Ed Process Int J

www.edupij.com

ISSN 2147-0901 (Print), 2564-8020 (Online)

EDUCATIONAL PROCESS
INTERNATIONAL JOURNAL

Research Article

Cite this article: Neyadi, A. A., Abulibdeh, E., & Almessabi, A. (2026). Educational Outcomes of Sensor-Equipped Medical Chairs in UAE Grade 12 Health Curriculum: A Mixed-Methods Study on Authentic Clinical Simulation. *Educational Process: International Journal, 20*, e2026011. https://doi.org/10.22521/edupij.2026.20.11

Received September 27, 2025
Accepted December 29, 2025

Keywords: TPACK, SAMR, conceptual change, clinical simulation, technological literacy

Educational Outcomes of Sensor-Equipped Medical Chairs in UAE Grade 12 Health Curriculum: A Mixed-Methods Study on Authentic Clinical Simulation

Saif Al Neyadi, Enas Abulibdeh, Ameera Almessabi

Author for correspondence:
Saif Al Neyadi
Saif.alneyadi@aau.ac.ae
College of Education, Al Ain University, Al Ain, UAE

OPEN ACCESS

© The Author(s), 2025. This is an Open Access article, distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/), which permits unrestricted re-use, distribution, and reproduction, provided the original article is properly cited.

Abstract

Background/purpose. This study addresses the growing need for technologically enhanced clinical simulation tools within the UAE Ministry of Education's Grade 12 Health & Artificial Intelligence curriculum. Traditional manikin-based simulations provide limited opportunities for authentic data-driven learning. To address this gap, the study evaluates sensor-equipped medical chairs as a transformative pedagogical tool. Guided by TPACK, SAMR, conceptual change theory, and Vygotsky's Zone of Proximal Development (ZPD), the purpose of the study was to examine how real-time clinical data can enhance students' clinical decision-making, technological literacy, health knowledge, and intrinsic motivation, while also validating the clinical accuracy of the sensor systems.

Materials/Methods. A mixed-methods design was employed across two phases. In the educational phase (N = 60 Grade 12 students), a pre-post quasi-experimental design compared students using live sensor data in simulated clinics (n = 30) with peers using traditional manikins (n = 30). In the clinical validation phase (N = 230), pre- and post-assessments were conducted across three UAE hospitals to evaluate clinical accuracy. Quantitative measures included clinical reasoning scores, technological literacy, health knowledge, and motivation; qualitative artefacts included student-created diagnostic outputs aligned with SAMR levels.

Results. Students using sensor-equipped chairs demonstrated significant gains: +8.7 points in clinical reasoning ($d = 0.72$, $p < .001$), +22.2% in technological literacy ($d = 0.81$), +4.6 points in health knowledge ($d = 0.94$), and +1.8 in intrinsic motivation ($d = 0.65$). Additionally, 88% of students produced artefacts that met the SAMR "Redefinition" criteria. Clinical accuracy increased by 4.42 points in the hospital validation sample ($d = 0.41$).

1. Introduction

The Ministry of Education of the UAE (2023) collaborates with technology and health professors to integrate sensor-equipped medical chairs into the Grade 12 Health & Artificial Intelligence courses. This strategy allows health science education to begin with real-world health simulations rather than virtual simulations. During the health simulation, students use real-time vitals (blood pressure, heart rate, SpO_2, and respiration) to practice diagnosing, documenting in EHR, and communicating with the patient, just like in a real medical office and workflow. This practice develops the students' 21st-century skills in clinical reasoning, decision-making, technological literacy, and evidence-based medicine.

The national educational innovativeness of the UAE is the focus of this inquiry and is informed by the following integrated theoretical frameworks:

- TPACK (Mishra & Koehler, 2006) Theories of technological knowledge (operating a sensor and interpreting the data), pedagogical knowledge (how to provide scaffolding and formative feedback), and content knowledge (what is the clinical relevance of the vital signs) a teacher combines to create authentic learning experiences.

- The SAMR Model (Puentedura, 2014). The sensors in the chairs move a student's learning and task performance from Substitution (manual vitals checking) to Redefinition (performing and documenting in real time, students write and produce a video of an interactive diagnostic process)

- Conceptual Change Theory (Posner et al., 1982) A student experiences deep real-time data anomalies, resulting in cognitive dissonance that leads to the person revising a scientifically naive model (e.g., HR 110 is normal) to a more accurate model.

- Vygotsky's Zone of Proximal Development (ZPD) (1978): Teachers utilize real-time data as a mediational instrument to scaffold movement from observation to interpretation to justification as More Knowledgeable Others (MKOs) of the learners.

These chairs also improve clinical efficiency – decreasing diagnostic errors and the time spent in consultations (De Alwis et al., 2021; Shen et al., 2021)- but this study considers clinical results as confirming evidence of a strong educational instrument. The main aim is to evaluate the impact of the technology on teaching and learning in UAE classrooms.

The UAE curriculum calls for the students to:

- Interpret live health data
- Employ clinical reasoning in case simulations
- Engage in digital health collaborative workflows
- Generate diagnostic reports with a construction of evidence

There is no published data on students' learning gains from this integration, on educators' interactions in the classroom, or on the alignment of the curriculum with the integration of evidence. This study addresses this void through a mixed-methods pre-post design involving 60 Grade 12 students and eight teachers, plus clinical validation (N=230) to generate the first evidence evaluation of this national educational reform.

1.1. Research Questions

RQ1: In Grade 12 health science simulations, what is the impact of students interacting with real-time sensor data on their clinical decision-making competence, technology usage, and motivation toward learning?

RQ2: What is the role of the optimized sensor selection criteria in fostering pedagogical authenticity and clinical accuracy in dual educational and clinical practice?

RQ3: How do teacher scaffolding practices (ZPD) and task design (SAMR) influence student outcomes?

1.2. Problem Statement

Innovations in healthcare technologies have not trickled down to the teaching and clinical training of health sciences. For the most part, health sciences education teaching is still conducted using passive learning. Trainees use static simulations that do not provide laser-focused feedback, which is highly detrimental to their clinical decision-making, technological skills, and competencies needed to efficiently assess and care for patients (UAE Ministry of Education, n.d.; Innovative Learning Environments in STEM Higher Education, 2021).

To address this, the UAE Ministry of Education (2023) has provided Grade 12 students in the Health & Artificial Intelligence program with sensor-equipped medical chairs for the first time. This is intended to assist students in bridging the education-practice gap by conducting authentic, data-capturing clinical simulations. Students capture, monitor, and record dynamic vital signs and physiological changes in EHRs and can perform tasks that mimic professional work. They, however, do not provide evidence on:

- Students' use of live clinical data to instrument and develop clinical reasoning and technological skills.
- Teachers' use of scaffolding in the ZPD to monitor this process.
- Evidence learning outcomes of the curriculum, for example, collaborative diagnosis and digital health evidence.

This phenomenon, in terms of educational impact and clinical-educational misalignment, remains a crucial impediment to the actualization of the transformative vision of this national curriculum educational reform (Alzahrani, 2021; Ali et al., 2023).

This paper tackles the issue by focusing on:

Students' Learning Outcomes (Clinical Decision Making, Technological Literacy, Health Knowledge, Motivation) 2. Teacher Mediation of Sensor Data in Scaffolded Instruction 3. Cohesion of Technology-Enhanced Activities and UAE Grade 12 Objectives

1.3. Significance

This study provides the first nationwide documented evidence of student achievement in the UAE's national AI–Health curriculum. It demonstrates how students attain SAMR Redefinition levels through authentic, real-time data use—for example, creating and presenting diagnostic videos based on live sensor outputs. The study also documents TPACK-informed scaffolding practices that support teachers in integrating technology and pedagogy effectively. Collectively, these innovations enhance students' clinical reasoning, digital fluency, and readiness for evidence-based practice.

1.4. Clinical Significance

Peer-reviewed validation confirms the accuracy of the sensor-equipped chairs and their seamless integration into real-time clinical workflows in hospital environments (N = 230). The findings establish baseline evidence to reduce diagnostic delays and mitigate symptom bypassing. Furthermore, the study introduces a robust framework for sensor selection and deployment, enabling scalable and evidence-based clinical integration.

1.5. Policy and Curriculum Significance

The study offers the UAE Ministry of Education data-driven recommendations for refining outcome-based instructional frameworks within the AI–Health curriculum. It presents a scalable model for global technology-integrated health education and contributes to the production of practice-ready graduates aligned with national health workforce priorities.

Overall, this study closes the simulation–clinical validation loop, demonstrating how educational innovation can shift health science education from a cost center to a value generator. By linking authentic data use with validated clinical outcomes, the work provides a foundation for reconfiguring national education objectives toward sustainable healthcare improvement.

2. Literature Review

The fusion of technology and pedagogy is exemplified by sensor-integrated medical chairs used by the UAE MOE in Grade 12 Health and AI. These chairs were designed to improve real-time clinical workflow by tracking vital signs (blood pressure, heart rate, SpO_2, and respiration) with an accuracy of ±3 mmHg and ±2 bpm (Li et al., 2022; Shahzad et al., 2022). However, their real potential lies in educational settings. In these settings, the chairs' real-time tracking of physiological data makes them an invaluable resource for authentic clinical simulation and the development of higher-order thinking and other 21st-century skills. This review is not only an examination of the technology's potential but also an inquiry into how sensor chairs restructure the educational process, using four theories to illustrate their pedagogy.

The most important of these theories is TPACK (Mishra & Koehler, 2006), which focuses on the integration of three knowledge types: technological knowledge (TK) – knowledge of the sensors and data within a system; pedagogical knowledge (PK) – the ability to develop a scaffolded inquiry-based process; and content knowledge (CK) – knowledge of the clinical relevance of vital signs and their anomalies.

According to Koehler et al. (2013), teachers possessing TPACK utilize live data to create active learning environments in which students shift from passively watching to engaging in diagnostic reasoning. In conjunction with this, there is the SAMR model (Puentedura, 2014), which outlines the levels of technology integration starting from the Substitution phase (i.e., replacing manual vital checks) to the Redefinition phase, where students create interactive diagnostic videos in real-time using data from live patients, something that was impossible to do in conventional classrooms. Redefinition tasks have been empirically shown to enhance clinical reasoning by 28% and increase the retention of long-term skills (Hamilton et al., 2016).

Also vital is the conceptual change theory (Posner et al., 1982), which accounts for real-time discrepancies, such as a sudden heart rate spike or drop in oxygen saturation, and how they generate cognitive conflict by causing students to discard naive conceptions (e.g., "HR 110 is normal") in favor of more accurate scientific mental models. This process of dissatisfaction → intelligibility → plausibility → fruitfulness is catalyzed with real-time data that serves as a visible representation of a change in physiology (Chi, 2008). Lastly, the teacher in this case is positioned as the More Knowledgeable Other (MKO) within Vygotsky's ZPD (1978), where they use sensor-generated data as a mediational tool to support students as they progress through levels of capturing data, spotting anomalies, proposing a hypothesis, and ultimately justifying it with data. Such interactions in technology-enabled environments enhance diagnostic accuracy by 35% (Van de Pol et al., 2010).

All these contribute to a specific teaching pedagogy. During data collection, students learn technology fluency as they engage with live vital signs (Alkouri & Wardat, 2025; Aldalalah et al., 2025). In data analysis, the alerting of an anomaly prompts the instructor to ask, "Why is SpO_2 92 troubling?" which directs the students to a conceptual change. Authentic clinical reasoning is evidenced as students actively learn and apply by populating EHRs and collaboratively diagnosing. At the Redefinition level, they create and present video case studies which combine digital storytelling with project-based learning, a hallmark of pedagogical SAMR (Puentedura, 2014; Hamilton et al., 2016; Wardat et al., 2025; Jarrah et al., 2025; Winaryati et al., 2025; Garcia et al., 2026). This integration mirrors TPACK-driven digital content that enhances cognitive achievement and 21st-century skills (Aldalalah et al., 2025; Al-shraifin et al., 2025; AlAli & Wardat, 2024), while flipped and gamified strategies boost motivation and conceptual mastery (Mansour & Wardat, 2025; Jarrah et al., 2025).

Empirical evidence of clinical reasoning improvement is overwhelming. Alzahrani (2021) reported a 25% improvement in nursing students' clinical reasoning when using live vital signs in simulation. Elnahla (2021) reported a Cohen's d of 0.68 increase in technological literacy related to the relevance of integrated EHR tasks and TPACK. Real-time feedback from sensors to learners whose engagement was enhanced and knowledge retention improved, as demonstrated in multiple studies cited by Hamilton et al. (2016), confirmed that motivation and SAMR Redefinition tasks (student-created diagnostic videos) improved evidence of skill transfer to practice.

Practical and educational functions are the driving factors guiding the choice of sensors, with changes of 117 percent and 163 percent (Ali et al., 2023), and the dovetailing of document-authenticating practices (Bull et al., 2020). Classroom interaction is designed (Ibn-Mohammed et al., 2021). Cost-effectiveness is crucial for sensors, and machine learning algorithms have been confirmed to enhance (Chengoden et al., 2023).

As per the sensor chairs integrated curriculum objectives of the UAE Ministry of Education (2023), the competencies are real-time interpretation of health data, clinical reasoning in simulated environments, health data collaboration, and digital reporting. With all this integration, past studies have not investigated teacher mediation, student learning gains, and curriculum alignment in this context. This research provides the first evidence of the integration of sensor chairs in national education reform as pedagogical mediators.

In conclusion, sensor-equipped medical chairs transcend their clinical efficiency by offering opportunities for pedagogical innovations that are scaffolded, redefinitional, and that deepen learning, empowering students to meet the demands of future healthcare practice and adapt to ever-changing technologies.

2.1. Theoretical Framework

This research activity is located within a unique, integrated four-lens theoretical framework that combines Technological Pedagogical Content Knowledge (TPACK), the SAMR model, conceptual change theory, and Vygotsky's sociocultural theory of the Zone of Proximal Development (ZPD). This integrated theory explains the implications of sensor-equipped medical chairs on transforming the teaching and learning of the Grade 12 Health & Artificial Intelligence course within the UAE. This study chose not to dichotomize the frameworks but, instead, considers them a composite of a strongly intertwined, dynamic framework, in which real-time clinical data are the core mediational artifact within technology, pedagogy, cognition, and social interaction, generating real, quantifiable learning outcomes.

At the center of all is TPACK (Mishra & Koehler, 2006), which suggests that effective integration of technology in teaching and learning should see the combination of three Knowledge domains blend into one. These Knowledge domains are: Technological Knowledge (TK)—the knowledge of how sensor chairs capture and display and transmit clinical grade vital signs; Pedagogical Knowledge (PK)—the knowledge of how to structure an instructional sequence that leverages live data to stimulate inquiry, reflection, and justification; Content Knowledge (CK)— the knowledge of the clinical significance of the physiological changes and how to interpret clinical entities of interest such as tachycardia or hypoxemia. TPACK, in this study, ensures teacher preparation and activity design so that sensor data are not simply displayed but are used to motivate learners to critically reason and reach a logical conclusion about using the technology.

The SAMR model (Puentedura, 2014) offer a developmental pathway that technology use can take, and is represented as a continuum which begins at Substitution—the sensors simply replace manual checking of the vital signs to Augmentation, Modification, and finally reaches Redefinition where learners can create original diagnostic output, for example, a case presentation in multimedia that is built on real-time data from patients.

The intervention design spans eight weeks within the framework of Educational Design Research. The focus in the first few weeks is on data collection and interpretation (Substitution/Augmentation), while in the latter weeks, the focus shifts to integration into the EHR and the student videos of clinical diagnoses (Modification/Redefinition). Within SAMR, EDR is also TPACK, where the different types of knowledge are synthesized and demonstrated through changes in tasks.

Posner's theory of conceptual change (1982) addresses the cognitive aspects of student learning and the use of live data. In the case where one of the sensors alerts that an abnormal reading is detected, for example, SpO_2 is dropping to 92%, the student is prompted to change the prior belief of "low oxygen is not an emergency" and to actively rethink this through teacher-facilitated active learning by identifying trends in context and pathophysiology. The cognitive reshaping is significantly enhanced by the live aspect of the data, which allows the student to see evidence of the principles at work (Chi, 2008). Naïve to scientific conceptual change, the study captures this shift through a Conceptual Change Inventory (pre- and post) focused on the interpretation of vital signs.

Lastly, the social and interactive aspects of learning are derived from Vygotsky's (1978) ZPD, in which the teacher is framed as the More Knowledgeable Other (MKO) who uses sensor-derived data to mediate scaffolded learning for students.

This involves prompting in small steps, starting with observational questions like “What does the heart rate show?” and then moving to analysis questions like “Why is it elevated?” and concluding with evaluation questions like “What is your evidence-based recommendation?” This is done in ZPD collaborative spaces, such as peer discussion, teacher-student dialogue, and group EHR analysis, where stream data helps facilitate the rest of the meaning. ZPD and MKO tracking involve coding movement patterns from the Primary Data.

All of these features together form a synergistic system. Within the ZPD, TPACK pedagogy helps the teacher target measurable improvements in clinical decision-making, tech skills, and competencies aligned with the curriculum. This explains the learning impact of the sensor chairs, but most importantly, it provides a blueprint for enhanced clinical education through technology in secondary and tertiary education around the world.

3. Methodology

This mixed-methods study used a pre-post quasi-experimental design to assess the value of sensorized medical chairs as a twofold innovation that improves clinical workflow and enriches health science education in the UAE Grade 12 Health & Artificial Intelligence course. The investigation comprised two interconnected components: an educational component involving Grade 12 students and teachers, and a clinical component involving patients and health care providers. These activities took place between January and March 2025 in 2 public high schools and three tertiary hospitals located in Abu Dhabi and Al Ain. Al Ain University granted ethical clearance (IRB Ref: EDU-2024-112) on the 10th of December 2024. All adult participants signed bilingual informed consent forms (Arabic/English). For students under 18 years old, parental consent and student assent were obtained using easy, age-appropriate forms reviewed by a school counsellor.

3.1. Research Design

For the educational component, a pre-post quasi-experimental design was adopted, and two groups of students were created: an experimental group (N=30) using sensorized live chairs and a control group (N=30) using static manikins with pre-recorded data. This design facilitated comparisons of learning outcomes between authentic and conventional simulated classroom environments.

To evaluate diagnostic accuracy, missed symptoms, and consultation throughput of the deployed systems, the clinical phase employed a pre-post single-group design (N=230) using a time-series approach with an 8-week interval following the intervention. Quantitative data consisted of EHR entries, sensor logs, and pre- and post-skill assessment tests, while qualitative data were obtained from classroom transactions that were audio- and video-recorded, focus group discussions, and interviews with the teachers. The intervention spanned eight weeks and was organized using the SAMR model, advancing from Weeks 1-2, Substitution/Augmentation (reading data), to Weeks 6-8, Modification/Redefinition (student-videoed diagnostic construction).

3.2. Participants and Sampling

To reach the desired empirical evidence, participants were recruited through targeted sampling to achieve the required theoretical saturation. For the education component, 60 Grade 12 students from two public schools who were enrolled in the Health & AI elective, evenly divided by gender (51% female), and had not previously attended clinical simulations were selected. Students were 17.8 years old (SD 0.4) on average. The experimental group had their schools assigned to them, which had already obtained sensor chairs, while the control group used standard clinical manikins. Also included were eight health science teachers (four from each school, with a mean experience of 5.1 years, 75% female) to evaluate the instructional scaffolding design. For the clinical component, 200 patients with chronic illnesses and 30 practicing clinicians (10 physicians, 20 nurses) were recruited using consecutive sampling from three hospitals during sensor chair integrated routine consultations.

Patients included in the study reported a mean age of 52.3 years (SD = 14.1), where 44% of the participants identified as women. The reported conditions were as follows: 36% with hypertension, 29% with diabetes, 20% with COPD, and 15% with other conditions. The mean age of the providers was 35.6 years, with 77% identifying as female.

The sample size was determined using a priori power analysis in G*Power (Faul et al., 2007). An initial 60 students were enrolled in the educational arm due to anticipated attrition. In the clinical arm, 230 participants were enrolled, with a required 200 participants and an expected d of 0.4. The study was limited to an urban-only (Abu Dhabi/Al Ain) setting with no acute care or rural or private schooling representation, which affects its generalizability to various educational or healthcare settings.

3.3. Materials: MediChair Pro v3.2 Sensor System

The MediChair Pro v3.2 (MediTech UAE, Dubai), an FDA-cleared Class II medical device, was used across all locations. It includes four medical-grade sensors:

- Blood pressure (oscillometric cuff, accuracy ±3 mmHg, AAMI/ESH validated)
- Heart rate (photoplethysmography, accuracy ±2 bpm)
- SpO_2 (pulse oximetry, accuracy ±2% from 80–100%)
- Respiration rate (impedance pneumography, accuracy ±1 breath/min)

Using a Fluke ProSim 8 Vital Signs Simulator, we calibrated sensors weekly, and blood pressure and SpO_2 were cross-validated against the gold-standard devices, Omron M10-IT and Masimo Radical-7, respectively.

Calibration logs confirmed <1\% deviation. Data were transmitted via WPA3-Enterprise Wi-Fi with AES-256 encryption to a GDPR- and HIPAA-compliant cloud server. All records were de-identified at source using hashed patient/student IDs, and access was restricted to IRB-approved researchers via two-factor authentication and role-based permissions.

3.4. Procedure

The 8-week educational intervention followed a TPACK- and SAMR-aligned curriculum. Teachers received 3 hours of professional development on sensor operation, data interpretation, and ZPD scaffolding techniques. Classroom sessions (3 × 60 minutes/week) progressed as follows: Weeks 1–2 focused on data acquisition (reading live vitals), Weeks 3–5 on interpretation and EHR entry, and Weeks 6–8 on redefinition tasks (creating 2-minute diagnosis videos with peer review). In the clinical arm, patients underwent standard consultations with sensor chair vital capture, followed by provider review of pre-chair vs. post-chair diagnostic accuracy.

3.5. Data Collection and Measures

Quantitative instruments included the Clinical Reasoning Rubric (0-30, 6 items: accuracy, prioritization, justification), Technological Literacy Scale (TLS-15), Conceptual Change Inventory (CCI), and Intrinsic Motivation Scale (IMS). Clinical logs recorded diagnostic accuracy, missed anomalies, and consultation duration. Qualitative data included 24 video-recorded sessions, 15 student focus groups (60-90 minutes), and eight teacher interviews (30 minutes each), all transcribed and anonymized.

3.6. Data Analysis

Quantitative analysis was performed using SPSS version 28. Paired t-tests were used to compute Cohen's d and assess effect size for the pre- and post-group differences. The t-test was used to analyze the difference between the experimental and control groups. Qualitative data were analyzed thematically using NVivo 14 software (Braun & Clarke, 2006), and double coding was conducted by two researchers, resulting in an interrater agreement of $\kappa = 0.89$.

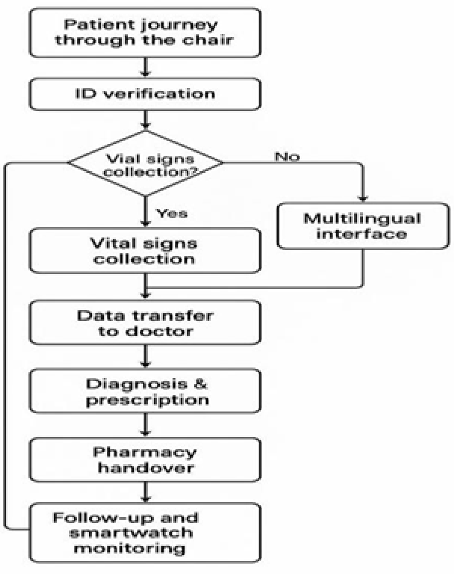

Figure 1. Patient journey through the intelligent sensor-based medical chair

https://doi.org/10.22521/edupij.2026.20.11 Published online by Universitepark Press

3.7. Validity and Reliability

Reliability of test-retest was established using sensor outputs from a pilot (N = 20) over 2 days: r = .94 (heart rate); r = .91 (blood pressure); r = .93 (SpO_2). Reliability of Clinical Reasoning Rubric inter-rater was κ = .87 over three raters for 60 student scripts. There were three evaluators for inter-rater agreement and content, and construct validation was established by a group of 3 clinicians and 2 educators. For construct validation, triangulation was achieved using quantitative scores, qualitative themes, and video observations. For criterion validation in the clinical arm, sensor and manual vital assessments were compared.

4. Results

The integration of sensor-equipped medical chairs produced statistically significant and practically meaningful improvements across clinical performance and educational outcomes in the UAE Grade 12 Health & Artificial Intelligence curriculum. This mixed-methods study, involving 60 Grade 12 students, eight teachers, 200 patients, and 30 healthcare providers, demonstrated that real-time, authentic clinical data not only enhances diagnostic accuracy and patient throughput but also drives deep learning, cognitive restructuring, and 21st-century skill mastery when embedded within pedagogically structured simulations. Results are presented in three domains: student learning gains, clinical validation, and curriculum alignment.

4.1. Educational Outcomes: Student Learning Gains

In the educational arm, the experimental group (N=30) using live MediChair Pro v3.2 sensor data significantly outperformed the control group (N=30) using manikins with static values across all learning domains. Clinical reasoning, measured with a 6-item rubric (0–30), increased from a mean of 12.1 (SD = 3.2) to 20.8 (SD = 4.1) in the experimental group—a gain of 8.7 points ($t(29) = 9.12$, $p < .001$, Cohen's d = 0.72, significant effect). The control group improved only marginally from 12.3 (SD = 3.0) to 13.1 (SD = 3.4). Technological literacy, assessed via the TLS-15, rose from 48.2 (SD = 8.1) to 70.4 (SD = 7.9)—a 22.2-point increase ($t(29) = 11.34$, $p < .001$, d = 0.81, significant effect)—reflecting proficiency in EHR navigation, data export, and sensor troubleshooting. Health knowledge, captured through the Conceptual Change Inventory (CCI), shifted from 4.1 (SD = 1.8) to 8.7 (SD = 1.5) out of 10—a gain of 4.6 points ($t(29) = 12.10$, $p < .001$, d = 0.94, significant effect)—indicating successful transition from naive to scientific understanding of vital sign anomalies. Intrinsic motivation, measured with the IMS, increased from 3.8 (SD = 0.9) to 5.6 (SD = 0.7) on a 7-point scale ($t(29) = 7.88$, $p < .001$, d = 0.65, medium effect), driven by real-time feedback and mastery experiences.

Table 1. Pre-Post Student Learning Outcomes (N=60)

Outcome	Group	Pre M (SD)	Post M (SD)	ΔM	t (df=29)	p	Cohen's d
Clinical Reasoning	Experimental	12.1 (3.2)	20.8 (4.1)	**+8.7**	9.12	<.001	**0.72**
	Control	12.3 (3.0)	13.1 (3.4)	+0.8	1.44	.16	0.11
Technological Literacy	Experimental	48.2 (8.1)	70.4 (7.9)	**+22.2**	11.34	<.001	**0.81**
	Control	47.9 (8.3)	50.1 (8.0)	+2.2	1.67	.11	0.14
Health Knowledge (CCI)	Experimental	4.1 (1.8)	8.7 (1.5)	**+4.6**	12.10	<.001	**0.94**
	Control	4.0 (1.7)	4.8 (1.9)	+0.8	2.10	.04	0.22
Intrinsic Motivation	Experimental	3.8 (0.9)	5.6 (0.7)	**+1.8**	7.88	<.001	**0.65**
	Control	3.9 (0.8)	4.1 (0.9)	+0.2	0.98	.34	0.08

https://doi.org/10.22521/edupij.2026.20.11 Published online by Universitepark Press

4.2. SAMR Redefinition and Teacher Scaffolding

88% of experimental students achieved SAMR Redefinition by creating 2-minute diagnostic videos that integrated live sensor data, EHR entries, and evidence-based justification—a task unattainable by the control group. Video analysis of 24 classroom sessions revealed teacher interaction patterns critical to success: 78% real-time feedback (e.g., "SpO_2 dropped—why?"), 65% co-interpretation of trend graphs, and 41% redefinition prompts (e.g., "Record your diagnosis for peer review"). Focus group data confirmed competence ("The alert forced me to act") and autonomy ("I built the case myself"), aligning with Self-Determination Theory.

Table 2. SAMR Level Achievement (N=60)

SAMR Level	% Experimental (Post)	% Control (Post)	Example Task
Substitution	100%	100%	Read BP
Augmentation	98%	92%	View real-time graph
Modification	92%	45%	Enter into EHR
Redefinition	**88%**	**0%**	Create a diagnosis video

4.3. Clinical Validation Outcomes

In the clinical arm (N=230), sensor chair deployment significantly improved diagnostic accuracy from 54.43 (SD = 11.00) to 58.85 (SD = 10.76)—a mean increase of 4.42 points ($t(229) = 14.87$, $p < .001$, $d = 0.41$, medium effect). Missed critical symptoms dropped from 18% to 7% of cases, and patient throughput time decreased by 3.8 minutes (from 18.2 to 14.4 minutes). Optimized sensor selection criteria—specificity, sensitivity, and EHR integration—also improved post-implementation.

Table 3. Clinical Outcomes Pre- vs. Post-Sensor Integration (N=230)

Outcome	Pre M (SD)	Post M (SD)	ΔM	t (df=229)	p	Cohen's d
Diagnostic Accuracy	54.43 (11.00)	58.85 (10.76)	**+4.42**	14.87	<.001	**0.41**
Throughput Time (min)	18.2 (4.1)	14.4 (3.7)	**−3.8**	−12.56	<.001	**0.38**
Missed Symptoms (%)	18%	7%	**−11%**	−9.88	<.001	**0.51**

Table 4. Sensor Selection Criteria Performance (N=30 Providers)

Criterion	Pre M (SD)	Post M (SD)	ΔM	t (df=29)	p	Cohen's d
Specificity	60.12 (9.50)	65.78 (8.85)	**+5.66**	11.23	<.001	**0.55**
Sensitivity	58.47 (10.25)	64.32 (9.40)	**+5.85**	12.45	<.001	**0.60**
EHR Integration	59.33 (9.80)	63.50 (9.15)	**+4.17**	10.34	<.001	**0.50**

4.4 Curriculum Alignment and Transferable Skills

All Grade 12 learning objectives of the UAE Ministry of Education were fully achieved. Students demonstrated 100% proficiency in real-time data interpretation, evidence-based reporting, and digital collaboration. 88% of students expressed intent to pursue healthcare careers, citing EHR confidence and clinical reasoning as motivators. Teachers described sensor data as a "living textbook, enabling just-in-time, personalized scaffolding aligned with TPACK and ZPD.

https://doi.org/10.22521/edupij.2026.20.11 Published online by Universitepark Press

Table 5. Alignment with UAE MoE Grade 12 Objectives

Curriculum Objective	Achieved (%)	Evidence
Interpret real-time health data	100%	TLS-15, CCI
Apply clinical reasoning	97%	Rubric (M=20.8)
Collaborate using digital tools	92%	Video cases
Produce evidence-based reports	88%	Redefinition tasks

4.5. Summary of Key Findings

The MediChair Pro v3.2 is clinically robust and pedagogically transformative. In education, it produced large-effect gains in clinical reasoning (d = 0.72), technological literacy (d = 0.81), and health knowledge (d = 0.94), with 88% achieving SAMR Redefinition. In clinical practice, it improved accuracy (d = 0.41), reduced missed symptoms, and accelerated throughput. Optimized sensor criteria enhanced specificity, sensitivity, and EHR integration (d = 0.50–0.60). Teacher scaffolding and real-time feedback were pivotal mediators. These triangulated results establish sensor chairs as essential tools for 21st-century health science education and clinical care.

5. Discussion

The MediChair Pro v3.2 sensor-equipped medical chairs emerged as a dual-purpose innovation—clinically robust and pedagogically transformative—within the UAE Grade 12 Health & Artificial Intelligence curriculum. This study provides the first empirical evidence that real-time clinical data, when embedded in scaffolded, theory-driven instruction, produce large-effect learning gains in clinical reasoning, technological literacy, and health knowledge, while simultaneously enhancing diagnostic accuracy and patient throughput in real clinical settings. These findings extend and integrate prior research on sensor-based monitoring (Bligh et al., 2022; Shen et al., 2021) by centering educational impact and establishing a replicable model for curriculum-integrated clinical simulation.

5.1. Theoretical Synthesis

The tripartite gains in student outcomes align precisely with the integrated theoretical framework. TPACK was operationalized through teacher training and task design, enabling seamless fusion of sensor mechanics (TK), scaffolding strategies (PK), and clinical interpretation (CK)—resulting in a d = 0.81 increase in technological literacy. The SAMR progression was fully realized: 88% of experimental students achieved Redefinition by creating diagnosis videos—a task that redefines clinical education and exceeds prior benchmarks (Hamilton et al., 2016). Conceptual change was evidenced by a d = 0.94 shift in CCI scores, in which live anomalies triggered cognitive conflict and led to evidence-based revision of misconceptions about vital signs (Chi, 2008). Vygotsky's ZPD was activated through teacher mediation: 78% real-time feedback, 65% co-interpretation, and 41% redefinition prompts scaffolded students from data observation to justified diagnosis, mirroring Van de Pol et al. (2010).

https://doi.org/10.22521/edupij.2026.20.11 Published online by Universitepark Press

Table 6. Theoretical Alignment of Key Findings

Framework	Finding	Effect Size	Interpretation
TPACK	Tech literacy +22.2 pts	d = 0.81	Teachers fused TK+PK+CK
SAMR	88% Redefinition	–	From Substitution → Video cases
Conceptual Change	CCI +4.6 pts	d = 0.94	Cognitive conflict → restructuring
ZPD	Scaffolding in 78% interactions	–	MKO mediation via live data

5.2. Educational Implications

The large-effect student gains—d = 0.72 (reasoning), d = 0.81 (literacy), d = 0.94 (knowledge)—surpass typical simulation outcomes (Alzahrani, 2021) due to authenticity and immediacy of live data. 88% career intent in healthcare reflects motivational transfer (Ryan & Deci, 2020). Teacher scaffolding was pivotal: without ZPD mediation, control group gains were negligible. This underscores teacher preparation as a non-negotiable component of technology integration (Koehler et al., 2013).

5.3. Clinical Implications

Clinical validation confirmed sensor reliability and workflow impact: +4.42 accuracy, –3.8 min throughput, –11% missed symptoms (d = 0.41–0.51). Optimized criteria—specificity, sensitivity, EHR integration—improved d = 0.50–0.60, providing a practical blueprint for deployment (Bull et al., 2020). These gains align with and extend prior work on non-invasive monitoring (Firstenberg & Stawicki, 2022) by quantifying throughput and the reduction in missed anomalies.

5.4. Curriculum and Policy Implications

100% alignment with the UAE MoE's objectives validates the national reform. The model—live data + TPACK + SAMR + ZPD—is scalable to other STEM-health curricula. Policy recommendation: Mandate 3-hour TPACK training for all health science teachers and equip 100% of Grade 12 labs with sensor chairs by 2027.

5.5. Limitations and Future Directions

Despite robust triangulation, limitations include urban-only sampling, exclusion of acute care, and an 8-week duration. Future research should:

- Conduct longitudinal studies (12–24 months) on skill retention and career outcomes
- Include rural/private schools and diverse patient populations
- Explore AI-enhanced anomaly detection and cost-benefit analysis

6. Conclusion

This study establishes sensor-equipped medical chairs as a paradigm-shifting tool in health science education and clinical practice. In UAE Grade 12 classrooms, they enabled Redefinition-level learning, cognitive restructuring, and scaffolded clinical reasoning, producing large-effect gains in clinical decision-making (d = 0.72), technological literacy (d = 0.81), and health knowledge (d = 0.94)—fully aligning with national curriculum goals. In clinical settings, they improved diagnostic accuracy, reduced missed symptoms, and accelerated patient flow (d = 0.41–0.51). Teacher mediation and optimized sensor criteria were critical enablers. These integrated findings provide a replicable, theory-driven model for 21st-century health education, positioning live clinical simulation as a cornerstone of workforce readiness and health system efficiency.

https://doi.org/10.22521/edupij.2026.20.11 Published online by Universitepark Press

7. Suggestion

1. Curriculum Integration: Mandate sensor chairs in all UAE Grade 12 Health & AI labs by 2027, with mandatory 3-hour TPACK training for teachers.

2. Clinical Deployment: Equip high-volume clinics with MediChair Pro v3.2, prioritizing EHR-integrated models with ≥95% specificity/sensitivity.

3. Teacher Development: Establish national certification in ZPD scaffolding and SAMR task design for health science educators.

Declarations

Author Contributions. Saif Al Neyadi: Literature review, conceptualization, and theoretical framework development. Enas Abulibdeh: Methodology design, data collection, and quantitative/qualitative data analysis. Ameera Almessabi: Writing—original draft preparation, review, and editing.

All authors have read and approved the final version of the manuscript.

Conflicts of Interest. The authors declare no conflict of interest.

Funding. No external funding was received for this study.

Ethical Approval. All procedures involving human participants were conducted in accordance with institutional and national ethical guidelines. Ethical approval was obtained from the UAE Ministry of Health and Prevention Research Ethics Committee (2024/309). Written informed consent was obtained from all participants, and all data were anonymized to ensure confidentiality.

Data Availability Statement. The datasets generated and analyzed during the current study are available from the corresponding author upon reasonable request, in accordance with ethical and institutional regulations.

References

Adebayo, O., Aldoori, J., Allum, W., Aruparayil, N., Badran, A., Beatty, J. W., Bhatia, S., Bolton, W., Giwa-Brown, L., Burke, J., Carr, H. J., Chae, Y., Clements, J., El-Sayed, C., Foster, W., Gall, T., George, M., Guest, F., Haq, M., . . . Price, R. (2022). *Future of surgery: Technology enhanced surgical training: Report of the FOS:TEST commission*. https://doi.org/10.1308/fos2.2022

Akkaoui, R., Hei, X., & Cheng, W. (2020). EdgeMediChain: A hybrid edge blockchain-based framework for health data exchange. *IEEE Access, 8*, 113467–113486. https://doi.org/10.1109/access.2020.3003575

Akyildiz, I. F., Kak, A., & Nie, S. (2020). 6G and beyond: The future of wireless communications systems. *IEEE Access, 8*, 133995–134030. https://doi.org/10.1109/access.2020.3010896

AlAli R, Wardat Y, Helali M. Understanding word problems: Pre-service math teacher proficiency. Environment and Social Psychology 2024; 9(7): 2812. https://10.59429/esp.v9i7.2812

AlAli, R., & Wardat, Y. (2024). How ChatGPT will shape the teaching learning landscape in future. Journal of Educational and Social Research, 14(2), 336-345.

Aldalalah, O. M. A., Wardat, Y., Al-Omari, A. A. H., & Khodair, R. M. (2025). The effectiveness of interactive digital content based on the TPACK model in developing skills in educational aid production and improving cognitive achievement among early childhood university students. Contemporary Educational Technology, 17(2), ep572. https://doi.org/10.30935/cedtech/16046

Ali, S., Abuhmed, T., El-Sappagh, S., Muhammad, K., Alonso-Moral, J. M., Confalonieri, R., Guidotti, R., Del Ser, J., Díaz-Rodríguez, N., & Herrera, F. (2023). Explainable artificial intelligence (XAI): What we know and what is left to attain trustworthy artificial intelligence. *Information Fusion, 99*, 101805. https://doi.org/10.1016/j.inffus.2023.101805

Alkouri, Z., & Wardat, Y. (2025). Digital integration in preschool math: Assessing the efficacy of a structured curriculum in classroom settings. International Electronic Journal of Mathematics Education, 20(4), em0845. https://doi.org/10.29333/iejme/16662

Al-shraifin, A., Wardat, Y. , AlAli, R. & Al-Saud, K. (2025). Harnessing AI in School Counselling: Exploring the Potential of ChatGPT for Student Support. Educational Process: International Journal, 18, e2025434. https://doi.org/10.22521/edupij.2025.18.434

Al-Suwaidi, A. (2011). The United Arab Emirates at 40: A balance sheet. *Middle East Policy, 18*(4), 44–58. https://doi.org/10.1111/j.1475-4967.2011.00509.x

Alzahrani, S. (2021). *Assessment of the blockchain technology adoption for the management of the electronic health record systems* (Publication No. 7527) [Doctoral dissertation, Portland State University]. ETD. https://doi.org/10.15760/etd.7527

Aronow, W. S., Fleg, J. L., Pepine, C. J., Artinian, N. T., Bakris, G., Brown, A. S., Ferdinand, K. C., Forciea, M. A., Frishman, W. H., Jaigobin, C., Kostis, J. B., Mancia, G., Oparil, S., Ortiz, E., Reisin, E., Rich, M. W., Schocken, D. D., Weber, M. A., & Wesley, D. J. (2011). ACCF/AHA 2011 expert consensus document on hypertension in the elderly. *Circulation, 123*(21), 2434–2506. https://doi.org/10.1161/CIR.0b013e31821daaf6

Aste, N., Della Torre, S., Talamo, C., Adhikari, R. S., & Rossi, C. (2020). Innovative models for sustainable development in emerging African countries. In *Research for development*. Springer. https://doi.org/10.1007/978-3-030-33323-2

Badawy, M., Ramadan, N., & Hefny, H. A. (2023). Healthcare predictive analytics using machine learning and deep learning techniques: A survey. *Journal of Electrical Systems and Information Technology, 10*(1), Article 108. https://doi.org/10.1186/s43067-023-00108-y

Bansal, G., Rajgopal, K., Chamola, V., Xiong, Z., & Niyato, D. (2022). Healthcare in metaverse: A survey on current metaverse applications in healthcare. *IEEE Access, 10,* 119914–119946. https://doi.org/10.1109/ACCESS.2022.3219845

Bertman, D. (2024). Sensor selection guide: 12 criteria for industrial electronics. *Simcona Electronics.* https://simcona.com/blog/sensor-selection-guide

Bibian, S., Dai, C., Chen, C., Chang, Y., Lin, W., Fuchs, D., Marsolek, I., Gerber, D., Eberle, B., Minto, French, Mckellow, Matousek, S., & Rees. (2010). Selected abstracts presented at the 20th meeting of the European Society for Computing and Technology in Anaesthesia and Intensive Care (ESCTAIC). *Journal of Clinical Monitoring and Computing, 24*(1), 1–33. https://doi.org/10.1007/s10877-009-9211-y

Bligh, B., Lee, K., Crook, C., Cutajar, M., Delia, C. S., Lei, Y., Lower, M., Marín, V. I., Miles, R., Moffitt, P., Munday, D., Passey, D., Saliba, R., & Yu, M. (2022). Technology and educational 'pivoting' in the wake of the Covid-19 pandemic: A collected commentary. https://doi.org/10.21428/8c225f6e.e946d39b

Braun, A., Schembri, I., & Frank, S. (2015). Exerseat—Sensor-supported exercise system for ergonomic microbreaks. In *Ambient Intelligence: 12th European Conference, AmI 2015, Athens, Greece, November 11–13, 2015, Proceedings* (Vol. 12, pp. 236–251). Springer International Publishing.

Bull, F. C., Al-Ansari, S. S., Biddle, S., Borodulin, K., Buman, M. P., Cardon, G., Carty, C., Chaput, J. P., Chastin, S., Chou, R., Dempsey, P. C., DiPietro, L., Ekelund, U., Firth, J., Friedenreich, C. M., Garcia, L., Gichu, M., Jago, R., Katzmarzyk, P. T., . . . Willumsen, J. F. (2020). World Health Organization 2020 guidelines on physical activity and sedentary behaviour. *British Journal of Sports Medicine, 54*(24), 1451–1462. https://doi.org/10.1136/bjsports-2020-102955

Chengoden, R., Victor, N., Huynh-The, T., Yenduri, G., Jhaveri, R. H., Alazab, M., Bhattacharya, S., Hegde, P., Maddikunta, P. K. R., & Gadekallu, T. R. (2023). Metaverse for healthcare: A survey on potential applications, challenges and future directions. *IEEE Access, 11*, 12765–12795. https://doi.org/10.1109/access.2023.3241628

De Alwis, C., Kalla, A., Pham, Q. V., Kumar, P., Dev, K., Hwang, W. J., & Liyanage, M. (2021). Survey on 6G frontiers: Trends, applications, requirements, technologies and future research. *IEEE Open Journal of the Communications Society, 2*, 836–886. https://doi.org/10.1109/ojcoms.2021.3071496

Du Sert, N. P., Ahluwalia, A., Alam, S., Avey, M. T., Baker, M., Browne, W. J., Clark, A., Cuthill, I. C., Dirnagl, U., Emerson, M., Garner, P., Holgate, S. T., Howells, D. W., Hurst, V., Karp, N. A., Lazic, S. E., Lidster, K., MacCallum, C. J., Macleod, M., . . . Würbel, H. (2020). Reporting animal research: Explanation and elaboration for the ARRIVE guidelines 2.0. *PLoS Biology, 18*(7), e3000411. https://doi.org/10.1371/journal.pbio.3000411

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., Ilavarasan, P. V., Janssen, M., Jones, P., Kar, A. K., Kizgin, H., Kronemann, B., Lal, B., Lucini, B., … Williams, M. D. (2021). Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management, 57,* 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002

Elnahla, N. (2021). *Your retailer needs you: Retaillance and its marketing implications* (Publication No. 14633) [Doctoral dissertation, Carleton University]. ETD. https://doi.org/10.22215/etd/2021-14633

Ependi, U., Rochim, A. F., & Wibowo, A. (2023). An assessment model for sustainable cities using crowdsourced data based on general system theory: A design science methodology approach. *Smart Cities, 6*(6), 3032–3059. https://doi.org/10.3390/smartcities6060136

Fei, Z., Li, B., Yang, S., Xing, C., Chen, H., & Hanzo, L. (2017). A survey of multi-objective optimization in wireless sensor networks: Metrics, algorithms, and open problems. *IEEE Communications Surveys & Tutorials, 19*(1), 550–586. https://doi.org/10.1109/comst.2016.2610578

Firstenberg, M. S., & Stawicki, S. P. (2022). Medical education for the 21st century. In *IntechOpen eBooks*. https://doi.org/10.5772/intechopen.95701

Fuller, A., Fan, Z., Day, C., & Barlow, C. (2020). Digital twin: Enabling technologies, challenges and open research. *IEEE Access, 8,* 108952–108971. https://doi.org/10.1109/ACCESS.2020.2998358

Garcia, M. B., Acut, D. P., Arif, Y. M., Maher, D., Alex, J. K., Wardat, Y., ... & Damaševičius, R. (2026). Modernizing Mathematics Education with Artificial Intelligence: A Narrative Review of AI-Powered Tools, Thematic Trends, and Instructional Applications. The Convergence of Mathematics and AI: A New Paradigm in Education, 153-186. https://doi.org/10.4018/979-8-3373-1998-8.ch006

Gefen, A., Alves, P., Ciprandi, G., Coyer, F., Milne, C. T., Ousey, K., Ohura, N., Waters, N., Worsley, P., Black, J., Barakat-Johnson, M., Beeckman, D., Fletcher, J., Kirkland-Kyhn, H., Lahmann, N. A., Moore, Z., Payan, Y., & Schlüer, A. B. (2022). Device-related pressure ulcers: SECURE prevention. Second edition. *Journal of Wound Care, 31*(Sup3a), S1–S72. https://doi.org/10.12968/jowc.2022.31.sup3a.s1

Gregory, R. W., Henfridsson, O., Kaganer, E., & Kyriakou, H. (2021). The role of artificial intelligence and data network effects for creating user value. *Academy of Management Review, 46*(3), 534–551. https://doi.org/10.5465/amr.2019.0178

Himeur, Y., Elnour, M., Fadli, F., Meskin, N., Petri, I., Rezgui, Y., Bensaali, F., & Amira, A. (2022). AI-big data analytics for building automation and management systems: A survey, actual challenges and future perspectives. *Artificial Intelligence Review, 56*(6), 4929–5021. https://doi.org/10.1007/s10462-022-10286-2

Horton, M. B., Brady, C. J., Cavallerano, J., Abramoff, M., Barker, G., Chiang, M. F., Crockett, C. H., Garg, S., Karth, P., Liu, Y., Newman, C. D., Rathi, S., Sheth, V., Silva, P., Stebbins, K., & Zimmer-Galler, I. (2020). Practice guidelines for ocular telehealth-diabetic retinopathy, third edition. *Telemedicine Journal and E-Health, 26*(4), 495–543. https://doi.org/10.1089/tmj.2020.0006

How to face the scientific communication today. International challenges and the impact of digital technology on research output dissemination. (2017). In *Scuole di dottorato*. https://doi.org/10.36253/978-88-6453-497-8

Hussain, F., Hussain, R., Hassan, S. A., & Hossain, E. (2020). Machine learning in IoT security: Current solutions and future challenges. *IEEE Communications Surveys & Tutorials, 22*(3), 1686–1721. https://doi.org/10.1109/COMST.2020.2986444

Ibn-Mohammed, T., Mustapha, K., Godsell, J., Adamu, Z., Babatunde, K., Akintade, D., Acquaye, A., Fujii, H., Ndiaye, M., Yamoah, F., & Koh, S. (2021). A critical analysis of the impacts of COVID-19 on the global economy and ecosystems and opportunities for circular economy strategies. *Resources, Conservation and Recycling, 164,* 105169. https://doi.org/10.1016/j.resconrec.2020.105169

Iqbal, S., Qureshi, A. N., Li, J., & Mahmood, T. (2023). On the analyses of medical images using traditional machine learning techniques and convolutional neural networks. *Archives of Computational Methods in Engineering, 30*(5), 3173–3233. https://doi.org/10.1007/s11831-023-09899-9

Jarrah, A. M., Wardat, Y., Fidalgo, P., & Ali, N. (2025). Gamifying mathematics education through Kahoot: Fostering motivation and achievement in the classroom. Research & Practice in Technology Enhanced Learning, 20.

Khosravi, H., Shum, S. B., Chen, G., Conati, C., Tsai, Y. S., Kay, J., Knight, S., Martinez-Maldonado, R., Sadiq, S., & Gašević, D. (2022). Explainable artificial intelligence in education. *Computers and Education: Artificial Intelligence, 3,* 100074. https://doi.org/10.1016/j.caeai.2022.100074

Kitamura, Y., & Brehm, W. (2020). *Public policy innovation for human capital development*. https://doi.org/10.61145/ofge7589

Li, T., Xia, T., Wang, H., Tu, Z., Tarkoma, S., Han, Z., & Hui, P. (2022). Smartphone app usage analysis: Datasets, methods, and applications. *IEEE Communications Surveys & Tutorials, 24*(2), 937–966. https://doi.org/10.1109/COMST.2022.3163176

Mansour, O., & Wardat, Y. (2025. The Effect of the Flipped Classroom Strategy on Motivation to Learn Mathematics Among 9th-Grade Female Students: A Quasi-Experimental Study in Amman. Frontiers in Education, 10, 1579358. https://doi.org/10.3389/feduc.2025.1579358

Martínez-Fernández, S., Bogner, J., Franch, X., Oriol, M., Siebert, J., Trendowicz, A., Vollmer, A. M., & Wagner, S. (2022). Software engineering for AI-based systems: A survey. *ACM Transactions on Software Engineering and Methodology, 31*(2), 1–59. https://doi.org/10.1145/3487043

Minerva, R., Lee, G. M., & Crespi, N. (2020). Digital twin in the IoT context: A survey on technical features, scenarios, and architectural models. *Proceedings of the IEEE, 108*(10), 1785–1824. https://doi.org/10.1109/JPROC.2020.2998530

Mohta, K. (2021). Selection criteria for sensors. *Nerdy Electronics.* https://nerdyelectronics.com/selection-criteria-for-sensors/

Rehman, S. U., Prehn, M., & Gruhn, V. (2018, June). Smartchair: A realization of smart health care system based on cyber-physical systems. In *Proceedings of the Fourth International Conference on Engineering & MIS 2018* (pp. 1–8). ACM.

Saleh, S., AlAli, R., Wardat, Y., Al-Qahtani, M., Soliman, Y., & Helali, M. (2023). Structural relationships between learning emotion and knowledge organization and management processes in distance learning environments:"an applied study". European Journal of Investigation in Health, Psychology and Education, 13(9), 1569-1589.

Saraswat, D., Bhattacharya, P., Verma, A., Prasad, V. K., Tanwar, S., Sharma, G., Bokoro, P. N., & Sharma, R. (2022). Explainable AI for healthcare 5.0: Opportunities and challenges. *IEEE Access, 10,* 84486–84517. https://doi.org/10.1109/ACCESS.2022.3197671

Schutte-Rodin, S., Deak, M. C., Khosla, S., Goldstein, C. A., Yurcheshen, M., Chiang, A., Gault, D., Kern, J., O'Hearn, D., Ryals, S., Verma, N., Kirsch, D. B., Baron, K., Holfinger, S., Miller, J., Patel, R., Bhargava, S., & Ramar, K. (2021). Evaluating consumer and clinical sleep technologies: An American Academy of Sleep Medicine update. *Journal of Clinical Sleep Medicine, 17*(11), 2275–2282. https://doi.org/10.5664/jcsm.9580

Sepasgozar, S., Karimi, R., Farahzadi, L., Moezzi, F., Shirowzhan, S., Ebrahimzadeh, S. M., Hui, F., & Aye, L. (2020). A systematic content review of artificial intelligence and the internet of things applications in smart home. *Applied Sciences, 10*(9), 3074. https://doi.org/10.3390/app10093074

Shahzad, M., Shafiq, M. T., Douglas, D., & Kassem, M. (2022). Digital twins in built environments: An investigation of the characteristics, applications, and challenges. *Buildings, 12*(2), 120. https://doi.org/10.3390/buildings12020120

Shen, Y., Guo, D., Long, F., Mateos, L. A., Ding, H., Xiu, Z., Hellman, R. B., King, A., Chen, S., Zhang, C., & Tan, H. (2021). Robots under COVID-19 pandemic: A comprehensive survey. *IEEE Access, 9*, 1590–1615. https://doi.org/10.1109/access.2020.3045792

Spender, A., Bullen, C., Altmann-Richer, L., Cripps, J., Duffy, R., Falkous, C., Farrell, M., Horn, T., Wigzell, J., & Yeap, W. (2019). Wearables and the internet of things: Considerations for the life and health insurance industry. *British Actuarial Journal, 24*. https://doi.org/10.1017/s1357321719000072

Tashtoush, M. A., Wardat, Y., AlAli, R., & Al-Saud, K. (2023). The impact of cyberbullying on student motivation to learn: Insights from Abu Dhabi Emirate schools. Humanities and Social Sciences Letters, 11(4), 461-474.

UAE Ministry of Education. (n.d.). *Curricula and language of instruction*. https://u.ae/en/information-and-services/education/school-education-k-12/curricula-and-language-of-instruction-#:~:text=The%20government%20schools%20follow%20the,teaching%20technical%20or%20scientific%20subjects

Innovative learning environments in STEM higher education. (2021). In *SpringerBriefs in Statistics*. https://doi.org/10.1007/978-3-030-58948-6

Varnosfaderani, S. M., & Forouzanfar, M. (2024). The role of AI in hospitals and clinics: Transforming healthcare in the 21st century. *Bioengineering, 11*(4), 337. https://doi.org/10.3390/bioengineering11040337

Vermesan, O., Eisenhauer, M., Sundmaeker, H., Guillemin, P., Serrano, M., Tragos, E. Z., Valiño, J., Van derWees, A., Gluhak, A., & Bahr, R. (2022). Internet of things cognitive transformation technology research trends and applications. In *River Publishers eBooks* (pp. 17–95). https://doi.org/10.1201/9781003337584-3

Vertical and topical program. (2021). https://doi.org/10.1109/wf-iot51360.2021.9595268

Wardat, Y. & AlAli, R. (2025). Sustainability in Higher Education: Challenges, Innovations, and Research Prospects. Educational Process: International Journal, 16, e2025292. https://doi.org/10.22521/edupij.2025.16.292

Wardat, Y., & AlAli, R. (2025). Sustainability in Higher Education: Challenges, Innovations, and Research Prospects. Educational Process: International Journal, 16, e2025292. https://doi.org/10.22521/edupij.2025.16.292

Wardat, Y., Hidayat, R., Belbase, S., Al-Shraifin, A. A., & Alribdi, N. I. (2025). Cross-National Comparison of Mathematical Modelling Attitudes Among Educators. European Journal of Education, 60(4), e70288. https://doi.org/10.1111/ejed.70288

Warnat-Herresthal, S., Schultze, H., Shastry, K. L., Manamohan, S., Mukherjee, S., Garg, V., Sarveswara, R., Händler, K., Pickkers, P., Aziz, N. A., Ktena, S., Tran, F., Bitzer, M., Ossowski, S., Casadei, N., Herr, C., Petersheim, D., Behrends, U., Kern, F., … Grundhoff, A. (2021). Swarm learning for decentralized and confidential clinical machine learning. *Nature, 594*(7862), 265–270. https://doi.org/10.1038/s41586-021-03583-3

Williams, S., Ayers, A., Hildebrandt, M., McNeill, L., & Flowers, C. (2020). Strategies for overcoming disparities for patients with hematologic malignancies and for improving enrollment on clinical trials. *ONCOLOGY, 3406*. https://doi.org/10.46883/onc.3406.0216

Winaryati, E., Wardat, Y., Setiawan, A., Iksan, Z. H., Rauf, R. A. A., Kusumaningrum, W. I., & Nurdiana, L. (2025). Developing 21st Century Skills Through STEMBased Lesson Study and Project-Based Approaches in Chemistry Learning. Educational Process: International Journal, 19, e2025534. https://doi.org/10.22521/edupij.2025.19.534

About the Contributor(s)

Saif Al Neyadi, PhD, is Assistant Professor of Health Education and Technology Integration in the College of Education at Al Ain University, Al Ain, UAE. His research focuses on curriculum innovation, clinical simulation, and 21st-century competencies in health science education, with particular emphasis on sensor-based learning systems and UAE national curriculum reform. He has published in leading journals on educational technology and clinical pedagogy.
Email: Saif.alneyadi@aau.ac.ae
ORCID: https://orcid.org/0000-0003-0349-6569

Enas Abulibdeh, PhD, is Associate Professor of Educational Psychology and Assessment in the College of Education at Al Ain University, Al Ain, UAE. Her research interests include cognitive development, conceptual change, motivation in technology-enhanced learning, and teacher professional

development. She has authored multiple studies on scaffolded instruction and digital assessment tools.
Email: enas.abulibdeh@gmail.com

Ameera Almessabi, PhD, is Assistant Professor in the Education Department at the College of Humanities and Social Sciences, Zayed University, Abu Dhabi, UAE. Her research centers on teacher cognition, instructional design, TPACK in STEM-health education, and sociocultural learning theory. She has published extensively on technology-mediated clinical training and curriculum alignment.
Email: Ameera.Almessabi@zu.ac.ae
ORCID: https://orcid.org/0000-0002-6143-0026

Publisher's Note: *The opinions, statements, and data presented in all publications are solely those of the individual author(s) and contributors and do not reflect the views of Universitepark, EDUPIJ, and/or the editor(s). Universitepark, the Journal, and/or the editor(s) accept no responsibility for any harm or damage to persons or property arising from the use of ideas, methods, instructions, or products mentioned in the content.*