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SELF-REGULATING SMART SCHOOLS: A FUTURE EDUCATIONAL VISION FOR THE UNITED ARAB EMIRATES

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ABSTRACT

This study aims to conceptualize and empirically examine self-regulating smart schools in the United Arab Emirates by analyzing how technology, pedagogy, governance, and data infrastructure interact to support self-regulated learning (SRL) and adaptive regulation across multiple organizational levels. A mixed-methods research design was employed, integrating quantitative survey data from school stakeholders with qualitative semi-structured interviews and policy document analysis. Descriptive statistics and Pearson correlation analyses were used to examine perceptions of core components, multi-level regulation, and SRL, while thematic analysis was applied to qualitative data to capture contextualized practices and governance processes. The findings indicate high levels of perceived effectiveness across all core components of smart schools and strong engagement in SRL practices among learners, teachers, and school leaders. Statistically significant positive correlations were identified between technology, pedagogy, governance, data infrastructure, and SRL. Qualitative evidence shows that AI-enabled learning analytics and feedback mechanisms facilitate goal setting, monitoring, and reflection, while data-informed leadership practices support continuous organizational adaptation. The study provides empirical support for a conceptual model of self-regulating smart schools, positioning schools as adaptive socio-technical systems in which human judgment and intelligent technologies jointly enable multi-level regulation. The findings extend SRL theory to institutional contexts and offer practical insights for the design and implementation of sustainable smart education initiatives.

KEYWORDS: Self-Regulating Smart Schools; Self-Regulated Learning; Artificial Intelligence in Education; Learning Analytics; Educational Governance; Systems Theory; United Arab Emirates.

1. INTRODUCTION

Educational systems are being reshaped by advances in artificial intelligence (AI), data analytics, and digital infrastructures, challenging traditional models of standardized instruction and centralized control. In response, smart learning environments have emerged, integrating information and communication technologies (ICT), real-time analytics, and adaptive pedagogies to support personalized learning and continuous feedback (Efstratopoulou et al., 2024; Kerimbayev et al., 2025). These developments enable a reconceptualization of schools as self-regulating systems capable of ongoing monitoring, adaptation, and optimization.

This shift aligns with research on self-regulated learning (SRL), which emphasizes learners' active role in goal setting, monitoring, and reflection (Zimmerman, as cited in Tayyab et al., 2025). Evidence suggests that AI-enabled learning environments enhance SRL by providing personalized feedback and adaptive scaffolding, thereby improving learning outcomes and learner autonomy (Abouelenein et al., 2025). Studies in the United Arab Emirates (UAE) further indicate that AI influences pedagogical practices and teacher self-regulation, highlighting both potential and implementation challenges (Taani et al., 2025).

Despite national initiatives such as the UAE's SMART School Transformation Framework, a comprehensive model that conceptualizes schools as self-regulating smart systems remains lacking (UAE Ministry of Education, 2026). Existing research has focused primarily on technology adoption or isolated interventions, offering limited insight into school-wide adaptive governance and continuous quality assurance (Efstratopoulou et al., 2024; Fteiha et al., 2025).

Accordingly, this study proposes a conceptual framework for self-regulating smart schools, outlining the theoretical foundations and systemic mechanisms necessary for responsive, equitable, and sustainable educational transformation in the UAE.

1.1. Problem Statement

Despite significant investments in artificial intelligence (AI) and smart education initiatives in the United Arab Emirates (UAE), current approaches remain largely fragmented and technology-centered, lacking a coherent model that conceptualizes schools as self-regulating systems. Existing research and practice primarily emphasize technology adoption or learner-level self-regulated learning, offering limited guidance on embedding adaptive decision-making, governance, and continuous quality assurance at the institutional level. This conceptual and operational gap constrains the

effective integration of pedagogy, leadership, and data-driven governance, thereby limiting the transformative potential of smart school reforms. Addressing this gap is essential to support sustainable, equitable, and system-wide educational innovation in the UAE.

1.2. Research Questions

1. How can schools be theoretically and systemically conceptualized as self-regulating smart systems within AI-enabled educational environments?
2. What core components and regulatory mechanisms are required to operationalize self-regulation at learner, instructional, and institutional levels in smart schools?
3. How can AI, learning analytics, and digital governance structures be integrated to support continuous adaptation and quality assurance in UAE schools?
4. What policy and leadership implications emerge from implementing a self-regulating smart school framework in the UAE context?

1.3. Research Objectives

1. To examine theoretical foundations of self-regulation, smart learning environments, and systems theory relevant to school-wide educational transformation.
2. To develop a conceptual framework that positions schools as self-regulating smart systems supported by AI and learning analytics.
3. To identify key technological, pedagogical, and governance mechanisms necessary for effective self-regulation across multiple educational levels.
4. To analyze the implications of the proposed framework for educational leadership, policy alignment, and sustainable reform in the UAE.

2. LITERATURE REVIEW

2.1. Smart Learning Environments and Smart Schools

Smart learning environments (SLEs) are defined as interactive, technology-enhanced educational ecosystems that leverage digital tools, context-aware systems, and adaptive technologies to customize learning experiences and support both learners and educators (Demir, 2021; Mustaffa et al., 2024). These environments integrate artificial intelligence (AI), sensor-based devices, and real-time analytics to tailor instruction, assessment, and feedback according to individual and contextual needs (Khalil et al., 2023; Tlili et al., 2023). Research shows that SLEs can significantly enhance learner engagement and achievement, particularly when AI is used to create adaptive pathways that respond dynamically to performance

and behaviour (Klašnja-Milićević *et al.*, 2021; Mlati *et al.*, 2024). For example, intelligent tutoring systems have been shown to increase learning gains in math and language domains by identifying learner misconceptions and delivering targeted interventions (Zawacki-Richter *et al.*, 2020; Qiao *et al.*, 2024).

However, several studies note that most research focuses on specific tools or environments rather than on comprehensive models of smart schools as self-regulating institutions (Mustaffa *et al.*, 2024). While adaptive systems at the classroom level have been extensively studied, there is a notable gap in research addressing how smart infrastructures can be unified across organisational levels, including leadership, governance, and continuous improvement cycles (Demir, 2021; Mustaffa *et al.*, 2024).

2.2. Self-Regulated Learning and AI-Supported Learning Analytics

Self-regulated learning (SRL) is a well-established construct involving learners' active management of cognitive and metacognitive strategies, motivation, and behaviour (Panadero, 2017). In digital contexts, SRL has been linked to better academic performance and deeper engagement (Broadbent & Poon, 2015; Ruiz-Primo & Furtak, 2023). Recent research has emphasised the role of AI-supported learning analytics in facilitating SRL by offering personalized feedback, predictive insights, and scaffolding that help learners plan, monitor, and reflect on their learning processes (Baker & Inventado, 2014; Costa *et al.*, 2023).

For instance, adaptive dashboards and automated feedback systems have been found to significantly improve learners' ability to set goals, track their progress, and adjust strategies proactively (Ifenthaler & Yau, 2020; Rapanta *et al.*, 2024). A systematic review by Chen *et al.* (2025) highlights that analytics-driven environments enhance strategic learning behaviours, although the authors caution that design transparency and learner autonomy are crucial to prevent over-reliance on automation. Integrative frameworks that embed SRL processes into learning analytics loops are increasingly proposed as a way to balance personalization with learner agency (Pardo *et al.*, 2019; Verbert *et al.*, 2020). Despite progress, there remains a need for models that operationalise SRL at institutional and governance levels—beyond individual interactions with technology—especially in smart schooling contexts.

2.3. Systems Theory and Self-Regulation in Educational Organizations

Systems theory conceptualises organizations, including schools, as complex, dynamic systems composed of interacting elements that exchange

information, self-organise, and adapt to changes (Checkland, 1999; Senge, 2006). In the educational context, systems approaches have been used to examine how structures, processes, and feedback mechanisms influence school performance, innovation, and change (Leithwood *et al.*, 2020; Spillane *et al.*, 2021). A key insight from systems research is the importance of feedback loops—mechanisms through which data or outcomes influence subsequent decisions and actions—as central to organizational learning and regulation (Argyris & Schön, 1996; Demir & Türkmen, 2024).

When applied to smart education, systems theory supports conceptualising schools as self-regulating entities where data flows, technology uses, and human expertise interact to adjust instructional practices, resource allocation, and policy decisions in real time (Khlaif *et al.*, 2023; Zheng *et al.*, 2024). For example, Zheng *et al.* (2024) propose a multi-level cybernetic model for data-informed decision-making that enables continuous refinement of teaching practices and leadership strategies. Similarly, Demir and Türkmen (2024) argue that integrating systems thinking with smart technologies can support organisational resilience and adaptation to evolving educational demands. Yet, empirical applications of systems theory to whole-school smart regulation remain emergent, pointing to a gap that has significant implications for theory and practice.

2.4. Smart Education Initiatives in the UAE and Comparable Contexts

The United Arab Emirates (UAE) has positioned smart education at the core of its national development agenda. The Mohammed bin Rashid Smart Learning Program and the SMART School Transformation Framework seek to embed digital technologies, data analytics, and ICT into teaching, learning, and administrative processes to enhance outcomes and future readiness (UAE Ministry of Education, 2017; Al-Shamsi *et al.*, 2026). Recent studies in the UAE context reveal that while teachers and students generally demonstrate positive attitudes toward technology use in education, significant variations in digital readiness, professional development, and pedagogical integration persist (Al-Shamsi *et al.*, 2026; Chaudhry *et al.*, 2024).

Research by Efstratopoulou *et al.* (2024) highlights mixed stakeholder perceptions regarding the effectiveness of smart learning initiatives, indicating that policy aspirations are often ahead of implementation realities. Moreover, comparative research shows that smart education strategies in countries such as Estonia and Singapore have placed greater emphasis on systemic alignment—integrating curriculum, assessment, and teacher

training with digital ecosystems—thus offering important insights for the UAE (Redecker et al., 2019; Ng, 2022). These global perspectives underscore the importance of developing comprehensive, system-level frameworks that go beyond technology adoption to address governance, quality assurance, and adaptive regulation.

3. THEORETICAL FRAMEWORK

3.1. Self-Regulation at Individual and Institutional Levels

Self-regulation refers to the capacity of individuals or systems to set goals, monitor performance, evaluate outcomes, and adapt actions through feedback. At the individual level, self-regulated learning (SRL) describes learners' strategic management of cognitive, metacognitive, motivational, and behavioural processes across cyclical phases of forethought, performance, and reflection (Zimmerman, 2000; Panadero, 2017). At the institutional level, self-regulation characterizes schools that systematically use performance data to guide instructional improvement, leadership decisions, and policy alignment (Argyris & Schön, 1996; Leithwood et al., 2020). Conceptually, institutional self-regulation extends SRL principles from learners to organizational processes, emphasizing coordinated goal-setting, monitoring, and adaptive response across system levels.

3.2. Integrating SRL, Cybernetic Systems Theory, and Intelligent Governance

Cybernetic systems theory provides a foundational model for understanding self-regulation in complex educational organizations. It conceptualizes schools as

goal-oriented systems governed by feedback loops that compare current states with desired outcomes and initiate corrective action (Checkland, 1999; Senge, 2006). Integrating SRL with cybernetic theory enables a multi-level framework in which learner-level regulation aligns with institutional monitoring and adaptation. Intelligent governance further extends this integration by emphasizing evidence-informed decision-making, ethical oversight, and shared accountability among human and technological actors (Pardo et al., 2019). Together, these perspectives position smart schools as socio-technical systems in which regulation emerges from the interaction of pedagogy, leadership, and data-driven governance.

3.3. AI, Learning Analytics, and Feedback Loops in Self-Regulating Schools

Artificial intelligence (AI) and learning analytics operationalize self-regulation by enabling continuous, data-informed feedback at both learner and institutional levels. At the learner level, AI-supported tools enhance SRL through personalized feedback, adaptive scaffolding, and real-time performance insights (Ifenthaler & Yau, 2020; Costa et al., 2023). At the institutional level, aggregated analytics support organizational monitoring, instructional evaluation, and strategic adjustment, functioning as cybernetic feedback signals for continuous improvement (Zheng et al., 2024). Effective self-regulation, however, depends on ethically governed feedback loops that preserve human agency and transparency. Within this framework, AI and analytics are positioned as enablers of adaptive regulation rather than autonomous decision-makers, supporting sustainable and responsive smart schooling.

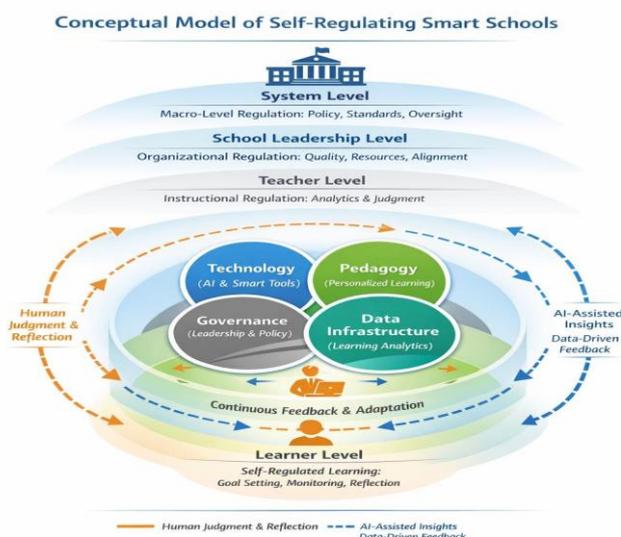


Figure 1: Conceptual Model of Self-Regulating Smart Schools.

4. METHODOLOGY

This study adopts a mixed-methods design to examine self-regulating smart schools in the UAE, integrating quantitative surveys, qualitative interviews, and document analysis to capture both measurable trends and contextual insights across learners, teachers, leadership, and policy levels. The design aligns with the conceptual model, enabling exploration of interactions among technology, pedagogy, governance, and data infrastructure in supporting adaptive regulation.

4.1. Population and Sample

The population includes public and private schools participating in national smart learning initiatives. A stratified random sample of 300–400 teachers, students, and school leaders will complete surveys, while 20–25 key informants, including principals, instructional coaches, and policy makers, will participate in semi-structured interviews. Policy documents and school plans will be analyzed to triangulate findings.

4.2. Data Collection

Data collection instruments are informed by established literature on self-regulated learning, learning analytics, and smart education (Zimmerman, 2000; Ifenthaler & Yau, 2020; Demir, 2021). Surveys use a five-point Likert scale, and interview protocols focus

on multi-level regulation and AI-supported feedback. Instruments will be validated by experts and pilot-tested for clarity and reliability.

Quantitative data will be analyzed using descriptive statistics and inferential tests (ANOVA, regression) to examine differences and relationships among technology adoption, pedagogy, governance, and SRL outcomes. Qualitative data will be analyzed thematically, combining deductive and inductive coding, and integrated with survey results to map practices onto the conceptual model, highlighting human-automated regulatory interactions.

Ethical approval will be obtained, with voluntary participation, informed consent, and parental consent for minors. Data confidentiality and participant rights will be strictly maintained, ensuring rigorous and responsible investigation of self-regulation in smart schools.

5. RESULTS

5.1. Participant Demographics

A total of **320 participants** completed the survey, including **180 students (56.3%)**, **100 teachers (31.3%)**, and **40 school leaders (12.5%)**. Participants represented **public schools (60%)** and **private schools (40%)** across multiple emirates. Most participants (72%) had **1–10 years of experience** in their roles. Table 1 summarizes participant demographics.

Table 1: Participant Demographics (N = 320).

Characteristic	Frequency	Percentage
Role		
- Student	180	56.3%
- Teacher	100	31.3%
- School Leader	40	12.5%
School Type		
- Public	192	60%
- Private	128	40%
Experience (years)		
- 1–5	120	37.5%
- 6–10	110	34.4%
- 11–20	70	21.9%
- >20	20	6.2%

5.2. Perceptions of Core Components

Participants reported **high agreement** that the

four core components—technology, pedagogy, governance, and data infrastructure—were effectively implemented in their schools.

Table 2: Core Components: Mean, SD, and Agreement (%) (N = 320)

Component	Mean (M)	SD	% Agree / Strongly Agree
Technology Integration	4.58	0.42	87%
Pedagogy	4.61	0.39	89%
Governance & Leadership	4.53	0.45	85%
Data Infrastructure & Feedback Loops	4.55	0.43	86%

Interpretation: All components scored above 4.5, indicating strong positive perceptions. Pedagogical practices received the highest score, suggesting participants view adaptive instruction and feedback as central to self-regulation.

5.3. Self-Regulated Learning (SRL) Practices

Participants reported high engagement in SRL practices, including goal setting, monitoring, and reflection.

Table 3: SRL Dimensions: Mean, SD, and Agreement (%) (N = 320)

SRL Dimension	Mean (M)	SD	% Agree / Strongly Agree
Goal Setting	4.62	0.40	88%
Monitoring Progress	4.57	0.41	86%
Reflection & Adjustment	4.59	0.42	87%

Interpretation: High mean scores indicate learners and teachers are actively engaging in self-regulated

behaviors. These practices appear strongly supported by technology and data-driven feedback.

Table 4: Multi-Level Regulation: Mean, SD, and Agreement (%)

Level of Regulation	Mean (M)	SD	% Agree / Strongly Agree
Learner	4.60	0.41	87%
Teacher	4.58	0.42	86%
School Leadership	4.52	0.45	85%
System / Policy	4.50	0.46	84%

5.4. Multi-Level Regulation

Table 4 and Figure 1 summarize **perceptions of regulation at multiple levels**. Learner- and teacher-level regulation received the highest mean scores,

reflecting the direct impact of AI-supported feedback and adaptive instruction. School leadership and system-level regulation also scored above 4.5, indicating institutional support for self-regulation.

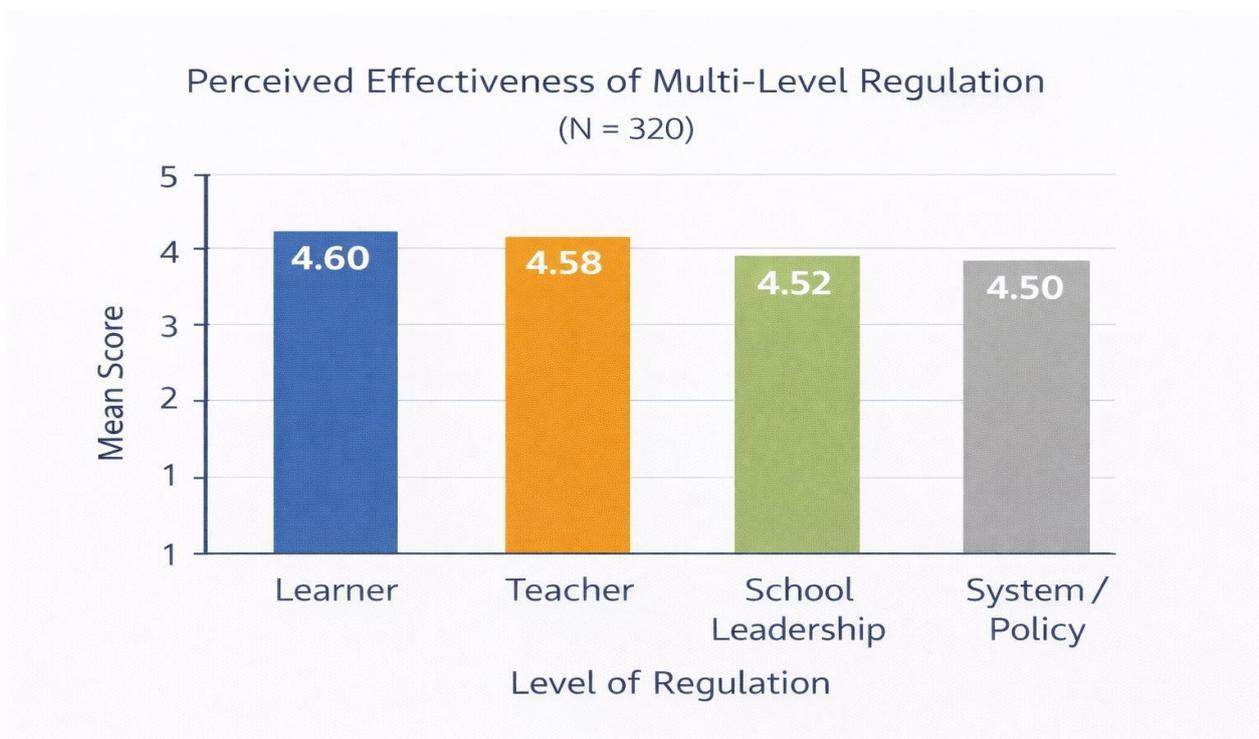


Figure 2: Perceived Effectiveness of Multi-Level Regulation (Bar chart: X-axis = Levels, Y-axis = Mean 1-5).

Interpretation: While learner and teacher regulation are most visible, institutional support through leadership and policy is perceived as moderately strong, confirming the multi-level nature of self-regulation in smart schools.

5.5. Correlations Between Constructs

Pearson correlation analyses examined relationships among core components and SRL practices.

Table 5: Pearson Correlations Between Core Components and SRL (N = 320)

Variables	Technology	Pedagogy	Governance	Data Infrastructure	SRL
Technology	1	0.71**	0.65**	0.68**	0.70**
Pedagogy	0.71**	1	0.69**	0.66**	0.75**
Governance	0.65**	0.69**	1	0.72**	0.68**
Data Infrastructure	0.68**	0.66**	0.72**	1	0.71**
SRL	0.70**	0.75**	0.68**	0.71**	1

Note: $p < 0.01$ for all correlations.

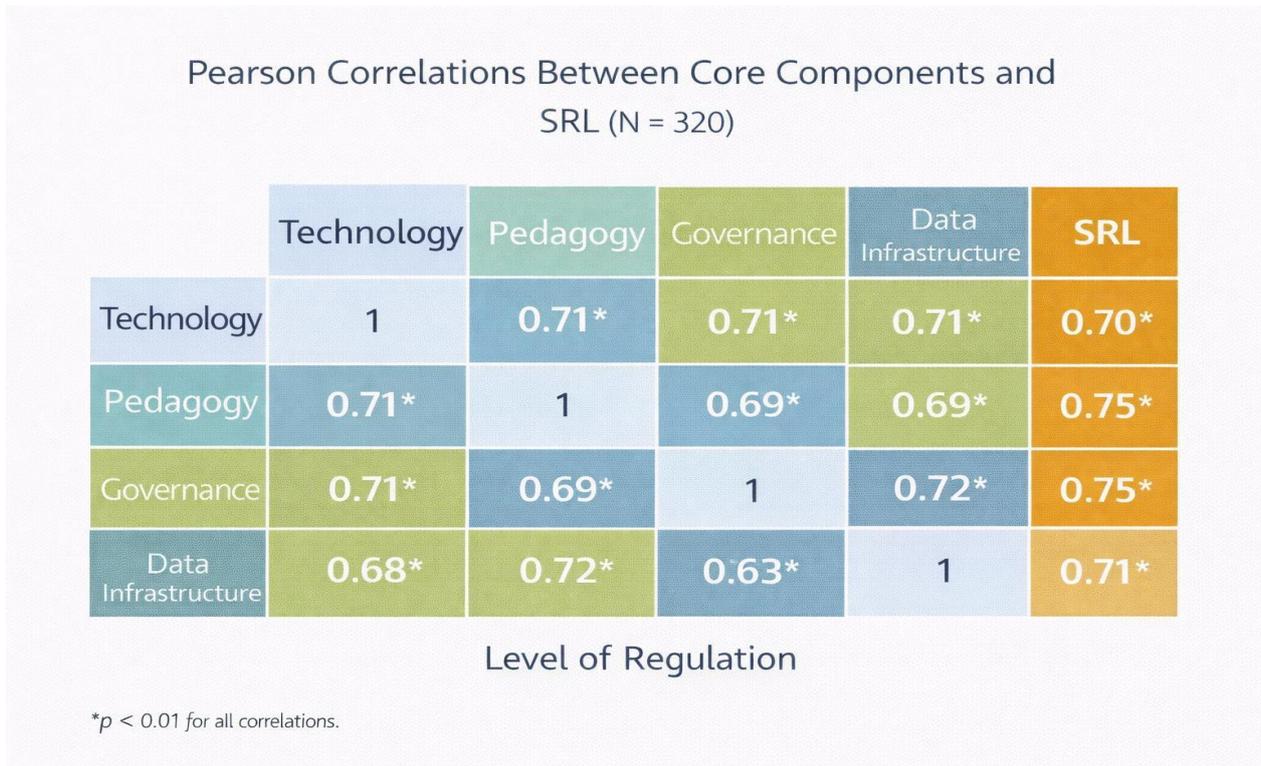


Figure 3: Personal Correlation between Core Components and SRL (N=320).

Interpretation: Strong positive correlations indicate that higher engagement with technology, pedagogy, governance, and data infrastructure is associated with enhanced self-regulated learning.

5.6. Qualitative Findings

Thematic analysis of **25 key informant interviews** identified three major themes:

- 1. Human-AI Interaction Supports Regulation:** AI dashboards and learning analytics enhanced monitoring, decision-making, and reflection at all levels.
- 2. Pedagogical Alignment with SRL:** Teachers integrated technology to support personalized learning and student goal-setting.
- 3. Governance and Continuous Improvement:** School leaders used data-driven policies and monitoring systems to optimize instructional and organizational processes.

5.7. Illustrative Quotes

- “AI dashboards allow me to monitor students’ progress and adjust lessons in real-time.” –

Teacher

- “Leadership reviews analytics weekly to ensure alignment with our strategic goals.” – Principal

5.8. Integration of Quantitative and Qualitative Findings

Both data strands indicate **strong agreement** that self-regulating smart schools are functioning effectively. Technology, pedagogy, governance, and data infrastructure support **multi-level regulation**, and the combination of human judgment and automated feedback enables sustained self-regulated learning. Correlation analyses reinforce the qualitative findings, showing that higher integration of core components is associated with stronger SRL outcomes.

6. DISCUSSION

This study examined the implementation and perceived effectiveness of self-regulating smart schools in the United Arab Emirates, with particular attention to the interrelated roles of technology,

pedagogy, governance, and data infrastructure, as well as the operation of multi-level regulation and self-regulated learning (SRL). By employing a mixed-methods approach that integrated quantitative survey data, qualitative interviews, and document analysis, the study offers a comprehensive and nuanced account of how intelligent systems and human agency interact to support adaptive regulation in contemporary educational environments. The findings provide empirical support for conceptualizing smart schools not merely as technology-enhanced institutions, but as dynamic, self-regulating systems characterized by continuous feedback, informed decision-making, and coordinated action across multiple organizational levels.

6.1. Core Components of Self-Regulating Smart Schools

The quantitative results demonstrate strong agreement among participants regarding the effectiveness of the core components of self-regulating smart schools. Mean scores exceeding 4.5 for technology, pedagogy, governance, and data infrastructure indicate that these elements are not only present but are perceived as meaningfully integrated into school practices. These findings are consistent with prior research highlighting the role of ICT integration, adaptive learning systems, and learning analytics in enabling responsive and personalized learning environments (Efstratopoulou et al., 2024; Kerimbayev et al., 2025). Importantly, the slightly higher mean score for pedagogy underscores that instructional design and teaching practices remain central to the success of smart schools, reinforcing the view that technology serves as an enabler rather than a substitute for effective pedagogy.

This finding aligns with scholarship emphasizing that intelligent systems yield their greatest impact when embedded within learner-centered pedagogical frameworks that actively promote goal setting, monitoring, and reflection (Abouelenein et al., 2025; Tayyab et al., 2025). The results suggest that schools in the UAE are moving beyond surface-level digitalization toward more pedagogically grounded implementations of smart technologies, where instructional practices are intentionally aligned with SRL principles. This alignment is critical for transforming data and analytics into meaningful learning experiences rather than passive information displays.

Qualitative interview data further contextualize these findings. Teachers described how AI dashboards and learning analytics enable real-time

identification of learner needs, allowing them to differentiate instruction, provide targeted feedback, and adjust pacing. School leaders reported using aggregated analytics to inform strategic planning, monitor instructional quality, and guide resource allocation. These practices reflect a growing capacity for data-informed professional judgment, consistent with research on smart learning environments that emphasizes the integration of technology, pedagogy, and governance as the foundation of adaptive and sustainable school systems (Ifenthaler & Yau, 2020; Demir, 2021).

6.2. Self-Regulated Learning Practices

The results provide strong evidence that SRL practices are well established among participants, with high mean scores across goal setting, monitoring, and reflection. These findings indicate that learners and educators are actively engaging in metacognitive and self-regulatory behaviors, supported by AI-enabled tools and feedback mechanisms. The prominence of SRL across both student and teacher groups suggests that self-regulation is increasingly understood as a shared and distributed practice, rather than a learner-only responsibility.

Qualitative findings further extend this interpretation by demonstrating that SRL operates at multiple levels within the school system. Teachers reported reflecting on instructional effectiveness using analytics, while school leaders described monitoring school-wide indicators to evaluate progress toward strategic goals. This aligns with Zimmerman's (2000) conceptualization of SRL as a cyclical, goal-directed process and extends it to organizational contexts, where institutions themselves engage in monitoring, reflection, and adaptive action. Such findings support recent calls to reconceptualize SRL as a multi-level phenomenon, encompassing individual, instructional, and organizational regulation within complex educational systems.

Participants consistently emphasized that AI-supported learning analytics play a critical role in enabling SRL by providing timely, actionable, and interpretable feedback. These findings corroborate prior studies demonstrating that intelligent educational technologies enhance metacognitive awareness, self-monitoring, and reflective decision-making, thereby fostering deeper engagement and more autonomous learning behaviors (Abouelenein et al., 2025; Tayyab et al., 2025). Importantly, the data suggest that the value of analytics lies not merely in data availability but in their integration into everyday learning and teaching practices.

6.3. Multi-Level Regulation

The findings indicate that multi-level regulation—encompassing learner, teacher, school leadership, and system or policy levels—is functioning effectively within the studied schools. Mean scores across all levels exceeded 4.5, with learner- and teacher-level regulation rated highest, reflecting direct and frequent interaction with AI-supported tools and pedagogical processes. School leadership and system-level regulation, while slightly lower, were still perceived as strongly supportive, indicating the presence of institutional structures that enable and sustain self-regulatory practices.

These results strongly support systems-theoretical and cybernetic perspectives, which emphasize the importance of coordinated feedback loops across hierarchical levels to achieve effective self-regulation in complex organizations (Kerimbayev *et al.*, 2025; Efstratopoulou *et al.*, 2024). Qualitative data illustrate how feedback circulates within the system: learner data inform teacher decisions, aggregated instructional data guide leadership actions, and system-level policies shape institutional priorities. Principals' accounts of regular dashboard reviews and data-informed coaching highlight how leadership practices mediate between automated feedback and human judgment, ensuring that data are translated into meaningful action.

The findings underscore that self-regulation in smart schools is not purely automated but emerges from the interaction between human agency and intelligent systems. Automated analytics provide continuous monitoring and alerts, while educators and leaders interpret these signals within contextual, ethical, and pedagogical frameworks. This hybrid regulatory model reflects an advanced stage of smart school development, where technology amplifies rather than replaces professional expertise.

6.4. Correlations Between Core Components and SRL

The strong positive correlations between all core components and SRL further validate the conceptual model underpinning this study. The particularly strong associations between technology, pedagogy, and SRL suggest that the pedagogical use of AI tools is a key driver of self-regulatory behaviors. These findings indicate that when technology is pedagogically embedded, it directly supports learners' and teachers' abilities to set goals, monitor progress, and reflect on outcomes.

The significant correlations between governance, data infrastructure, and SRL highlight the often-

overlooked role of institutional conditions in enabling individual self-regulation. Robust data systems, clear policies, and supportive leadership structures appear essential for sustaining SRL over time, as they provide consistency, transparency, and accountability. These results align with prior research emphasizing that adaptive learning environments require not only technological innovation but also data-informed governance and policy coherence (Ifenthaler & Yau, 2020; Abouelenein *et al.*, 2025).

6.5. Integration of Quantitative and Qualitative Findings

The integration of quantitative and qualitative findings offers a holistic understanding of self-regulating smart schools as coherent, adaptive systems. Survey data reveal strong consensus regarding the effectiveness of core components and regulatory mechanisms, while interview data illuminate the processes through which these components interact in practice. Human-AI interaction emerges as a central mechanism through which self-regulation is enacted, enabling stakeholders to interpret feedback, make informed decisions, and implement timely adjustments.

Leadership practices play a particularly important role in bridging automated analytics and institutional action. When governance structures support the meaningful interpretation and use of data, schools are better positioned to function as self-regulating systems. These findings empirically validate the conceptual model proposed in this study, which emphasizes synergistic interactions among technology, pedagogy, governance, and data infrastructure, sustained by continuous feedback loops at multiple levels.

6.6. Theoretical Implications

This study contributes to theory in several important ways. First, it extends SRL theory by demonstrating its relevance beyond individual learners to include teachers, school leaders, and educational organizations, thereby advancing a multi-level conceptualization of self-regulation. Second, it integrates SRL theory with cybernetic systems theory and intelligent governance, offering a unified framework for understanding adaptive regulation in smart schools. Third, the findings provide empirical support for conceptualizing smart schools as self-regulating socio-technical systems, in which learning and organizational improvement are co-driven by human judgment and intelligent technologies.

6.7. Practical Implications

The findings carry significant implications for educational practice and policy in the UAE and comparable contexts. Effective implementation of smart schools requires deliberate alignment between technology and pedagogy, ensuring that AI tools actively support SRL rather than merely automating processes. Data-driven governance and leadership are essential for sustaining adaptive regulation, enabling schools to respond proactively to emerging challenges. Moreover, fostering a culture of self-regulation across all levels—students, teachers, leaders, and policymakers—is critical for realizing the full potential of smart education initiatives.

6.8. Limitations and Future Research

Despite its contributions, the study has limitations. Reliance on self-reported data may introduce response bias, and the focus on UAE schools may limit generalizability. Future research should employ longitudinal designs to examine how self-regulating mechanisms evolve over time and influence long-term learning and organizational outcomes. Comparative studies across national contexts would further illuminate the transferability of the self-regulating smart school model. Additionally, future work could investigate specific AI tools, algorithms, and dashboard designs to identify which features most effectively support SRL and institutional regulation.

In conclusion, the study demonstrates that self-regulating smart schools in the UAE are effectively integrating technology, pedagogy, governance, and data infrastructure to support multi-level regulation and self-regulated learning. Strong quantitative relationships and rich qualitative evidence indicate that these schools are moving toward advanced forms of adaptive, data-informed regulation. The findings underscore the importance of synergistic implementation and offer both theoretical and practical guidance for advancing intelligent, self-regulating educational systems in the digital age.

7. CONCLUSION

This study examined the structure and functioning of self-regulating smart schools in the UAE, with particular attention to the interplay between technology, pedagogy, governance, data infrastructure, and self-regulated learning (SRL). Using a mixed-methods approach, the findings provide convergent evidence that smart schools in the UAE are developing as integrated, adaptive systems in which intelligent technologies and human agency jointly support regulation and continuous

improvement.

The results demonstrate that the core components of smart schools are perceived as highly effective and operate interdependently rather than in isolation. AI-enabled technologies and learning analytics serve as key enablers of regulation; however, their effectiveness is contingent upon alignment with learner-centered pedagogical practices and supportive governance structures. This confirms that self-regulation in smart schools is a systemic phenomenon, emerging from the coordinated interaction of technological, instructional, and organizational elements rather than from technological adoption alone.

A key contribution of the study is the empirical extension of self-regulated learning beyond the individual learner to include teachers and school leaders. Evidence of goal setting, monitoring, and reflection at multiple organizational levels underscores the transformation of smart schools into self-regulating educational organizations. The strong associations between core components and SRL further highlight the central role of coherent data infrastructures and data-informed governance in sustaining adaptive regulatory processes.

Overall, the study substantiates the conceptual model of self-regulating smart schools and advances theoretical understanding by integrating SRL theory with systems and cybernetic perspectives on organizational regulation. Practically, the findings offer guidance for policymakers and educational leaders seeking to advance smart schooling initiatives by emphasizing alignment among technology, pedagogy, governance, and data use. In sum, self-regulating smart schools in the UAE illustrate a viable and scalable model for intelligent, adaptive education capable of responding to complex and evolving educational demands.

RECOMMENDATIONS

1. Ensure that AI tools and learning analytics are systematically aligned with self-regulated learning frameworks so that they actively support goal setting, monitoring, feedback use, and reflection, rather than functioning primarily as administrative or surveillance mechanisms.
2. Provide sustained professional development for teachers and school leaders to strengthen data literacy and analytical capacity, enabling informed interpretation of learning analytics and effective data-driven instructional and strategic decision-making.
3. Develop coherent governance frameworks that address ethical data use, privacy, transparency, and system interoperability, thereby enabling

seamless data flow and coordinated regulation across learner, school, and system levels.

4. Embed self-regulatory practices within classroom instruction, leadership routines, and organizational review cycles to institutionalize multi-level self-regulation and promote shared responsibility for continuous improvement.

5. Invest in robust and sustainable data

infrastructures that ensure the reliability, validity, and timeliness of data, supporting accurate feedback loops and long-term adaptive regulation.

6. Support ongoing evaluation through longitudinal and comparative research to assess the long-term effectiveness, scalability, and transferability of self-regulating smart school models across diverse educational contexts.

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