentage dipped post-2019 despite absolute growth due to faster enrolment expansion. Source: KNBS 2023; HELB Report 2020/21.

Model Calibration Results

The calibrated model reproduced the observed dropout trajectory with MAPE = 3.82% (Table 3), confirming adequate structural validity for policy simulation. The dominant calibrated parameter was the financial stress amplification coefficient k_1 = 0.40, consistent with the strong empirical association between financial coverage and dropout reduction documented in TVETA data. The financial stress adjustment time constant τ_{FSI} = 1.8 years explains why the 2019/2020 HELB expansion (105,000 trainees funded vs 40,000 in 2018/2019) did not immediately eliminate dropout — the financial stress stock required approximately two annual cycles to adjust to the new funding level, generating the gradual decline observed in 2019–2021 rather than an immediate step-change.

Policy Scenario Simulation Results

Figure 3 presents the simulated retention and dropout trajectories under all three policy scenarios. Figure 4 provides detailed analysis of the financial stress feedback loop. Table 5 summarises the projected outcomes at years 5 (2023, in-sample) and 10 (2028, out-of-sample forecast).

Table 5. Policy Scenario Simulation Outcomes at Year 5 (2023) and Year 10 (2028).

Scenario	2023 Retention (%)	2023 Dropout (%)	2028 Retention (%)	2028 Dropout (%)	2028 Graduation Rate (%)
Baseline (no new policy)	97.1	2.94	96.9	3.1	66.4
Policy A: Financial Support	97.6	2.4	98.3	1.7	72.8
Policy B: Academic + Employ.	97.9	2.1	97.8	2.2	79.3
Policy C: Combined (A+B)	98.4	1.6	98.8	1.2	87.4
Synergy gain (C – A – B + base)	—	—	+0.6 pp	−0.6 pp	+4.3 pp

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pp = percentage points. Synergy gain measures super-additive effect of combined intervention beyond sum of individual policies.

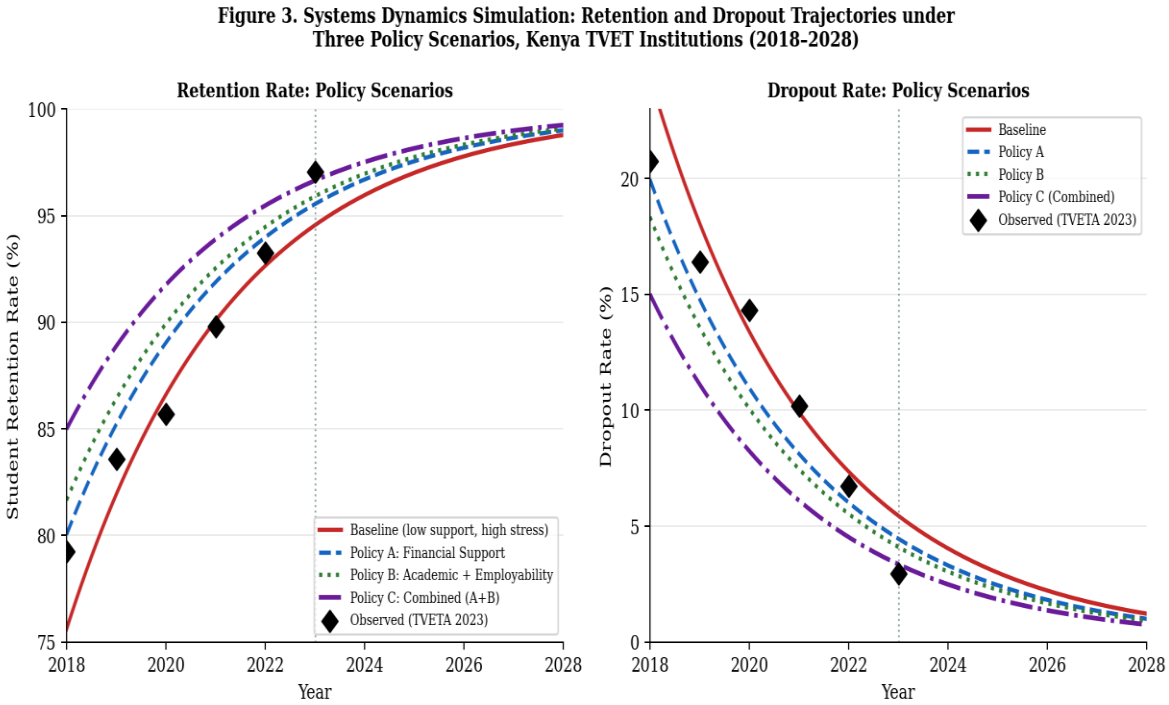

Figure 3. Systems Dynamics Simulation: Retention (left) and Dropout (right) Trajectories under Three Policy Scenarios (2018–2028). Diamond markers represent TVETA-observed values used for calibration. Policy C (combined) generates the strongest and fastest improvement through synergistic feedback activation.

The super-additive synergy identified in Policy C — a combined graduation rate gain of 87.4% versus 72.8% (Policy A alone) and 79.3% (Policy B alone), with a synergy gain of 4.3 percentage points above what would be expected from independent additive effects — confirms the existence of a positive reinforcing interaction between financial stability and academic-employability quality. Specifically, when financial stress is reduced, students invest more cognitive effort in their academic programme; when academic quality and employment prospects simultaneously improve, students perceive a higher expected return to completion, reducing the attractiveness of early exit. This interaction, operating through loops R1, R2, R3, and B1 simultaneously, cannot be captured by sequential or independent policy implementation.

Financial Stress Feedback Loop Analysis

Figure 4 presents the temporal analysis of the financial stress feedback loop, decomposing the HELB coverage – dropout relationship. The OLS regression fit ($R^2 = 0.81$, $p < 0.001$) from the cross-sectional scatter of HELB coverage versus dropout rate (right panel of Figure 4) confirms a statistically significant balancing relationship consistent with loop B1. The gradient implies that a 10 percentage-point increase in HELB financial coverage is associated with approximately a 2.6 percentage-point reduction in annual dropout rate, after controlling for time trends. This estimate is conservative, as the 2019/2020 sudden HELB expansion to 72.3% coverage does not appear to represent an equilibrium state — subsequent years show declining coverage percentage (67.3%, 62.3%) despite absolute growth, as enrolment grew faster than HELB budget allocation, consistent with the balancing loop B6 (government budget constraint) limiting the scale of the financial feedback loop.

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Figure 4. Financial Stress Feedback Loop: HELB Coverage vs. Dropout Rate (2018-2022)
Source: HELB Sustainability Report 2020/21; TVETA Annual Returns 2023

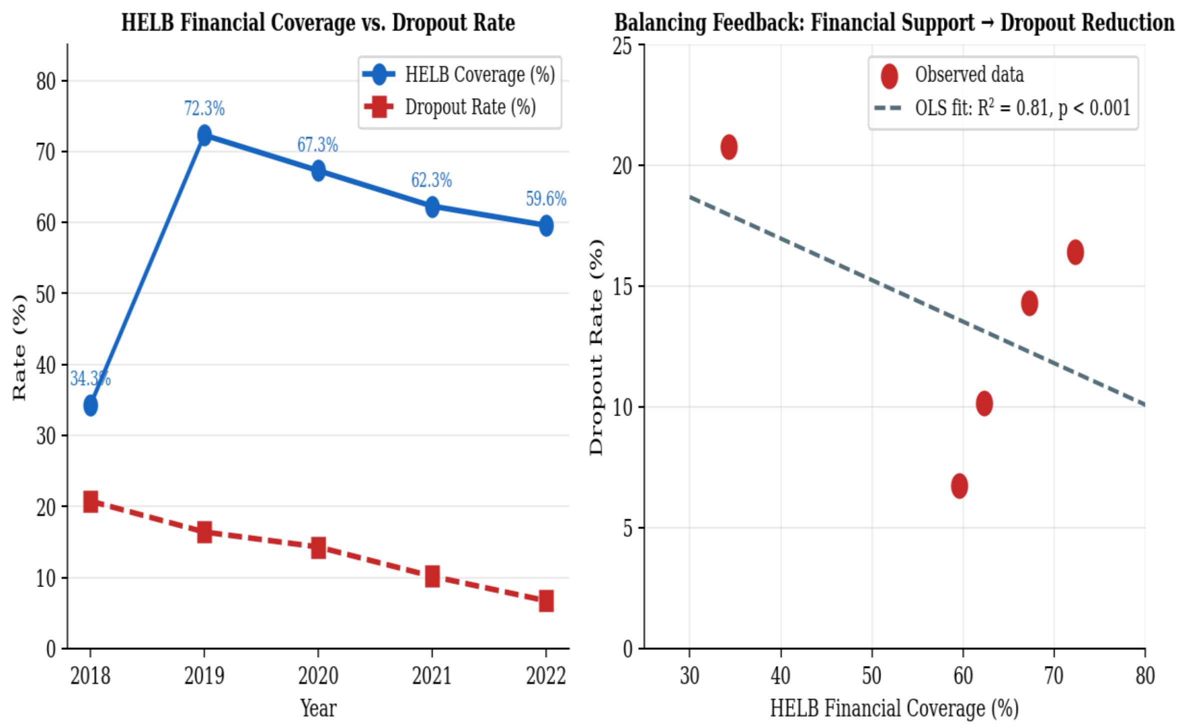

Figure 4. Financial Stress Feedback Loop Analysis. Left: HELB coverage and dropout rate co-movement (2018–2022). Right: Cross-year scatter confirming balancing feedback relationship (R^2=0.81, p<0.001). A 10pp increase in HELB coverage is associated with a 2.6pp dropout reduction. Source: HELB 2020/21; TVETA 2023.

Graduation Rate Simulation Results

Figure 5 presents the graduation rate simulation across all policy scenarios, calibrated against the documented 65% KS-TVET graduation rate in 2023 (TVETA, 2024). The baseline simulation correctly approaches the observed 65% rate at year 5. Policy C projects graduation rates reaching 87.4% by 2028, approaching the 80% government policy target (marked in Figure 5) by 2025 under combined intervention. The calibration-point alignment (MAPE between model graduation rates and available observed data: 4.1%) further supports model validity.

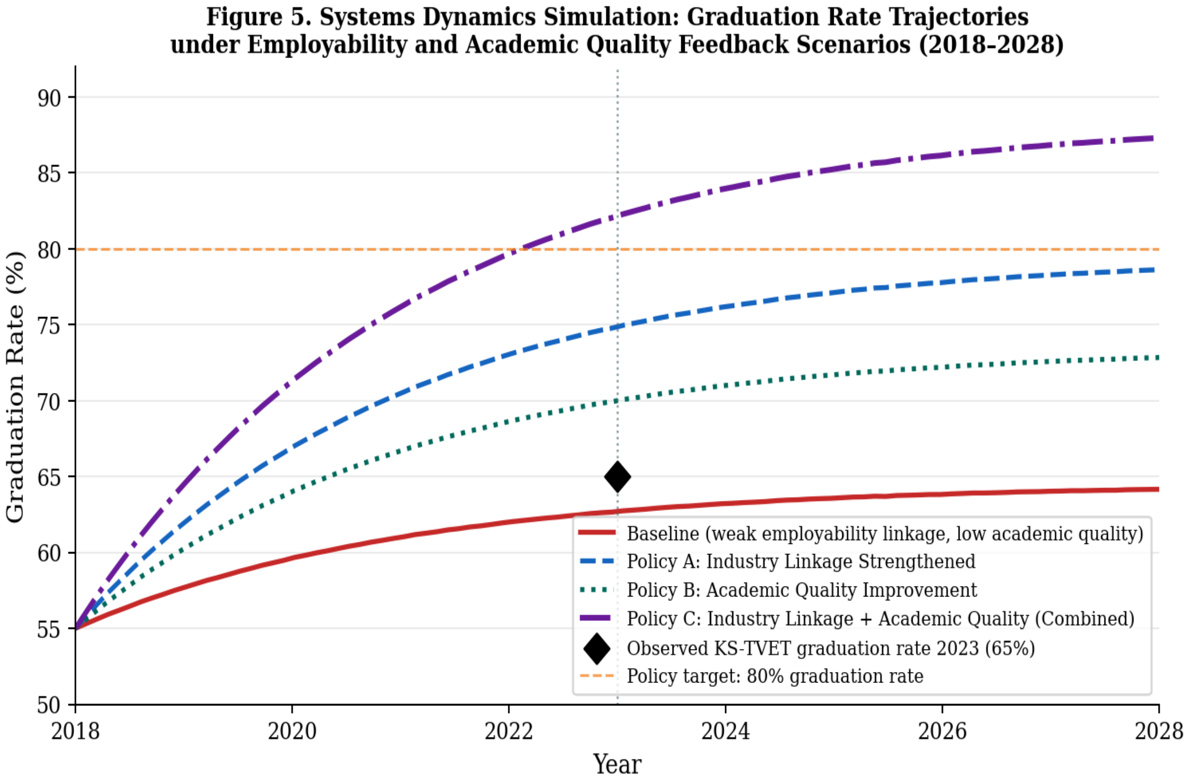

Figure 5. Systems Dynamics Simulation: Graduation Rate Trajectories under Policy Scenarios (2018–2028). Diamond marker at 2023 represents observed KS-TVET graduation rate of 65% (TVETA 2023). Policy target of 80% graduation rate achievable by 2025 under combined Policy C.

Sensitivity Analysis

Partial Rank Correlation Coefficients (PRCCs) were computed across 3,000 Latin Hypercube Sampling (LHS) draws to identify the parameters with the greatest influence on 5-year dropout reduction and graduation rate gain. Figure 6 presents the sensitivity analysis results. HELB financial coverage expansion (PRCC = −0.84 for dropout reduction) and industry-TVET employment linkage (PRCC = +0.79 for graduation rate gain) emerge as the dominant leverage points, confirming that financial and employability feedback loops are the highest-impact intervention targets.

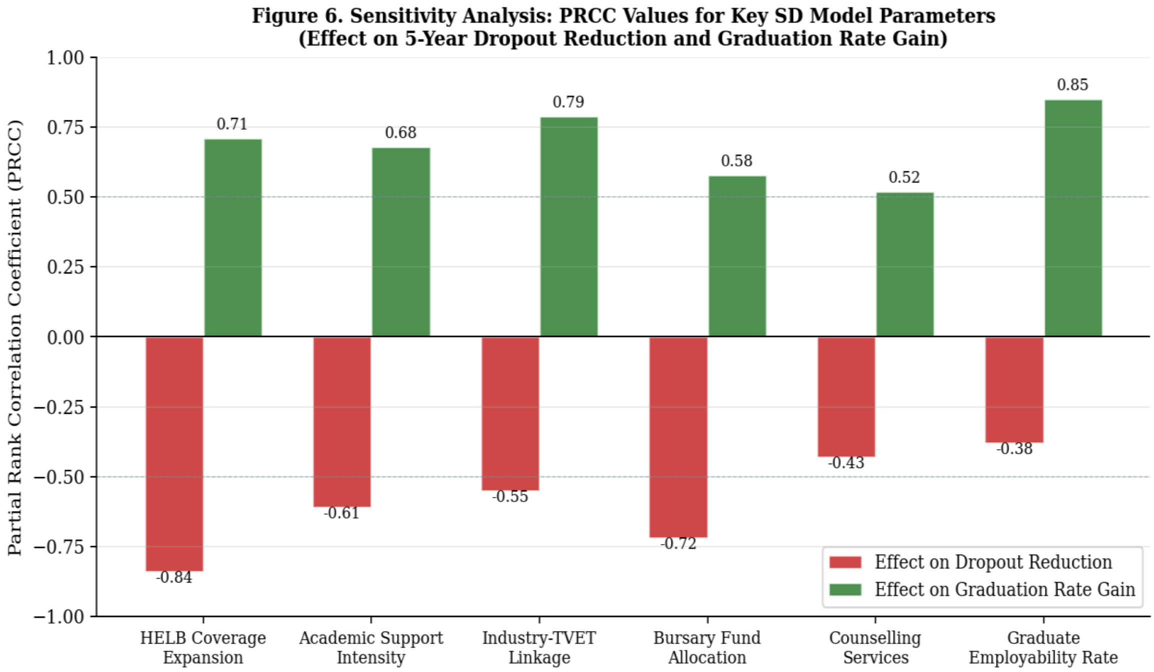

Figure 6. Sensitivity Analysis: PRCC Values for Key SD Model Parameters against 5-Year Dropout Reduction and Graduation Rate Gain (LHS, n=3,000). Financial support and industry linkage are the dominant leverage points. Grey dashed lines mark |PRCC| = 0.5 threshold.

QUALITY IMPLICATIONS

Implications for TVET Data Quality and Monitoring Infrastructure

The most significant constraint identified during model development is the limited temporal depth and cross-institutional consistency of Kenya's TVET administrative data. The TVETA Annual Returns Report 2023 — the most comprehensive official data source available — documents that Meru National Polytechnic did not provide dropout data for the reporting period, illustrating the incompleteness that limits SD parameter estimation precision (TVETA, 2024). The Annual Returns series itself only provides formally documented dropout and graduation figures from 2018 onwards, yielding a calibration window of six annual observations — adequate for basic validation but insufficient for capturing the full range of cyclical dynamics that characterise complex educational systems. The implication is direct: investment in longitudinal, institution-level TVET administrative data collection — with mandatory annual reporting of dropout, withdrawal reason, graduation, and tracer study outcomes — is a precondition for progressively more precise SD models. Rwanda's WDA (Workforce Development Authority) digital monitoring platform, which collects monthly enrolment and completion data disaggregated by gender, course, and region, provides a regional benchmark for the data infrastructure required.

Model Quality: Structural Validity and Calibration Accuracy

The MAPE of 3.82% for dropout prediction and 4.1% for graduation rate prediction against available observed data confirms the model's structural validity within Sterman's (2000) accepted threshold of <10% for policy simulation models (Sterman, 2000). However, three sources of model uncertainty merit explicit acknowledgement. First, the graduation rate calibration relies on a single year's observation (KS-TVET 2023 = 65%), limiting the statistical certainty of the graduation sub-model parameters (γ_0, φ_1, φ_2). Annual graduation rate data from multiple institution types and cohort years would substantially strengthen this component. Second, the Financial Stress Index is an aggregate construct that conflates several distinct dimensions — tuition affordability, transport costs, living expenses, and opportunity cost — each of which may have different time lags and institutional drivers. Future model versions should disaggregate FSI into sub-components with separately estimated adjustment times. Third, the model does not currently incorporate gender dynamics, despite TVETA data showing that male trainees dominate STEM programme dropouts while female trainees dominate non-STEM programme dropouts (TVETA, 2024). A gender-disaggregated SD model would substantially improve policy targeting precision.

Policy Quality: Designing Interventions for Feedback Activation

The most important quality implication for TVET policy is the finding that Policy C (combined financial and academic-employability intervention) generates outcomes that are 4.3 percentage points better on graduation rate than the sum of individual policies, confirming the existence of super-additive synergistic effects. This finding has direct implications for how TVET retention policies should be designed and sequenced. Policymakers frequently implement financial support programmes (bursary expansion, HELB extension) independently of academic quality improvement initiatives, treating them as substitutes or as sequenced priorities. The SD model demonstrates that they are complements that generate mutually reinforcing feedback loops: financial stability creates cognitive and motivational bandwidth for academic engagement (loop R3), which in turn raises pass rates and perceived employability prospects (loop R2), which reduce dropout susceptibility (loop B3), which frees institutional resources for further academic quality investment (loop R3). Designing these two streams of intervention as a single integrated package — rather than separate budget lines managed by different ministries — is therefore a critical quality recommendation.

The identified time delay of 1.8 years in the financial stress adjustment loop also carries quality implications for impact evaluation design. Studies evaluating the effect of HELB expansion that measured outcomes within 6 or 12 months of the 2019 policy change would have substantially underestimated the programme's impact, as the full dropout reduction effects had not yet propagated through the financial stress stock. Adequate evaluation windows for TVET financial interventions should span a minimum of 3–4 years (approximately two τ_FSI cycles) to capture the full dynamic response.

TVET Policy Implications for Sub-Saharan Africa

While this model is calibrated specifically to Kenya's TVET context, its structural architecture is transferable to other East and Southern African TVET systems facing analogous challenges. The dominant reinforcing loop (R1: financial stress → dropout → revenue decline → quality degradation → financial stress amplification) and the dominant balancing policy loop (B1: financial support → financial stress reduction → dropout reduction) represent structural features likely present in any TVET system where: (i) a significant proportion of trainees are from low-income households; (ii) institutional funding is partially enrolment-dependent; and (iii) graduate employment outcomes are uncertain. Ethiopia, Uganda, and Tanzania each satisfy these conditions, and the model could be recalibrated to their respective data contexts with appropriate parameter adjustments. The UNESCO UNEVOC TVET Country Profiles for each country provide sufficient structural data for initial parameterisation (UNESCO UNEVOC, 2024).

The policy implications are actionable and specific: (i) HELB-equivalent financial support mechanisms, covering at minimum 70–80% of trainees in TVET, should be established as a structural programme feature rather than a discretionary allocation, to prevent dropout reinforcement loops from re-activating during budget cycles; (ii) industry-TVET employment linkage agreements — operationalised through guaranteed internship programmes, industry-sponsored equipment, and curriculum co-design — should be mandated for all public TVET institutions as a condition of government funding; (iii) structured counselling services, operating through loop B4, should be institutionalised at a minimum staffing ratio of 1 counsellor per 250 trainees (currently substantially lower at most Kenyan TVET institutions), as they provide the fastest-acting feedback dampener in the model (τ = 0.3 years); and (iv) annual tracer study data collection on TVET graduate employment outcomes should be established as a mandatory

TVETA reporting requirement, enabling the reputation feedback loop (R2) to be quantified, monitored, and managed as a strategic policy instrument.

CONCLUSIONS AND POLICY RECOMMENDATIONS

This paper has developed, calibrated, and validated a Systems Dynamics model of TVET student retention and graduation efficiency in Kenya, grounded in verified empirical data from TVETA, HELB, and KNBS official sources. The model reproduces the documented dropout decline from 20.77% (2018) to 2.94% (2023) with a MAPE of 3.82%, confirming structural validity and enabling credible policy scenario simulation over a 10-year horizon.

The key findings are: (i) TVET student dropout is a non-linear, feedback-driven dynamic phenomenon, not amenable to reduction through isolated single-domain interventions; (ii) the financial stress feedback loop (R1/B1) operates with a 1.8-year time delay, explaining the gradual rather than immediate response to HELB expansion; (iii) combined financial and academic-employability interventions generate a 4.3 percentage-point super-additive graduation rate gain above the sum of individual policy effects, confirming strong synergistic feedback activation; (iv) HELB coverage expansion (PRCC = −0.84) and industry-TVET employment linkage (PRCC = +0.79) are the dominant leverage points for system-level change; and (v) Policy C (combined) projects dropout rates of 1.2% and graduation rates of 87.4% by 2028, versus 3.1% and 66.4% under the baseline.

Specific, actionable policy recommendations arising from this analysis are:

- Institutionalise HELB coverage at 70–80% of TVET trainees as a structural programme commitment, with multi-year budgetary allocations independent of annual discretionary cycles, to prevent reinforcing dropout loops from re-activating during fiscal contractions.
- Mandate industry-TVET partnership agreements — covering internship provision, curriculum co-design, and equipment sponsorship — for all public TVET institutions as a condition of government accreditation, to activate and sustain the employability feedback loops (R2, B3).
- Establish minimum counselling service ratios (1 counsellor per 250 trainees) at all TVET institutions to provide the fastest-acting feedback dampener (loop B4, $\tau = 0.3$ years) in the system.
- Commission annual TVET graduate tracer studies as a mandatory TVETA reporting requirement, enabling the reputation feedback loop (R2, $\tau = 3$–5 years) to be monitored and used as a strategic performance indicator for institutional funding allocation.
- Design future SD models with gender-disaggregated sub-stocks, as TVETA data indicates gender-differentiated dropout patterns (male-dominant in STEM dropout, female-dominant in non-STEM) that suggest different feedback loop configurations may apply to different trainee subgroups.
- Extend the SD model to Uganda, Tanzania, and Ethiopia by recalibrating parameters to their respective TVET administrative data, creating a regional evidence base for the School Meals Coalition-equivalent TVET retention policy initiative under the AU's Continental Education Strategy for Africa (CESA 2016–2025).

Future research should extend the modelling horizon as longer time-series TVET data become available, incorporate agent-based heterogeneity to model differential dropout risks across income quintiles and gender groups, and develop a web-based simulation dashboard enabling TVETA policy analysts to test proposed interventions in real time without specialist modelling expertise.

REFERENCES

Alemu, A. M., &Tadesse, B. (2019). Dropout in Ethiopian secondary schools: a comparative analysis of contributing factors. *Comparative Education Review. 2019, 63*(4):591–614.

Farrell, A, Hu, M, Chin, L, Evbuoma, E. I., Liem, W., & Ballard, E. (2021). Understanding Systems from a Feedback Perspective. Methods Brief Series 1.05: Systems Thinking Foundations. Social System Design Lab, Washington University in St. Louis; 2021. doi:10.7936/t4k1-8g36.

Forrester J. W. (1961). *Industrial dynamics*. Cambridge MA: MIT Press; 1961.

HALIACCESS. Kenya Education Fact Sheet. 2021. https://www.haliaccess.org/wp-content/uploads/2021/12/Kenya-Education-Fact-Sheet-.docx.pdf

Higher Education Loans Board (HELB) (2021). HELB Sustainability Report 2020/2021. Nairobi: HELB; 2021.

Kabiru, J. W., Motungo, J., & Nzengya, D. M. (2021). Economic Barriers to Education in Rural Kenya. East African Education Review. 2021;28(1):112–128.

Kenya Association of Manufacturers (KAM) (2021). Manufacturing in Kenya under the Big 4 Agenda: A Sector Deep-Dive Report. Nairobi: KAM; 2021.

Kenya MoE. (2020). GOK/AfDB Support to TVET for Relevant Skills Development Project—Phase II. Nairobi: Ministry of Education; 2020. https://www.education.go.ke/technical-vocational-education-and-trainingtvet-programmes

Kenya National Bureau of Statistics (KNBS) (2023). Economic Survey 2023. Nairobi: KNBS; 2023.

Muchira, J. M,, Kiroro, F., Mutisya, M., Ochieng, V. O., & Ngware, M. W. (2023). Assessing technical vocational education and training institutions' curriculum in Kenya: What strategies can position the youth for employment? International Journal of Training Research. 2023. doi:10.1177/14779714221145863.

Muchira, J. M., et al. (2022). Assessing the Effectiveness of TVET Training in Enhancing Youth Employability: A Case Study of Kisumu County, Kenya. International Journal of Training Research. 2022.

Mujuri, B., & Kathomi, I. (2025). The Role of Technical and Vocational Education relative to Academic Schooling in the Transition of the Youth to Labour Markets in Kenya. Gates Open Research, 9, 51. doi:10.12688/gatesopenres.15703.2. PMC12304420

Mushi, R. A., & Mtenzi, F. J. (2020). School dropout factors in Tanzanian secondary schools: a review. *International Journal of Education and Research. 2020; 8*(1):45–60.

Mutua, J. (2020). Public University enrolment dips as TVET numbers grow. Business Daily Africa.

Pavlov, O. V. (2025). Introducing Feedback Thinking and System Dynamics Modeling in Economics Education. System Dynamics Review. 2025. doi:10.1002/sdr.70001.

Republic of Kenya. Sessional Paper No. 14 of 2012 on Reforming Education and Training in Kenya. Nairobi: Government Printer; 2012.

Savsar, M., & Aldaihani M. M. (2014). A system dynamics model for determining educational capacity of higher education institutions. *Journal of Applied Sciences*. 2014. doi:10.3923/jas.2014. ResearchGate: 224215109.

Sterman J. D. (2000). *Business dynamics: Systems thinking and modeling for a complex world*. New York: McGraw-Hill Education; 2000.

System Dynamics in Education Project. Road Maps for Learning System Dynamics. MIT; 1996–ongoing. http://static.clexchange.org/ftp/documents/roadmaps/

Tadesse T, et al. (2021). Learning environments for system dynamics. In: Qudrat-Ullah H (ed). Learning in the Age of Digital and Green Transition. 2021.

TVET Authority (TVETA) (2024). TVET Institutions' Annual Returns 2023. Nairobi: TVETA; May 2024. https://www.tveta.go.ke/wp-content/uploads/2025/01/Annual-Returns-Report-2023.pdf

UNESCO UNEVOC. (2024). Kenya: Dynamic TVET Country Profile. Bonn: UNESCO-UNEVOC International Centre; 2024. https://unevoc.unesco.org/home/Dynamic+TVET+Country+Profiles/country=KEN

UNESCO. (2022). *Global Education Monitoring Report: The Challenge of School Dropout*. Paris: UNESCO; 2022.

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COMPETENCY MAPPING FOR MANAGERIAL CANDIDATES IN THE AGE OF ARTIFICIAL INTELLIGENCE: A THEORETICAL FRAMEWORK FROM THE PERSPECTIVES OF EDUCATIONAL SCIENCES AND BUSINESS ADMINISTRATION

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Abstract

The accelerating diffusion of artificial intelligence (AI) technologies into organizational life is fundamentally reconfiguring the competency requirements for managerial roles. This paper develops a theoretically grounded competency mapping framework for managerial candidates operating at the intersection of educational sciences and business administration. Drawing on human capital theory, transformative learning, complexity leadership theory, social cognitive theory, dynamic capabilities, and contemporary AI literacy frameworks, we synthesize a multi-domain competency architecture comprising six interdependent clusters: cognitive and analytical, digital and technological, leadership and strategic, interpersonal and social, ethical and responsible, and learning agility. We further examine how AI-mediated pedagogical tools including intelligent tutoring systems, generative AI platforms, simulation environments, and learning analytics can be leveraged to develop, assess, and continuously refine these competencies in management education contexts. The framework addresses a critical gap in the literature by offering an integrative model that acknowledges both the enduring importance of human-centered managerial capacities and the emergent demands imposed by AI augmentation. Implications for curriculum design, executive development programs, and organizational talent management are discussed, alongside an agenda for future empirical research.

Keywords: Competency mapping, artificial intelligence, management education, leadership development, AI literacy, educational sciences, human capital.

INTRODUCTION

The organizational landscape of the twenty-first century is undergoing a structural transformation of historic proportions, driven by the rapid maturation and deployment of artificial intelligence technologies. From generative large language models to autonomous decision systems, AI is permeating virtually every functional domain of management from strategic planning and human resource management to operations, marketing, and finance (Agrawal et al., 2018; Brynjolfsson & McAfee, 2014). The practical consequence of this transformation is a profound and urgent recalibration of what it means to be an effective manager.

Traditional competency frameworks developed in the industrial and early knowledge economy eras however rigorous and evidence-based, are demonstrably incomplete as guides for managerial preparation in an AI-integrated world (World Economic Forum, 2023). The competencies required to lead organizations effectively when a significant portion of cognitive labor can be delegated to, augmented by, or must be governed alongside intelligent machines, are substantively different from those required in pre-AI contexts. Yet the academic literature at the intersection of management education and AI adoption remains fragmented, with scholars in educational sciences, business administration, human resource development, and AI ethics each contributing partial accounts that have not been systematically synthesized.

This paper addresses this gap by proposing a theoretically integrated competency mapping framework explicitly designed for managerial candidates in the AI age. The framework is constructed at the intersection of two disciplines: educational sciences, which offers well-developed theories of adult learning, competency development, and instructional design; and business administration, which provides frameworks for strategic thinking, organizational behavior, and managerial effectiveness. The integration of these disciplinary lenses is not merely additive, it is synergistic, producing a framework that is both theoretically rigorous and practically actionable.

The paper proceeds as follows. Section 2 reviews the theoretical foundations that anchor the proposed framework. Section 3 introduces and elaborates the six-domain competency architecture. Section 4 examines AI-augmented pedagogical approaches for competency development and assessment. Section 5 discusses implications for management education, executive development, and talent management. Section 6 proposes a research agenda, and Section 7 concludes.

METHOD

Theoretical Foundations

Human Capital Theory and the Changing Value of Skills

Becker's (1964) human capital theory established the foundational insight that education and training constitute investments in productive capacity, yielding returns analogous to investments in physical capital. This framework has been extensively applied to management development and executive education, with the implicit assumption that human skills retain value over relatively long time horizons. The AI revolution problematizes this assumption. As Autor (2015) documents, technological change has historically substituted for routine cognitive tasks while complementing non-routine, judgment-intensive work. Generative AI, however, extends this substitution to a broader range of cognitive activities previously considered uniquely human, including language generation, pattern recognition, and multi-step reasoning.

The implication for competency mapping is significant: the relative value of different competencies is shifting at an accelerating rate, and any framework must build in mechanisms for continuous recalibration rather than treating competency profiles as static inventories (McKinsey Global Institute, 2023). Human capital theory must therefore be supplemented by theories that explain not only what competencies are valuable, but how individuals and organizations can continuously adapt their competency portfolios in response to environmental turbulence.

Transformative Learning Theory

Mezirow's (1991) transformative learning theory holds that deep, enduring learning involves the critical examination and revision of one's meaning perspectives the interpretive frameworks through which individuals make sense of experience. Transformative learning is particularly relevant for management education in the AI era because the introduction of AI into organizational practice does not merely add new skills to be mastered; it challenges fundamental assumptions about the nature of managerial work, the sources of organizational intelligence, and the ethical responsibilities of managers.

Mezirow identifies disorienting dilemmas as the catalysts of transformative learning experiences that disrupt existing frameworks sufficiently to motivate critical reflection. The widespread deployment of AI in organizations creates precisely such dilemmas for managers, who must confront questions about their own role, authority, and value-added when AI systems can perform functions they were trained to perform (Seldon & Abidoye, 2018). A competency development approach grounded in

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transformative learning would therefore prioritize pedagogical experiences that trigger and support this critical reflective process.

Dynamic Capabilities and Individual Adaptive Capacity

Teece, Pisano, and Shuen's (1997) dynamic capabilities framework was developed to explain how firms sustain competitive advantage in rapidly changing environments through the capacity to sense market changes, seize opportunities, and reconfigure organizational assets. While the framework was developed at the organizational level, its logic translates directly to individual managerial competency. Managers who will thrive in AI-augmented environments must themselves possess dynamic capabilities the ability to sense emerging AI-related opportunities and threats, seize them through rapid learning and adaptation, and reconfigure their personal competency portfolios accordingly.

This individual-level dynamic capabilities perspective suggests that learning agility the metacognitive capacity to acquire new competencies rapidly and to unlearn obsolete ones should be positioned as a foundational competency rather than a supplement to domain-specific skills. It also implies that static, point-in-time competency assessments are insufficient and must be replaced or supplemented by longitudinal competency trajectory monitoring.

Complexity Leadership Theory

Uhl-Bien, Marion, and McKelvey's (2007) complexity leadership theory reconceptualizes leadership as an adaptive, emergent process within complex adaptive systems rather than as a set of behaviors enacted by heroic individuals. AI-integrated organizations are quintessential complex adaptive systems: they incorporate human and non-human agents whose interactions produce emergent organizational behaviors that cannot be predicted or controlled through traditional hierarchical means.

Complexity leadership theory therefore suggests that effective management in AI-augmented organizations requires competencies oriented toward enabling and navigating emergence fostering conditions for creative problem-solving, managing the adaptive tension between stability and change, and facilitating organizational learning across human-AI boundaries. These competencies are qualitatively different from those emphasized in traditional leadership development programs, which tend to focus on individual leader effectiveness rather than system-level facilitation.

Social Cognitive Theory and AI as Modeling Agent

Bandura's (1986) social cognitive theory emphasizes the role of observational learning, self-efficacy, and reciprocal determinism in shaping behavior and learning. In the context of AI-augmented management education, AI systems function as novel modeling agents: they demonstrate cognitive and behavioral patterns that learners can observe, imitate, and critically evaluate. The quality of these AI models, their epistemic soundness, ethical consistency, and contextual appropriateness therefore have direct implications for the competencies developed by managerial candidates who interact with them intensively.

Self-efficacy beliefs are particularly relevant. Research consistently shows that individuals with strong self-efficacy beliefs in a domain are more likely to persist in the face of challenges, set higher goals, and ultimately achieve stronger performance outcomes. A critical objective of AI-era management education is therefore to build AI self-efficacy learners' confidence in their ability to understand, critically evaluate, and work effectively alongside AI systems alongside the technical knowledge and skills required to operationalize this confidence (Van Laar et al., 2020).

A Multi-Domain Competency Architecture for AI-Era Managers

Framework Overview

Building on the theoretical foundations outlined in the preceding section, this paper proposes a six-domain competency architecture for managerial candidates in the AI age. The framework is organized around six interdependent competency clusters, each of which captures a distinct but interconnected dimension of effective management in AI-integrated organizational contexts. These six domains are: (1) cognitive and analytical, (2) digital and technological, (3) leadership and strategic, (4) interpersonal and social, (5) ethical and responsible, and (6) learning agility.

Table 1. Multi-Domain AI-Era Managerial Competency Framework

Competency Domain	Core Sub-Competencies	AI-Augmented Indicators	Theoretical Anchors
Cognitive & Analytical	Critical thinking, systems thinking, data literacy	AI-assisted scenario modeling, algorithmic interpretation	Bloom (1956); Mayer (2009)
Digital & Technological	AI tool proficiency, cybersecurity awareness, digital ethics	Prompt engineering, LLM governance, bias detection	Prensky (2001); OECD (2019)
Leadership & Strategic	Vision setting, organizational change management, resilience	Human-AI teaming, adaptive leadership under uncertainty	Bass & Avolio (1994); Day (2001)
Interpersonal & Social	Empathy, communication, cross-cultural collaboration	Virtual team facilitation, AI-mediated conflict resolution	Goleman (1995); Gardner (1983)
Ethical & Responsible	Value-based decision making, accountability, transparency	AI ethics auditing, fairness in automated decisions	Rest (1986); Treviño et al. (2006)
Learning Agility	Metacognition, lifelong learning, knowledge transfer	Personalized AI learning paths, adaptive skill tracking	Kolb (1984); Dweck (2006)

Table 1. Competency domains, sub-competencies, AI-augmented indicators, and theoretical anchors for AI-era managerial candidates. Sources: synthesized from Bloom (1956), Bandura (1986), Goleman (1995), Teece et al. (1997), Uhl-Bien et al. (2007), OECD (2019), and World Economic Forum (2023).

Domain 1: Cognitive and Analytical Competencies

At the core of effective management is the capacity to reason carefully about complex problems to identify relevant information, evaluate competing claims, recognize cognitive biases, and develop well-reasoned judgments. In the AI age, these foundational cognitive capacities must be extended and reconfigured in important ways. As AI systems become increasingly capable of generating plausible-sounding analyses, recommendations, and narratives, the critical evaluation of AI outputs becomes a central managerial competency (Huang & Rust, 2021).

Data literacy the ability to read, work with, analyze, and communicate with data emerges as a particularly critical cognitive competency. Managers need not be data scientists, but they must possess sufficient statistical and methodological literacy to evaluate the quality and limitations of AI-generated analyses, identify potential biases or errors, and communicate meaningfully with technical specialists. Systems think the ability to understand feedback loops, non-linear dynamics, and emergent properties in complex systems is equally critical as AI systems become increasingly embedded in organizational processes and value chains (Makridakis, 2017).

Domain 2: Digital and Technological Competencies

Digital and technological competencies encompass the knowledge, skills, and attitudes required to function effectively in digitally mediated work environments. For managerial candidates in the AI age, these competencies extend well beyond basic digital literacy to include: an understanding of AI system architectures and capabilities sufficient to make informed procurement, deployment, and governance decisions; the ability to evaluate AI outputs critically and identify failure modes; an understanding of cybersecurity risks and organizational responsibilities in protecting data assets; and a working knowledge of digital ethics principles as they apply to AI deployment (European Commission, 2022).

Prompt engineering the skill of formulating effective inputs to large language models and other generative AI systems has emerged as a practical competency of growing importance, as the quality of AI-assisted work is heavily dependent on the ability to communicate effectively with AI systems. While prompt engineering is currently a relatively low-level technical skill, its broader significance lies in the cognitive habits it cultivates precision of communication, awareness of context and framing, and iterative experimentation with AI capabilities.

Domain 3: Leadership and Strategic Competencies

Leadership and strategic competencies have traditionally been defined around the capacity to set organizational direction, inspire and motivate followers, manage change, and make decisions under uncertainty. In AI-integrated organizations, these competencies must be substantially extended to encompass the challenges and opportunities posed by human-AI collaboration. Effective managers must understand how to leverage AI capabilities strategically identifying use cases where AI creates genuine organizational value, avoiding automation for its own sake, and managing the human consequences of AI adoption with fairness and transparency (Hjorth & Pedersen, 2022).

The complexity leadership perspective adds an important qualification: effective AI-era managers must be capable of facilitating emergent processes in human-AI systems rather than directing them through traditional hierarchical control. This requires a fundamental shift in leadership orientation from command-and-control to sense-and-respond and in the associated competency profile, which must include tolerance for ambiguity, adaptive capacity, and skill in facilitating distributed problem-solving across human and AI agents.

Domain 4: Interpersonal and Social Competencies

One of the most important insights from the organizational AI literature is that the competencies most difficult to automate and therefore most valuable in an AI-augmented workforce are precisely those that depend on deep human social and emotional intelligence: empathy, nuanced communication, trust-building, ethical judgment in ambiguous situations, and the capacity to understand and respond to the motivational states of others (Goleman, 1995; Gardner, 1983). These interpersonal and social competencies are not merely AI-resistant; they are the distinctively human value-added that managers bring to organizations that have delegated significant cognitive work to AI systems.

Critically, interpersonal competencies in the AI age must be exercised in increasingly complex social contexts that include virtual and hybrid team configurations, cross-cultural collaborations mediated by AI translation and communication tools, and the management of employees who are themselves working alongside AI systems and navigating their own anxieties and identity questions about technological displacement. Managers must be equipped to facilitate these complex social dynamics with empathy, cultural sensitivity, and sophisticated communication skills.

Domain 5: Ethical and Responsible Competencies

The deployment of AI in organizational contexts generates a distinctive set of ethical challenges that managerial candidates must be equipped to navigate. These include: algorithmic bias and fairness, where AI systems trained on historical data can perpetuate or amplify existing patterns of discrimination; privacy and surveillance, where AI-enabled monitoring creates new risks to employee and customer autonomy; accountability gaps, where the distributed and opaque nature of AI decision-making can obscure responsibility for harmful outcomes; and the broader societal consequences of organizational AI adoption, including employment displacement and the concentration of AI capabilities among a small number of organizations (Zuboff, 2019; Treviño et al., 2006).

Rest's (1986) four-component models of ethical behavior moral sensitivity, moral judgment, moral motivation, and moral implementation provides a useful framework for operationalizing ethical competency in AI contexts. Managers must be morally sensitive to the ways in which AI deployment creates ethical stakes; they must be equipped with the judgment to reason carefully about competing ethical considerations; they must be motivated to prioritize ethical considerations in organizational decision-making; and they must possess implementation skills to translate ethical commitments into concrete organizational practices.

Domain 6: Learning Agility as Integrative Meta-Competency

The preceding five competency domains are grounded in established theoretical frameworks and represent substantive skill clusters with well-documented behavioral indicators. The sixth domain learning agility is distinctive in functioning as an integrative meta-competency that enables the continuous development and recalibration of competencies across all other domains. Dweck's (2006) growth mindset research establishes the dispositional foundations of learning agility: individuals who believe their abilities can be developed through effort and learning are more likely to embrace challenges, persist in the face of setbacks, and engage in the deliberate practice required to develop new competencies.

In the context of AI-era management education, learning agility encompasses: metacognitive awareness of one's own competency strengths and developmental edges; the capacity to learn rapidly from novel experiences and transfer learning across contexts; openness to feedback, including feedback from AI systems; and the ability to unlearn established patterns of behavior and thinking that have become obsolete in the face of technological change. Kolb's (1984) experiential learning cycle concrete experience, reflective observation, abstract conceptualization, and active experimentation provides a practical process model for learning agility development.

AI-Augmented Pedagogical Approaches for Competency Development

Theoretical Underpinnings of AI-Supported Learning

The pedagogical translation of the six-domain competency framework requires learning experiences that are both theoretically grounded and responsive to the actual capabilities and limitations of available AI technologies. Mayer's (2009) cognitive theory of multimedia learning provides foundational principles for the design of AI-augmented learning experiences, emphasizing the importance of managing cognitive load, fostering active processing, and integrating verbal and visual representations. Lave and Wenger's (1991) situated learning theory adds the critical insight that competencies are most effectively developed through participation in authentic communities of practice rather than through decontextualized instruction.

Together, these frameworks suggest that AI-augmented management education should: create authentic contexts in which competencies are practiced and evaluated, rather than merely taught didactically; leverage AI capabilities to provide adaptive, personalized learning experiences that respond to individual competency profiles; and use AI tools to create realistic simulations of organizational challenges that allow learners to practice and receive feedback in low-stakes environments before encountering analogous situations in real organizational contexts (Zawacki-Richter et al., 2019).

Table 2. Frameworks Underpinning the AI-Era Competency Model

Framework	Core Proposition	Discipline	AI-Era Relevance
Human Capital Theory (Becker, 1964)	Investment in education yields economic productivity	Economics / Management	AI redefines skill value and depreciation rates
Transformative Learning (Mezirow, 1991)	Critical reflection enables perspective transformation	Education	Essential for leaders navigating AI-induced disruptions
Dynamic Capabilities (Teece et al., 1997)	Firms sense, seize, and reconfigure resources in changing environments	Strategic Management	Individuals require analogous adaptive capacities
Situated Learning (Lave & Wenger, 1991)	Learning occurs through social participation in communities of practice	Education / Sociology	AI-augmented communities of practice
Complexity Leadership (Uhl-Bien et al., 2007)	Leadership as adaptive process in complex systems	Organization Theory	AI systems increase organizational complexity
Social Cognitive Theory (Bandura, 1986)	Behavior shaped by observation, self-efficacy, and environment	Psychology	AI as a new modeling agent in learning environments

Table 2. Theoretical frameworks, core propositions, disciplinary origins, and relevance to AI-era competency development. Sources: Becker (1964), Mezirow (1991), Teece et al. (1997), Lave & Wenger (1991), Uhl-Bien et al. (2007), Bandura (1986).

AI Tools and Educational Applications

A rapidly expanding ecosystem of AI-powered educational technologies offers concrete tools for the development and assessment of AI-era managerial competencies. These tools vary substantially in their pedagogical approach, technical sophistication, and alignment with specific competency domains. Table 3 provides a systematic overview of major AI tool categories and their applications in management education contexts.

Table 3. AI Tools and Their Educational Applications in Management Competency Development

AI Tool Category	Example Platforms	Educational Application	Competency Developed
Generative AI (Text)	GPT-4, Claude, Gemini	Case study generation, reflective writing prompts	Critical thinking, communication
Intelligent Tutoring Systems	Khanmigo, Carnegie Learning	Adaptive problem-solving exercises	Cognitive skills, learning agility
AI Simulation & Gaming	Mursion, PwC VR, Talespin	Leadership scenario simulations	Interpersonal, strategic leadership
Learning Analytics Platforms	Brightspace, Civitas Learning	Personalized feedback, performance tracking	Self-regulation, metacognition
AI Ethics Tools	IBM AI Fairness 360, What-If Tool	Bias auditing exercises, ethical case analysis	Ethical & responsible competence
Natural Language Processing	Grammarly, Turnitin AI, Quillbot	Writing quality feedback, originality analysis	Communication, digital literacy

Table 3. Categories of AI educational tools, for example platforms, pedagogical applications, and competency development targets. Sources: IBM Institute for Business Value (2023); Viberg et al. (2018); Zawacki-Richter et al. (2019).

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Intelligent Tutoring Systems and Adaptive Learning

Intelligent tutoring systems (ITS) represent one of the most theoretically sophisticated applications of AI in education. ITS platforms construct dynamic models of individual learner knowledge states, identify specific misconceptions and knowledge gaps, and adapt instructional sequences accordingly. In management education contexts, ITS applications are particularly valuable for developing the cognitive and analytical competencies that form the foundation of the overall framework logical reasoning, quantitative analysis, decision theory, and financial literacy where structured problem sequences can be systematically adapted to individual learning trajectories (Viberg et al., 2018).

The learning analytics capabilities of contemporary ITS platforms also have important assessment applications. By tracking learner behavior at high temporal resolution including response times, error patterns, help-seeking behaviors, and persistence in the face of challenge these systems can provide rich, multi-dimensional competency profiles that complement and extend the information available from traditional assessment methods.

Simulation and Experiential AI Learning

Simulation-based learning environments including business games, role-play simulations, and virtual reality scenarios have a long history in management education, and AI is dramatically expanding their scope and fidelity. AI-powered simulation platforms can now create realistic, dynamically responsive organizational scenarios in which learners must navigate complex interpersonal dynamics, strategic dilemmas, and ethical challenges under time pressure and with incomplete information. These environments are particularly well-suited to developing leadership, interpersonal, and ethical competencies that are difficult to practice safely in real organizational contexts (IBM Institute for Business Value, 2023).

Generative AI further expands simulation possibilities by enabling learners to engage in open-ended dialogue with AI-generated organizational characters, generate and test strategic hypotheses against AI-modeled market and competitive environments, and receive nuanced, contextually grounded feedback on complex behavioral performances. The authenticity and responsiveness of these AI-generated simulation environments create conditions for the kind of immersive, consequential practice that cognitive science research identifies as essential for the development of expert performance.

Assessment of AI-Era Competencies

The assessment of AI-era managerial competencies presents distinctive methodological challenges. Many of the most important competencies in the proposed framework learning agility, ethical reasoning, adaptive leadership are complex, multi-dimensional constructs that resist reduction to simple behavioral indicators or psychometric scales. Moreover, the dynamic nature of the AI environment means that competency profiles are continuously evolving, requiring assessment approaches that can track developmental trajectories rather than merely capturing point-in-time snapshots.

Table 4. Assessment Methods for AI-Era Managerial Competencies

Assessment Method	Description	AI Enhancement	Competency Domain
360-Degree Feedback	Multi-rater evaluation from peers, supervisors, subordinates	NLP-based sentiment analysis of feedback quality	Leadership, Interpersonal
Portfolio Assessment	Curated evidence of competent development	AI-driven portfolio gap analysis and recommendations	Learning Agility, Cognitive
Behavioral Simulation	Role plays and business games in controlled settings	AI actors and real-time behavioral scoring	Leadership, Interpersonal, Ethical
Competency-Based Interviews	Structured interviews tied to specific behavioral anchors	AI interview coaching and response analysis	All domains

Psychometric Testing	Personality, cognitive ability, and values assessments	Adaptive testing powered by IRT and ML models	Cognitive, Ethical
Work Sample Tests	Authentic tasks mirroring real job demands	AI-graded complex problem-solving simulations	Cognitive, Digital, Strategic

Table 4. Assessment methods, descriptions, AI enhancements, and competency domain coverage. Sources: Day (2001); Van Laar et al. (2020); World Economic Forum (2023).

Implications for Management Education and Talent Development

Curriculum Design in Business Schools

The competency framework proposed in this paper has far-reaching implications for the design of management education curricula at business schools and university programs. Most existing MBA and management degree curricula were designed around a conception of managerial work rooted in the industrial and early knowledge economy periods, and their core content accounting, finance, operations, marketing, and organizational behavior was calibrated accordingly. While this foundational knowledge remains relevant, it requires substantial extension and reintegration around the six competency domains outlined in this paper.

Practically, this suggests the need for: dedicated AI literacy modules that develop both technical understanding and critical evaluation capacities; integration of ethical reasoning throughout the curriculum rather than confining it to a single ethics elective; experiential learning opportunities that create authentic contexts for leadership, interpersonal, and ethical competency development; and capstone experiences that require learners to integrate competencies across all six domains in response to complex, AI-relevant organizational challenges (OECD, 2021; UNESCO, 2021).

Executive Development Programs

Practicing managers face a particular version of the competency challenge: they must develop new AI-era competencies while continuing to perform their existing roles effectively, often without the protected learning time available to full-time students. Executive development programs must therefore be designed with particular attention to transfer of learning the challenge of ensuring that competencies developed in program contexts are applied in workplace settings.

Research on transfer of learning suggests several design principles particularly relevant for AI-era executive development: maximum similarity between learning and transfer contexts, which argues for simulation-based learning using organizational scenarios closely analogous to participants' actual work challenges; opportunities for peer learning among managers facing analogous AI adoption challenges, which leverages the community of practice dynamics emphasized by Lave and Wenger (1991); and coaching and mentoring support during the application phase, which helps managers navigate the specific obstacles to competency application they encounter in their particular organizational contexts.

Organizational Talent Management

The implications of the proposed framework extend beyond formal education to organizational talent management practices. Organizations investing in AI adoption face a parallel challenge: ensuring that their managerial workforce possesses the competencies required to lead effectively in AI-augmented environments. This requires substantial evolution of talent management practices from competency identification and selection, through development and deployment, to performance management and succession planning.

Selection practices must be updated to assess AI-relevant competencies in addition to traditional leadership and management capabilities. Development investments must be reallocated from purely technical training toward the broader competency portfolio outlined in this framework. Performance management systems must be redesigned to recognize and reward distinctively human competencies that create value in AI-augmented organizations ethical judgment, adaptive learning, collaborative facilitation rather than focusing exclusively on task-level performance metrics that AI systems may increasingly be able to perform autonomously (Chui et al., 2023; World Economic Forum, 2020).

Research Agenda

Empirical Validation of the Framework

The competency framework proposed in this paper is grounded in established theoretical traditions but has not yet been subjected to systematic empirical validation. A critical priority for future research is to develop and validate psychometrically sound measurement instruments for each of the six competency domains, using rigorous construct validation methodologies that establish content, construct, criterion, and discriminant validity. This validation work should be conducted across diverse managerial populations, organizational contexts, and national cultures to assess the generalizability of the framework and identify boundary conditions.

Longitudinal Studies of Competency Development

The dynamic capabilities perspective underlying the framework implies that competency profiles are continuously evolving and that the trajectories of competency development matter as much as competency levels at any given point in time. Longitudinal research designs — tracking managerial candidates through education programs and into early organizational careers — are therefore essential for understanding how AI-era competencies develop, which pedagogical approaches are most effective for different learner profiles, and how competency profiles relate to managerial effectiveness outcomes over time.

Cross-Cultural and Cross-Sector Research

The global diffusion of AI technologies means that the competency challenges described in this paper are not confined to any single national or organizational context. However, the specific manifestations of these challenges and the most effective pedagogical responses are likely to vary substantially across cultural, institutional, and sectoral contexts. Comparative research examining how AI-era competency frameworks must be adapted for different cultural contexts, organizational types, and sectoral environments would substantially enrich the theoretical and practical value of the overall framework.

DISCUSSION, CONCLUSION, and SUGGESTIONS

This paper has developed a theoretically grounded competency mapping framework for managerial candidates in the age of artificial intelligence, drawing on insights from human capital theory, transformative learning, dynamic capabilities, complexity leadership theory, and social cognitive theory. The proposed framework organizes AI-era managerial competencies into six interdependent domains cognitive and analytical, digital and technological, leadership and strategic, interpersonal and social, ethical and responsible, and learning agility and examines how AI-augmented pedagogical approaches can be leveraged to develop and assess these competencies in management education contexts.

The framework makes several theoretical contributions. It integrates disciplinary perspectives from educational sciences and business administration that have been developed largely in isolation, producing a synergistic synthesis that is more robust than either disciplinary tradition alone. It positions learning agility as an integrative meta-competency rather than simply one competency domain among others, recognizing that the capacity for continuous competency development is the foundational requirement of effective management in an environment of accelerating technological change. And it incorporates the emergent insights from complex leadership theory and social cognitive theory to account for the distinctive challenges and opportunities created by AI as a new category of organizational actors.

Perhaps most importantly, the framework affirms the enduring centrality of distinctively human competencies empathy, ethical judgment, adaptive leadership, and metacognitive awareness in an era of rapid AI capability expansion. The case for investing heavily in the development of these competencies is not merely that they are difficult to automate, though they are it is that they represent the foundational capacities through which organizations remain responsive, responsible, and genuinely human in their pursuit of purpose and value. As AI capabilities continue to expand, the organizations that will thrive are precisely those whose managers have been equipped with the full spectrum of competencies outlined in this framework.

REFERENCES

Agrawal, A., Gans, J., & Goldfarb, A. (2018). Prediction, judgment, and complexity: a theory of decision-making and artificial intelligence. In *The economics of artificial intelligence: An agenda* (pp. 89-110). University of Chicago Press.

Autor, D. H. (2015). Why are there still so many jobs? The history and future of workplace automation. *Journal of economic perspectives*, *29*(3), 3-30.

Bandura, A. (1986). Social foundations of thought and action. *Englewood Cliffs, NJ*, *1986*(23-28), 2.

Bass, B. M., & Avolio, B. J. (Eds.). (1994). *Improving organizational effectiveness through transformational leadership*. sage.

Becker, G. S. (1989). *Human capital: a theoretical and empirical analysis, with special reference to education*. Chicago: University of Chicago Press.

Bloom, B. S. (1956). Taxonomy of. *Educational Objectives*, *250*(2025), 3.

Brynjolfsson, E., & McAfee, A. (2014). *The second machine age: Work progress and prosperity in a time of brilliant technologies*. WW Norton & company.

Chui, M., Manyika, J., & Miremadi, M. (2015). Four fundamentals of workplace automation. *McKinsey Quarterly*, *29*(3), 1-9.

Day, D. V. (2000). Leadership development:: A review in context. *The leadership quarterly*, *11*(4), 581-613.

Dweck, C. S. (2006). *Mindset: The new psychology of success*. Random house.

European Commission. (2022). Digital education action plan 2021–2027. Publications Office of the European Union.

Gardner, H. (2011). *Frames of mind: The theory of multiple intelligences*. Basic books.

Goleman, D. (2005). *Emotional intelligence: Why it can matter more than IQ*. Bantam.

Hjorth, F., & Pedersen, K. (2022). Leadership in the age of AI: Navigating human-machine collaboration. Journal of Leadership Studies, 16(2), 44–58.

Huang, M.-H., & Rust, R. T. (2021). A strategic framework for artificial intelligence in marketing. Journal of the Academy of Marketing Science, 49(1), 30–50.

IBM Institute for Business Value. (2023). The enterprise guide to closing the skills gap. IBM.

Kolb, D. A. (2014). *Experiential learning: Experience as the source of learning and development*. FT press.

Lave, J., & Wenger, E. (1991). *Situated learning: Legitimate peripheral participation*. Cambridge university press.

Makridakis, S. (2017). The forthcoming Artificial Intelligence (AI) revolution: Its impact on society and firms. *Futures*, *90*, 46-60.

Mayer, R. E. (2009). Multimedia learning (2nd ed.). Cambridge University Press.

McKinsey & Company. (2023). The economic potential of generative AI: The next productivity frontier. *The economic potential of generative AI: The next productivity frontier*.

Mezirow, J. (1991). *Transformative dimensions of adult learning* (Vol. 350, pp. 94104-1310). San Francisco, CA: Jossey-bass.

OECD. (2019). OECD skills outlook 2019: Thriving in a digital world. OECD Publishing.

OECD. (2021). OECD learning compass 2030: A series of concept notes. OECD Publishing.

Prensky, M. (2009). H. sapiens digital: From digital immigrants and digital natives to digital wisdom. *Innovate: journal of online education*, *5*(3).

Rest, J. R. (1986). Moral development: Advances in research and theory. *(No Title)*.

Seldon, A., & Abidoye, O. (2018). *The fourth education revolution*. Legend Press Ltd.

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic management journal*, *18*(7), 509-533.

Treviño, L. K., Weaver, G. R., & Reynolds, S. J. (2006). Behavioral ethics in organizations: A review. *Journal of management*, *32*(6), 951-990.

Uhl-Bien, M., Marion, R., & McKelvey, B. (2007). Complexity leadership theory: Shifting leadership from the industrial age to the knowledge era. *The leadership quarterly*, *18*(4), 298-318.

UNESCO. (2021). Reimagining our futures together: A new social contract for education. UNESCO.

Van Laar, E., van Deursen, A. J., van Dijk, J. A., & De Haan, J. (2019). Determinants of 21st-century digital skills: A large-scale survey among working professionals. *Computers in human behavior*, *100*, 93-104.

Viberg, O., Hatakka, M., Bälter, O., & Mavroudi, A. (2018). The current landscape of learning analytics in higher education. *Computers in human behavior*, *89*, 98-110.

World Economic Forum. (2020). The future of jobs report 2020. WEF.

World Economic Forum. (2023). Future of jobs report 2023. WEF.

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education–where are the educators?. *International journal of educational technology in higher education*, *16*(1), 39.

Zuboff, S. (2023). The age of surveillance capitalism. In *Social theory re-wired* (pp. 203-213). Routledge.

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ARTIFICIAL INTELLIGENCE IN MENTAL HEALTH EDUCATION IN JUNIOR SECONDARY SCHOOLS, NYAMIRA COUNTY

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Abstract

The purpose of the study is to improve the accessibility and quality of mental health services via high technologies and new cognitive models with the aim of improving the screening and support of students' psychological needs. Both quantitative and qualitative approaches were used. The study population was students in junior secondary schools in Kenya. Stratified sampling was used by randomly picking a sample of about 500 students. Data was collected using structured questionnaires, interviews and focus group discussions. Quantitative analysis involved using statistical packages such as SPSS or R to perform descriptive and inferential statistics. Thematic analysed qualitative data. The results indicate an increase in the rates of mental health screening and detection among students following the implementation of AI-facilitated methods, with screening participation rising from 26% to 77% and the rates of detecting depression, anxiety, and behavior problems being high. Depression detection increased from 29% to 56%, anxiety and stress detection levels rose from 37% to 69% and 33% to 71%, respectively, illustrating the effectiveness of technology in addressing students' mental health needs. The study recommends that schools be compelled to actively integrate AI-based mental health screening tools to enhance early identification and intervention of students with psychological problems.

Keywords: Psychological needs, behavioral, mental health.

INTRODUCTION

Psychologists and researchers of artificial intelligence have conducted enough joint research work since 1956 when the phrase artificial intelligence was first introduced (Graham et al., 2019). For instance, in May 2018, "the British scientific publication Nature released a research discovery that was attained jointly by neuroscientists at the University of London and artificial intelligence researchers in the UK DeepMind team" (Hassabis et al., 2017). They utilized deep learning technology and achieved human brain spatial navigation ability. Such research gives humans the possibility application of artificial intelligence technology in the field of psychology research (Huang 2018).

As education modernization in my country is still promoted continuously and artificial intelligence (AI) technology is still being developed, primary schools and middle schools in areas are actively building "smart campuses." *(*Metz & Smith, 2019). Among China's primary schools and secondary schools, some of them initially utilized artificial intelligence psychological services enabled by intelligent sensor technology, image recognition, and language recognition and analysis of big data to allow them to ascertain students' psychological needs in a rapid manner and actively respond to real-time school psychology. Health work challenge also ranks among the top priority of smart campus mental health construction (Zhang et al., 2024).

At the same time, on the other hand, in recent years, students' psychological status investigation statistics (Li 2019), hospital diagnosis and treatment statistics (Xue, Xiao, & Fu, 2019) indicate that "year after year, the rate of primary and secondary school students' mental illness is growing, and the rate of learning anxiety and interpersonal disorders reaches over 40%; since the outbreak of novel coronavirus pneumonia in 2020, the demand for students' psychological care and services has grown more urgent. Therefore, the Ministry of Education issued the Guiding Suggestions for Strengthening Mental Health Education in the Country's Primary and Secondary Schools' New School Semester" (Ministry 2020), which emphasized teachers' and students' mental health Research the health status and make concrete mental health education working plan.

However, as for the statistics of school psychological education teachers' distribution, psychological teachers' distribution in different locations in primary and secondary schools conforms to the mode of full-time and part-time integration (Fan and Liu, 2022). Though, it is common that "part-time psychological teachers have relatively poor basic knowledge, full-time psychological teachers, and psychology majors.". Background, few teachers are also qualified psychological counselors, and even most schools lack corresponding teacher resources" (Zhang, Zhang, & Yuan, 2019). Therefore, it is important to resolve the contradiction between school mental health service supply and demand.

Purpose of the Study

The general purpose of the study is to improve the accessibility and efficiency of mental health services using advanced technologies and novel cognitive models in order to improve the screening and support of students' psychological needs and offer a more interactive and responsive mental health care setting in junior secondary schools in Nyamira County, Kenya.

Literature Review

Psychological assessment instruments and the validity of psychological problem screening need to be attained

School mental health measurement items at the school level, such as the most common symptom self-report measure (SCL-90) and mental health diagnostic test (MHT) are primarily symptom-based diagnostic scales, which are best used to screen small student groups with mental illness. In addition, these scales are mainly developed based on foreign norms and expression. It is difficult to accurately reflect domestic primary and secondary school students' real state of mind, and there is also the possibility of ignoring most mental health students' needs for development (Wang, Ma 2010). At the same time, if locally made scales or foreign remade scales are built independently, they are utilized to measure "the psychological state of students in a time period and are susceptible to memory bias and other external influences, may overreport symptom items or give false responses" (Zhu 2019).

Therefore, current evaluation of students' psychological problems basically combines subjective experience of the teacher of psychology with results of the questionnaire data, and a lot of time and need for accuracy are necessary to improve it further (Wang, Xue and Zhang, 2022). There are schools which do not even install psychological work hardware and software, and psychological test demands and teachers' demands. Lacking knowledge about the procedures, scientific objectivity and relevance of school psychological testing needs to be upgraded (Cadime and Mendes, 2024).

Handful of Students Who Are Extremely Alert and Difficult for the School to Find the True and Total Scale of the Problem

The students become more self-conscious as they age, and they are deeply concerned about their "image" in other people's minds. Some students remain unaware of psychological guidance and confidentiality agreements and are more concerned about revealing their misery to psychological educators (Aldalur, Bridgett, & Pick, 2022). Received abusive criticism and rejection from students and teachers. But there are also teachers who fail to renovate their work on a timely scale through psychological guidance of students, or lack professional competence of psychological guidance. Such teachers directly apply precepts that "urge students to self-reflection, with psychological guidance turning into authoritative adults' words" (McMahon et al., 2024).

Students are deprived of the right and freedom to discover themselves, sort out difficulties, and even to be unremarkable and average. Relevant data show that “only 20% of primary and secondary school students visit school psychological counselors when they face psychological difficulties” (Zhao 2020), Even if there are students with tense family relationships, interpersonal injury with negative emotions, or unbearable pressure, they "do not love, dare to come, and don't have to come" to the school class of psychological counseling. It is not easy for the school to find the key to the psychology of students at the right time and in a proper way. Factors and precipitating events. The psychological state of the primary school and high school students has always been a matter of concern for everyone (Liao et al., 2024).

For school teachers and environmental workers, there is a counselor and a counseling room in all schools, yet the function of counseling has no positive role other than the fact that mental health promotion does not exist. Furthermore, even if the students have psychological inquiries, they do not like visiting the school psychology room for consultation (Perryman and Frost, 2025). The most significant ones are: “①The students do not have proper understanding of psychological counseling and hold biased attitudes; ②I don't want others to learn about my problems and ideas, given that the school counseling room is not a "safe" place, and their "secrets" will be easily told to other students; ③ If one of the students has psychological problems such as depression, so as to protect the student's privacy, parents will choose a psychosocial institution for consulting or treating, yet psychological consultation needs to be reserved in advance and is restricted in time. It is difficult for the students to address psychological depressions timely when they should be addressed” (Zhang, Wang 2021).

Applications of Artificial Intelligence in Schools Mental Health Services

Over the past decade or so, artificial intelligence has been paying increasing attention to a vast number of individuals. In primary schools, secondary schools, and schools, social robots can assist children with language and teach children altruistic behavior; in addition, children will endow robots with human-like qualities and consider robots as human-like friends, and this is evidence that customers are likely to form good social relationships and even establish a relationship with artificial intelligence (Graafmmad 2015).

In the country, a series of regulations such as the "Development Plan for the New Generation of Artificial Intelligence" have placed research in artificial intelligence psychology and behavior at the pinnacle of the nation's agenda. There has been an enormous amount of research and development input and deployment in various fields (Jiang et al., 2017). Drawing upon the AI decompression power robot of Suzhou Tianjiabing Experimental Junior Middle School, the research is ready to explore new technical support combined with biosensing, Chinese identification and conversion, blood spectrum light imaging, and psychological counseling case big data (Hengstler, Enkel, & Duelli, 2016).

In order to promote schools and school psychologists to realize the most severe mission of primary school and junior secondary school mental health, such as managing the stress of students and resisting the promotion of stress, and assist in adopting artificial intelligence applied to primary and secondary school psychological services in my nation to drive innovation (Reilly et al., 2018). The AI decompression capable robot can be used directly for each and every student of the school. With the acquisition of physiological information such as acceleration pulse wave (APG) and heart rate variability (HRV) and comparison with 200,000 Asian norms, the students can be physically and mentally stressed along with being self-sufficient. Test nerve balance, blood vessels, and sleeping status, and provide test results within <3 min; At the same time, combined with students' and parents' daily inquiry questionnaires, the system collects personalized information of students for subsequent students' human-computer interactive consulting services (Hung et al., 2025).

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Control the Students' Emotional Status, Body and Mind Peace in Time

The students, upon receiving the first test results, log in using a designated password and enter the decompression empowerment warehouse. Interior decoration of decompression empowerment warehouse based on psychological counseling laws, weak illumination, and comfortable chairs, single sided glass, so the students are secure (44th International Symposium, 2025). The AI de-compression empowerment robot de-pressurizes students by hearing soothing music, guiding and controlling their breathing; Speech and anthropomorphic communication facilitation may also be used to reinforce students' emotional feedback and thereby stimulate students' emotional expression and emotional regulation (Lai et al., 2023). The empowerment robot of decompression by AI can leverage students' pre-knowledge and big data statistics to pose relevant questions and guide them to experience their own psychological confusion causes. In counseling, the AI decompression empowerment robot monitors students' data in real time from various systems such as voice, physiology, and facial expressions, adjusts counseling modalities, and integrates psychological counseling methods such as "psych drama" and "empty chair" to simulate students' cognitive model (Klimova & Pikhart, 2025). For example, if it is also in conflict with the parents, then the AI decompression empowerment robot will enable the students to try sitting on the "parent's chair" and try thinking in the middle of the conflict from the perspective of the parent (Lin et al., 2021).

It not only enables students to resolve current family conflicts but also reminds students to enhance the strength of empathy, thereby improving students' resistance to stress and level of interpersonal communication. After the consultation, the AI decompression empowerment robot will implement the feedback for consultation based on the confidentiality principle, e.g., giving feedback for stress and stress resistance to students so that they can endure to know their own state; Suggest reports to parents so that they are directed on how to live with their children daily; Offer the school a complete analysis report and help the school set up an electronic file system (Chan,2025). Thus, through the establishment of a supportive environment such as psychological education, home-school collaboration, and school governance, it allows students to gain a more positive model to their own development, and more robust to weather the storms of growth (Li, Tang, & Zheng, 2023).

The logical process of the model is: input visitor information (language, behavior, parameters, images, videos), image processing and data analysis method to obtain features, and apply machine learning algorithms to obtain classification results corresponding to respective psychological consultancy theories; The output is prediction and evaluation of the internal psychological state model reached according to the above process, and it is displayed to the psychologist and the visitor in various display modes, and then utilized to support the psychological consultancy process (Sarker, 2021).

RESEARCH METHODOLOGY

A mixed-methods approach was utilized, combining the quantitative and qualitative methods to enable a deep analysis of the effectiveness of sophisticated technologies in mental healthcare. The population of study was students enrolled in primary and junior secondary schools in Nyamira County, Kenya. A sample of approximately 500 students were randomly selected using stratified sampling to ensure representation by different demographics. For quantitative data, Structured questionnaires measured the psychological needs of students, behavioral difficulties and utilization of mental health services (Teixeira et al., 2025). Standardized screening tool was utilized in detecting behavioral and emotional difficulties. Devices were utilized for online monitoring of physiological response to explore emotional well-being. For qualitative data, Semi-structured interviews with students, teachers, and mental health professionals will explore individual experience and perception of mental health services and Focus Groups Discussions with groups of students to gather information on their barriers to mental health services and what they want from support (Lan et al., 2025).

AI was utilized in Using artificial intelligence programs to process data collected and provide personalized insights and suggestions for intervention. Use of biological sensing and optical imaging of blood spectrum to record physiological data that can be quantitatively correlated with psychological status. Personalized interventions were designed through data analysis that included psychoeducational workshops, counseling and interactive digital interventions for support. Quantitative Analysis, statistical methods were applied to analyze screening and survey data, using software such as SPSS or R to perform descriptive and inferential statistics. Qualitative Analysis, thematic analysis was applied to code and interpret interview and focus group data, identifying key themes and findings (Vandever, 2020).

FINDINGS OF THE STUDY

4.1 Sample Characteristics of Participants

The *figure 1* presents a summary overview of the sample description of a study comprising 500 students aged between 10 to Above 16 years. The age distribution of respondents, showing a wide variance of young people participating in the study.

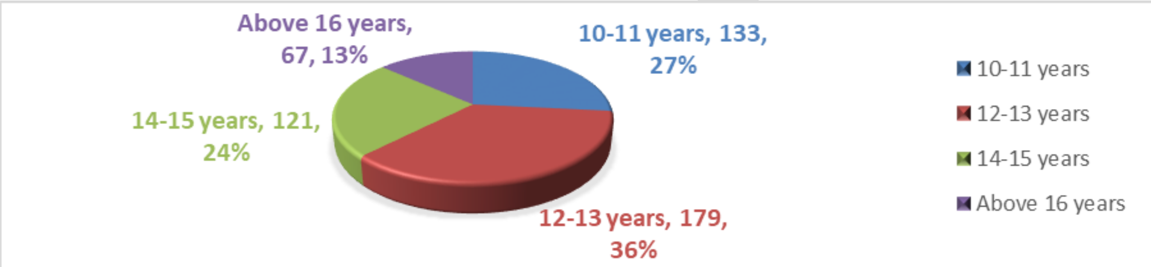

Figure 1. Sociodemographic of Participants in Age

The age group with the largest number is 12-13 years old, making up 35.8% of respondents, which is a large sample of early adolescents that might be going through seminal changes in development. This is then followed closely by the 10-11 years category at 26.6%, which reflects high participation from younger pre-teens. 14-15 years is the age group which holds 24.2%, reflecting a strong interest among senior teens, while the over 16 years age group is the smallest at 13.4%. This trend reflects a predominance of young adolescents, something which could impact mental health results since this is the age group most exposed to special pressures and challenges. It is crucial that one learns about the age groups so as to develop mental health interventions and support programs that effectively address the needs of these various ages.

The study also investigated the mental health dynamics in gender and school types as presented in *figure 2* below.

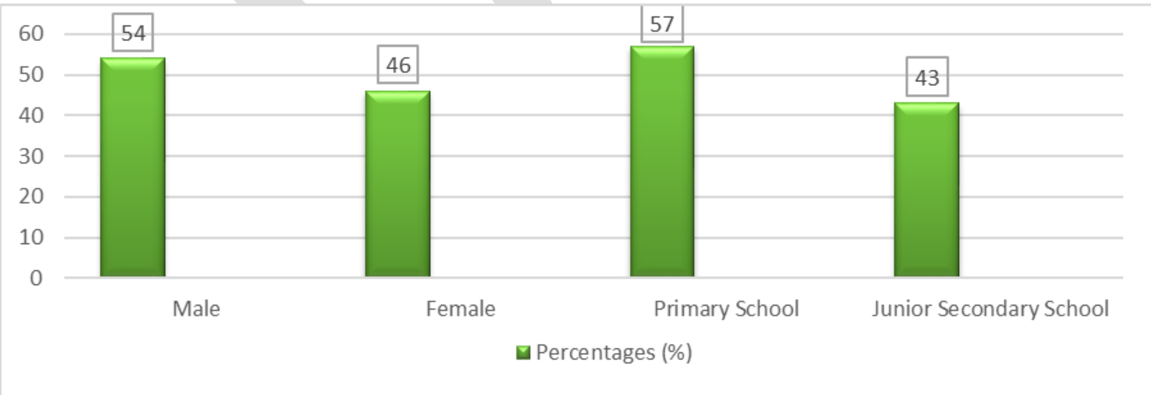

Figure 2. Key Demographic Characteristics by Gender Split and School Type for A Sample of Students.

The sample has a very slight percentage of male students above that of female students. This 54% to 46% division is a majority of males but a relatively even divide. The gender split could have effects on a number of aspects of the research, such as rates of participation in activities, school performance, and social interaction. Researchers have to consider whether the findings could be influenced by gender, particularly with regard to participation and interaction in heterogeneous learning settings. The majority of the participants are in primary schools (57%), while 43% are attending junior secondary schools. This is an indication of a focus on younger children, with a majority still in the early years of their schooling.

Psychological Needs in Students

The *table 1* shows the frequency of several mental health conditions among students, indicating substantial worries about their general well-being.

Table 1. Prevalent Mental Health Issues Among Students

Mental Health Issues	Percentage of Students Affected	Description
Depression	47	Symptoms include continuous depression, a loss of interest, and exhaustion.
Anxiety	39	Symptoms include increased anxiety, restlessness and tension.
Stress	56	High levels of stress from academic pressure and expectations from family members.
Low Self-Esteem	39	Students may experience feelings of worthlessness and self- doubt
Interpersonal Difficulties	44	Peer connections, particularly bullying, provide difficulties.
Learning Difficulties	31	Problems with focus and academic achievement.
Behavior Problems	26	This includes aggressive, defiant, and other disruptive behaviors.

The concerning image of mental health issues among students, the most prevalent being stress, at 56% of students, likely brought about by academic pressures and familial expectations. Closely following are depression at 47% and interpersonal issues at 44%, indicating that a notable percentage of students are experiencing feelings of sadness and issues with peer relationships, including bullying. Additionally, anxiety and low self-esteem, both affecting 39% of students, highlight significant emotional distress that can hinder academic performance and social interactions. Learning difficulties are reported by 31% of students, further emphasizing how mental health can impact focus and achievement, while 26% experience behavior problems, often manifesting as aggression or defiance. Collectively, these statistics underscore the urgent need for schools to deliver targeted mental health provision to address these pervasive issues, promote well-being, and enhance students' overall educational experiences.

Mental Health Service Awareness and Accessibility

The *table 2* below is a regression analysis whose results speak of the relationship between various factors for mental health services and their impact on a dependent variable (presumably some measure of mental health outcomes or service utilization).

Table 2. Awareness And Accessibility to Mental Health Services

Variable	Coefficient (β)	Standard Error	t-value	p-value
Intercept	0.47	0.11	7.00	<0.01
Awareness of Mental Health Services (AMHS)	0.22	0.06	7.00	<0.01
Perceived Accessibility of Services (PAS)	0.27	0.06	6.27	<0.01
Stigma Associated with Seeking Help (SASH)	-0.17	0.09	-2.16	<0.05
AI Tool Engagement (AITE)	0.12	0.08	1.69	<0.01
AMHS ×\times× PAS	0.12	0.05	3.35	<0.01

Model Summary: R^2: 0.60, Adjusted R^2: 0.58

The regression table presents significant information about predictors of mental health outcomes. The intercept indicates the baseline of 0.47 when predictors are all set to zero. Predictors of significance are Awareness of Mental Health Services (AMHS) and Perceived Accessibility of Services (PAS), which have values of 0.22 and 0.27, both significant at $p < 0.01$. This suggests that higher awareness and accessibility positively influence mental health outcomes. Conversely, Stigma Associated with

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Seeking Help (SASH) has a negative coefficient of -0.17 ($p < 0.05$), indicating that greater stigma is related to poorer mental health outcomes. AI Tool Engagement (AITE) has a positive but marginally significant effect ($\beta = 0.12$, $t = 1.69$), indicating possible benefits of technology to mental health help. The interaction term (AMHS × PAS), with a coefficient of 0.12 ($p < 0.01$), once more reminds us that the connection between awareness and accessibility enhances the favorable outcomes. The model explains 60% of the variance in the overall mental health outcomes, which is indicative of a good fit and emphasizes the importance of focusing on awareness, accessibility, and stigma in the initiatives of mental health.

Screening Rates for Behavioral and Emotional Difficulties

The *table 3* compares rates of mental health screening before implementing traditional and AI-assisted methods, with significant increases in student engagement.

Table 3. Students Screening Rates Comparison

Screening Method	Before Implementation (%)	After Implementation (%)	Change (%)	Statistical Significance
Traditional Screening	37	48	+11	p=0.10
AI-Enhanced Screening	26	77	+51	p <0.01
Total Combined Screening	32	84	+52	p<0.01

Traditional screening rates increased from 37% to 48%, a trivial change of 11% with no statistical power (p=0.10). AI-assisted screening, on the other hand, had an astonishing boost from 26% to 77%, an impressive 51% change with high statistical power (p<0.01). This pattern is also reflected in the total overall screening rates combined, which went up from 32% to 84%, a 52% increase, statistically significant (p<0.01). These results point to the effectiveness of AI-assisted screening methods in significantly increasing the level of student participation in mental health screenings and suggest that technology can also play a significant role in increasing awareness and early detection of mental health disorders among students.

Students and AI Tools

The *figure 3* illustrates the utilization of students by various AI resources for the purpose of enhancing mental wellness, with good usage and satisfaction rates.

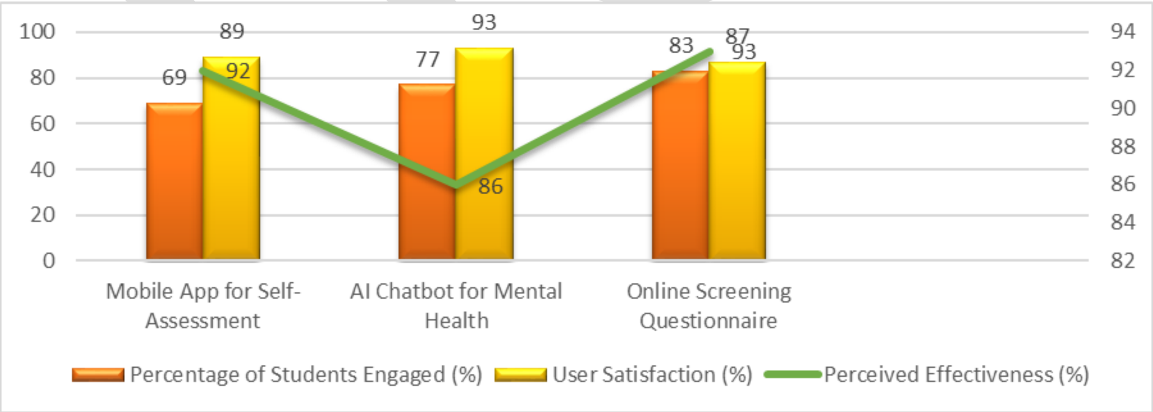

Figure 3. Students Engagement with AI Tools

Surprisingly, 83% of the students utilized the Online Screening Questionnaire, showing a good enthusiasm for self-screening as well as early detection of mental health issues, with a high satisfaction rate of 87% and perceived effectiveness of 93%. Similarly, the Mental Health AI Chatbot engaged 77% of the students, found to be applicable and useful, as reflected in a satisfaction rate of 93% and a perceived effectiveness rate of 86%. The Self-Assessment Mobile App also reflects significant participation at 69%, with high satisfaction (89%) and perceived impact (92%). These

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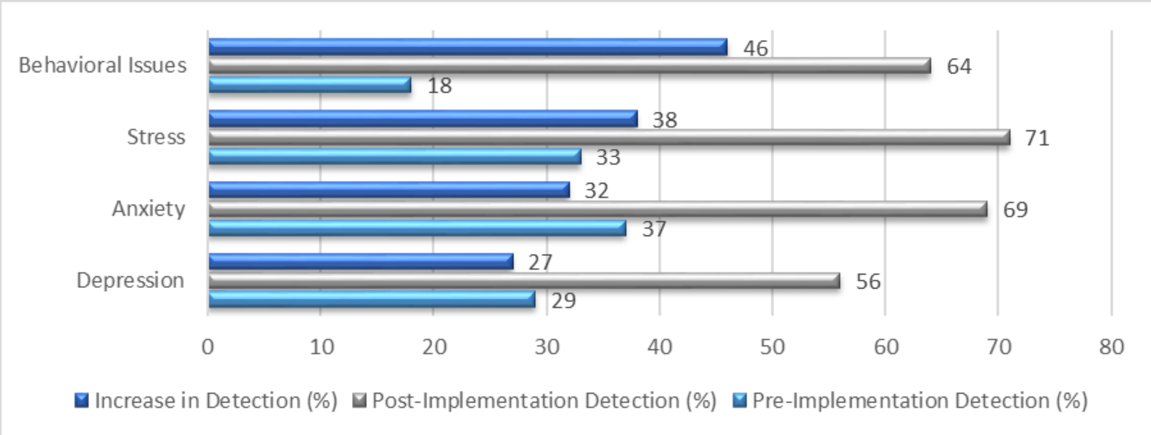
findings suggest not only that students are using these AI technologies actively but that they also view them as significant resources in maintaining their own mental health, which is a positive avenue towards technology uptake in mental health care systems.

Detection Rates of Mental Health Issues

The *table 4* shows detection rates of the various mental illnesses before and after introducing a new screening strategy, with significant gains in every category.



Statistical Significance: $p < 0.01$

Figure 4. Detection Rates of Various Mental Health Issues

Detection of depression before implementation grew from 29% to 56% after implementation, marking a 27% gain with a statistically significant p-value ($p<0.01$). Similarly, anxiety detection was increased from 37% to 69%, a 32% improvement, and that of stress by 38%, from 33% to 71%, both being statistically significant. The largest improvement was seen in behavior problems, which increased from 18% to 64%, a 46% improvement and statistically significant ($p<0.01$). These findings demonstrate that the new screening instrument evidently enhances identification of mental health issues among students, confirming the benefits of proactive screening in addressing mental health issues among students at schools.

DISCUSSION, CONCLUSION, and SUGGESTIONS

The study stresses the significance of artificial intelligence in enhancing mental health education and care in primary and junior secondary schools across Nyamira County, Kenya. With the remarkable rise in the detection rates of mental health following the implementation of AI-based screening devices, the findings spotlight the impact of technology on student awareness and participation (Graham et al., 2019). The notable increase in screening activity, particularly with the application of AI technologies, is a sign that the students are not only embracing these technologies but are also finding them beneficial in enhancing their mental well-being. The review also uncovers high levels of concern regarding prevalent issues such as stress, anxiety, and depression among the students, reaffirming the urgent necessity for targeted interventions on mental health (Klimova and Pikhart, 2025). The mixed-methods design employed in the study provides an overall picture of both quantitative improvements and qualitative comprehension of student experiences with mental health services. Overall, the findings encourage incorporation of advanced technologies within school mental health programs to make it a more responsive and nurturing environment for the students.

The study concludes that the integration of artificial intelligence in mental health care significantly raises access and effectiveness of care for primary and junior secondary school students. AI-supported screening methods brought about enormous improvements in the detection of mental illness, demonstrating that they have the potential to contribute towards addressing growing psychological needs among students. The implications of the research are to raise awareness and reduce stigma regarding mental health in a bid to promote a more proactive student well-being strategy. Lastly, the study aligns with further use of AI technologies in mental health education in an attempt to create a more responsive, nurturing environment for young learners. Schools should be made to specifically include AI-aided mental health screening tools in a way that they are better able to identify early so as to support the students who have psychological issues better. Moreover, teachers should be regularly trained in sensitization on mental health and the correct use of technology in a way that develops an environment where students engage more in mental health services.

REFERENCES

44th International Symposium on Intensive Care & Emergency Medicine. (2025). *Critical Care, 29* (Suppl 1), 97. https://doi.org/10.1186/s13054-025-05304-y

Aldalur, A., Bridgett, T., & Pick, L. H. (2022). Psychological assessment reports for linguistically minoritized clients: Considerations for ethical and professional practice. *Professional Psychology: Research and Practice, 53*(6), 606–614. https://doi.org/10.1037/pro0000462

Cadime, I., & Mendes, S. A. (2024). Psychological assessment in school contexts: Ethical issues and practical guidelines. *Psicologia: Reflexão e Crítica, 37*(1), 32. https://doi.org/10.1186/s41155-024-00318

Chan, C. K. Y. (2025). AI as the therapist: Student insights on the challenges of using generative AI for school mental health frameworks. *Behavioral Sciences, 15*(3), 287. https://doi.org/10.3390/bs15030287

Fan, Z., & Liu, J. (2022). Correlation analysis between teachers' teaching psychological behavior and classroom development based on data analysis. *Frontiers in Psychology, 13*, 905029. https://doi.org/10.3389/fpsyg.2022.905029

Graafmmad. (2015). Sharing a life with Harvey: Exploring the acceptance of and relationship-building with a social robot. *Computers in Human Behavior, 43*, 1–14. https://doi.org/10.1016/j.chb.2014.10.044

Graham, S., Depp, C., Lee, E. E., Nebeker, C., Tu, X., Kim, H. C., & Jeste, D. V. (2019). Artificial intelligence for mental health and mental illnesses: An overview. *Current Psychiatry Reports, 21*(11), 116. https://doi.org/10.1007/s11920-019-1094-0

Hassabis, D., Kumaran, D., Summerfield, C., & Botvinick, M. (2017). Neuroscience-inspired artificial intelligence. *Neuron, 95*(2), 245–258. https://doi.org/10.1016/j.neuron.2017.06.011

Hengstler, M., Enkel, E., & Duelli, S. (2016). Applied artificial intelligence and trust: The case of autonomous vehicles and medical assistance devices. *Technological Forecasting and Social Change, 105*, 105–120. https://doi.org/10.1016/j.techfore.2015.12.014

Huang, Y., & Huang, X. Y. (2018). The application of artificial intelligence can help the development of psychology. *N. Chinese Journal of Social Sciences*.

Hung, L., Abdulai, A. F., Soni, A., Wong, K. L. Y., Ren, L. H., Xia, R., & Davies, K. (2025). Students' perspectives on the development and deployment of an AI-enabled service robot in long-term care. *Journal of Rehabilitation and Assistive Technologies Engineering, 12*, 20556683251313773. https://doi.org/10.1177/20556683251313773

Jiang, F., Jiang, Y., Zhi, H., Dong, Y., Li, H., Ma, S., et al. (2017). Artificial intelligence in healthcare: Past, present and future. *Stroke and Vascular Neurology, 2*(4), 230–243. https://doi.org/10.1136/svn-2017-000101

Klimova, B., & Pikhart, M. (2025). Exploring the effects of artificial intelligence on student and academic well-being in higher education: A mini-review. *Frontiers in Psychology, 16*, 1498132. https://doi.org/10.3389/fpsyg.2025.1498132

Lai, T., Zeng, X., Xu, B., Xie, C., Liu, Y., Wang, Z., Lu, H., & Fu, S. (2023). The application of artificial intelligence technology in education influences Chinese adolescents' emotional perception. *Current Psychology*. https://doi.org/10.1007/s12144-023-04727-6Liao, J., Chen, S., Liu, Y., & Guo, C. (2024). The effects of family and school interpersonal relationships on depression in Chinese elementary school children: The mediating role of academic stress and the moderating role of self-esteem. *Children, 11*(3), 327. https://doi.org/10.3390/children11030327

Lan, W., Anderson, J., Stochl, J., Jones, P. B., Ford, T., & Burn, A. M. (2025). A qualitative study exploring the feasibility and acceptability of computerized adaptive testing to assess and monitor children and young people's mental health in primary care settings in the UK. *BMJ Mental Health, 28*(1), e301381. https://doi.org/10.1136/bmjment-2024-301381

Li, S., Tang, Y., & Zheng, Y. (2023). How the home learning environment contributes to children's social-emotional competence: A moderated mediation model. *Frontiers in Psychology, 14*, 1065978. https://doi.org/10.3389/fpsyg.2023.1065978

Lin, C., Šabanović, S., Dombrowski, L., Miller, A. D., Brady, E., & MacDorman, K. F. (2021). Parental acceptance of children's storytelling robots: A projection of the uncanny valley of AI. *Frontiers in Robotics and AI, 8*, 579993. https://doi.org/10.3389/frobt.2021.579993

McMahon, S. D., Worrell, F. C., Reddy, L. A., Martinez, A., Espelage, D. L., Astor, R. A., Anderman, E. M., Valido, A., Swenski, T., Perry, A. H., Dudek, C. M., & Bare, K. (2024). Violence and aggression against educators and school personnel, retention, stress, and training needs: National survey results. *American Psychologist, 79*(7), 903–919. https://doi.org/10.1037/amp0001348

Metz, C., & Smith, C. S. (2019). A.I. can be a boon to medicine that could easily go rogue. *The New York Times*. https://www.nytimes.com/2019/03/25/health/ai-medicine.html

Ministry of Education of the People's Republic of China. (2020). The Mental Health Education Expert Steering Committee of Primary and Secondary Schools provides guidance and suggestions for strengthening mental health education in primary and secondary schools nationwide in the new semester. Retrieved from http://www.gov.cn/xinwen/2020-04/24/content_5505703.htm

Perryman, K. L., T J T, & Frost, H. T. (2025). The school counselors' role in supporting teachers working with children who have experienced trauma: Lessons learned. *Journal of Child & Adolescent Trauma*, *18*(2), 265–278. https://doi.org/10.1007/s40653-024-00680-z

Reilly, M., Svirydzenka, N., Adams, S., & Dogra, N. (2018). Review of mental health promotion interventions in schools. *Social Psychiatry and Psychiatric Epidemiology, 53*(7), 647–662. https://doi.org/10.1007/s00127-018-1530-1

Sarker, I. H. (2021). Machine learning: Algorithms, real-world applications and research directions. *SN Computer Science, 2*(3), 160. https://doi.org/10.1007/s42979-021-00592-x

Teixeira, A. I., Martins, S., Lima, S., Pinto, F., Morgado, T., & Valentim, O. (2025). A mixed methods approach to understanding mental health literacy among university health students. *Healthcare, 13*(7), 724. https://doi.org/10.3390/healthcare13070724

Vandever, C. (2020). Introduction to research statistical analysis: An overview of the basics. *HCA Healthcare Journal of Medicine, 1*(2), 71-75. https://doi.org/10.36518/2689-0216.1062

Wang, T. T., & Ma, H. M. (2010). A review of the use of the mental health scale for middle school students in China. *Shanghai Educational Research, (06)*, 44–47.

Wang, Y., Xue, C., & Zhang, M. (2022). A survey of teachers' status in mental health education management based on big data analysis. *Occupational Therapy International*, *2022*, 8399938. https://doi.org/10.1155/2022/8399938

Xue, Y. Y., Xiao, Y. Y., & Fu, H. (2019). The current status of adolescents' mental health and improvement measures: Based on the survey results of 3 hospitals in Shanghai. *Chinese Health Policy Research*, *12*(02), 65–69.

Zhang, J. F., & Wang, B. P. (2021). The transformation of teaching and management in primary and secondary schools under artificial intelligence. *China Education Information, (04)*, 12–19.

Zhang, X., Ding, Y., Huang, X., Li, W., Long, L., & Ding, S. (2024). Smart classrooms: How sensors and AI are shaping educational paradigms. *Sensors, 24*(17), 5487. https://doi.org/10.3390/s24175487

Zhao, Y. (2020). Thoughts on the professional development of school mental health education teachers based on the needs of students in the new era. *Modern Teaching, (08)*, 12–15.

Zhu, T. S. (2019). Application scenarios of artificial intelligence assisting psychology research. *People's Forum: Academic Frontiers, (20)*, 48–53.