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Artificial Intelligence for Sustainable Public Procurement in Small Developing Economies: Perceptions and Readiness of Procurement Officials in Bhutan

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Abstract

Artificial intelligence (AI) technologies offer unprecedented potential for enhancing sustainable public procurement (SPP) in small developing economies (SDEs), yet empirical research on AI adoption readiness in developing economy public sectors remains sparse. This integrated study: (i) develops a conceptual framework synthesizing Technology Acceptance Model (TAM), Technology-Organization-Environment (TOE), and Responsible AI Governance principles; (ii) presents an AI Procurement Maturity Model (AIPMM) tracing evolution from traditional to intelligent procurement; (iii) provides empirical evidence from 96 Bhutanese procurement officials; and (iv) proposes research propositions linking organizational readiness to adoption. Organisational readiness: encompassing ICT infrastructure, management support, and training—emerges as the primary adoption predictor ($\beta = 0.280$, $R^2 = 0.407$). Critically, a 0.70-point discrepancy emerges between personal adoption willingness (M = 4.03, 86.5%) and perceived organisational readiness (M = 3.33, 37.5%), indicating barriers are systemic rather than individual. Primary barriers include resistance to change (28.1%), policy gaps (24.0%), and infrastructure deficits (19.8%). The paper contributes by contextualising technology adoption theory to SDE institutional realities, advancing responsible AI governance frameworks for developing governments, and demonstrating how alternative value frameworks (Gross National Happiness) reshape procurement AI objectives. Five research propositions advance understanding of AI adoption in resource-constrained public sectors.

1. INTRODUCTION

Public procurement represents a critical lever for achieving economic development, environmental sustainability, and social equity across all national contexts. In developing nations, public procurement expenditure constitutes an estimated 30–40% of Gross Domestic Product (GDP), positioning government purchasing decisions as primary mechanisms for advancing macroeconomic and policy objectives (Kumar and Donthu, 2026). Concurrently, the 2030 Sustainable Development Goals and Paris Climate Agreement have intensified global pressure on public sector agencies to embed Environmental, Social, and Governance (ESG) criteria into procurement decisions, a paradigm shift toward Sustainable Public Procurement (SPP) that extends beyond traditional cost-minimization objectives.

Artificial intelligence technologies, encompassing machine learning, natural language processing, predictive analytics, and autonomous decision-making systems. offer unprecedented capacity for operationalizing SPP objectives through real-time supplier performance monitoring, carbon footprint quantification, predictive risk modelling, and automated compliance verification (Berbig et al., 2026). Recent bibliometric analyses document exponential growth in AI procurement research, with publications increasing 340% over the past decade; however, this literature exhibits pronounced geographic bias, with 68% of studies concentrating on developed economies and fewer than 12% examining developing economy contexts (Berbig et al., 2026; Rejeb et al., 2023). Moreover, empirical research on AI adoption in public sector procurement within small developing economies remains virtually absent from the literature.

Small Developing Economies (SDEs) operate under fundamentally different structural parameters than developed nations, creating distinctive challenges for AI adoption that conventional technology adoption frameworks inadequately address: Market Constraints (highly concentrated supplier markets, limited SME digital capacity); Institutional Constraints (fiscal deficits, fragmented digital infrastructure, acute digital skills gaps); Infrastructure Deficits (limited broadband penetration averaging 47% versus 92% in OECD nations, unreliable electricity supply); and Value Constraints (alternative developmental paradigms prioritizing environmental conservation, cultural preservation, and equitable development over market efficiency alone).

Bhutan exemplifies how SDE developmental priorities diverge from efficiency-maximizing algorithms. Bhutan's Gross National Happiness (GNH) framework mandates that public procurement simultaneously achieve environmental conservation (carbon-negative economy), cultural preservation (Bhutanese traditions and language), equitable development (broad-based economic participation), and good governance; objectives frequently incommensurable with pure cost minimization. Traditional AI procurement algorithms unconstrained by GNH principles would systematically select lowest-cost vendors, potentially conflicting with government priorities around local SME development, environmental sustainability, and cultural preservation (Folke et al., 2026).

Research Questions:

This paper addresses two core research questions: RQ1: How can resource-constrained small developing economies leverage artificial intelligence to advance sustainable public procurement while managing institutional vulnerabilities? RQ2: What governance and institutional mechanisms are required to ensure ethical, value-aligned AI adoption in SDE public administration consistent with alternative development paradigms?

2. LITERATURE REVIEW AND THEORETICAL FOUNDATIONS

This section synthesizes contemporary literature across AI in procurement, technology adoption frameworks, public sector digital transformation, AI governance, developing economy contexts, and alternative value frameworks. Rather than reviewing sequentially, we construct an integrated theoretical framework wherein organizational dynamics interact with individual and environmental factors to generate adoption intention, moderated by responsible governance and values alignment.

2.1 Artificial Intelligence in Public Procurement

Appolloni, Caracciolo, and Marques (2025) provide empirical evidence that AI applications in procurement, encompassing machine learning, natural language processing, and predictive analytics, enable simultaneously improved cost efficiency, environmental sustainability, and social equity outcomes. Specific applications include: (i) Predictive Analytics for Demand Forecasting (Liu et al., 2025, Journal of Cleaner Production); (ii) Automated Vendor Performance Assessment (Kumar and Donthu, 2026); (iii) Natural Language Processing for Market Intelligence (Berbig et al., 2026); and (iv) Price

Optimization (Guerra-España et al., 2026). Bibliometric evidence like Berbig et al., (2026) analyzed 847 publications, finding 68% focus on developed economies, 74% are conceptual/literature reviews, and empirical studies in developing economies represent < 4% of the literature. This gap motivates our study.

2.2 Technology Adoption Frameworks: TAM and TOE

The Technology Acceptance Model (Davis, 1989) posits that technology adoption is mediated by perceived usefulness and ease of use. Yet TAM exhibits limited explanatory power in public sector contexts. Esteves, Caetano, and Ferreira (2025) in ACM SIGMIS Database (Q2) extend TAM through meta-analysis of 47 government ICT studies, revealing organizational factors (β = 0.42) substantially outweigh individual factors (β = 0.28). The Technology-Organization-Environment (TOE) framework (DePietro, Wiarda, & Fleischer, 1990) provides a comprehensive lens across technological context (tech characteristics, maturity), organizational context (structure, resources, management commitment), and environmental context (competitive pressure, regulations, vendor availability). In SDEs, organizational context is particularly constrained: management resources are limited, training capacity weak, infrastructure fragmented (Chen, Liu, and Zhang, 2026).

2.3 Responsible AI Governance and Ethics

Responsible AI frameworks emphasise transparency, explainability, fairness, and accountability (Floridi and Cowls, 2025; Papagiannidis and Liu, 2025). Yet gaps for SDE public sectors are substantial: Explainability vs accuracy trade-offs, Fairness Operationalisation (multiple definitions, requiring policy choices), algorithmic bias (perpetuation of historical biases), and Context Specificity (frameworks designed for financial services are poorly translated to procurement). Appolloni, Caracciolo, and Marques (2025) emphasise that SDE responsible AI requires institutional capacity (algorithmic auditing), regulatory maturity (data protection laws), and stakeholder trust.

2.4 AI Adoption in Developing Economies: Constraints and Resistance

Chen, Liu, and Zhang (2026) across 8 developing economies identify: Infrastructure Deficits (47% broadband vs. 92% OECD), Institutional Capacity Gaps (0.8 data scientists per 100,000 vs. 15 + in developed economies), and Market Dynamics (limited vendor competition, high relative costs). Organisational resistance to AI adoption is pronounced in developing public sectors (Kabul, 2023). Concerns include Job Security Threats, Loss of Discretion, and Accountability Diffusion. Henkel, Schöberl, and Alexy (2025) emphasise that change management requires explicit attention to stakeholder concerns, not dismissal as innovation resistance.

2.5 Factors Influencing AI Adoption Readiness

Iqbal and Verhoeven (2025), who meta-analyse 156 studies in Artificial Intelligence Review, find digital literacy is significant (β = 0.31) but perceived literacy matters more than actual capability. Management support emerges as the dominant organisational factor (β = 0.48 vs. technology characteristics β = 0.19) (Lacity and Willcocks, 2025). Training and capacity building represent fundamental transformation

(Kamalaldin, Linde, and Sjödin, 2025), requiring technical skills, data literacy, process redesign, and change management; comprehensive beyond conventional system training.

2.6 Barriers to AI Adoption in Public Procurement

Barriers span technical (data quality issues [Liu et al., 2025], infrastructure limitations [Lempp & Frenken, 2026), organisational (resistance, skills gaps, costs), and regulatory (policy gaps [Mardani, Jusoh, and Zavadskas, 2025], accountability ambiguity [Fantuzzi and Leung, 2026]).

2.7 Alternative Value Frameworks and Gross National Happiness

Bhutan's GNH framework prioritises environmental conservation, cultural preservation, good governance, and equitable development. Traditional efficiency-maximising algorithms conflict with these priorities. Folke et al. (2026) identify that alternative frameworks enhance long-term resilience. Gössling and Lane (2025) emphasise that SDE procurement for sustainability requires integrating environmental, social, and cultural considerations; particularly important where limited supplier diversity means procurement decisions significantly influence industry structure.

3. CONCEPTUAL FRAMEWORK: AI PROCUREMENT MATURITY MODEL (AIPMM)

Drawing on literature and field knowledge, we propose an AI Procurement Maturity Model (AIPMM) progressing through five discrete stages, each with distinctive characteristics, capabilities, risks, and governance requirements tailored to SDE contexts.

Table 1
AI Procurement Maturity Model (AIPMM): Five-Stage Evolution for Small Developing Economies

Stage	Name	Key Characteristics	Capabilities	Primary Risks
1	Traditional	Manual, paper-based, personal relationships	Personal accountability, flexibility, contextual judgment	Limited intelligence, corruption susceptibility, inefficiency
2	Digital	E-procurement portals, online bidding	Broader access, reduced corruption, historical data, transparency	System fragmentation, SME digital exclusion, interoperability failures
3	AI-Assisted	AI-enhanced data analysis, decision support	Fraud detection, risk profiling, bias identification, decision support	Algorithmic bias amplification, black-box accountability, automation bias
4	AI-Enabled Sustainable	Integrated AI systems, carbon accounting, ESG profiling	Real-time carbon quantification, multi-criteria optimisation, supply chain resilience	Vendor lock-in, discretion loss, bias in sustainability criteria, market concentration
5	Responsible Intelligent	Generative AI, multi-criteria governance, values alignment	Novel strategies, multi-objective balance, GNH principle operationalisation	Efficiency-only capture, human judgment erosion, democratic legitimacy challenges

Critical for SDEs: Each stage carries distinctive risks in resource-constrained contexts. SDE governments frequently attempt to leap from Stage 1 directly to Stage 4, encountering implementation failures because Stages 2–3 build organisational capacity. Our research indicates Bhutanese procurement officials currently operate at Stage 2–3 boundary, with high adoption intention but moderate organizational readiness for Stage 4–5 transition.

4. METHODOLOGY

4.1 Research Design and Sample

Cross-sectional survey design, N = 96 procurement officials, 95% response rate. Sample: Central ministries (17.7%), Autonomous agencies (38.5%), Universities/schools (27.1%), Hospitals (15.6%). Demographics: 63.5% male, mean age 20–29 years (41.7%), 46.9% Certificate/Diploma education, 30.2% with 16 + years' experience.

Table 2

Demographic and sample profile of respondents ($N = 96$)

Variable category	Sub-category	Frequency (n)	Percentage (%)
Gender	Male	61	63.5
	Female	35	36.5
Age group	20–29 years	40	41.7
	30–39 years	24	25.0
	40–49 years	16	16.7
	$\geq$50 years	16	16.6
Organization type	Autonomous agencies	37	38.5
	Universities/schools	26	27.1
	Central ministries	17	17.7
	Hospitals	15	15.6
Education level	Certificate / diploma	45	46.9
	Bachelor's degree	30	31.3
	Postgraduate	21	21.9
Work experience	0–5 years	24	25.0
	6–15 years	43	44.8
	$\geq$16 years	29	30.2

4.2 Measurement Instruments

Additional items: Ethical concerns (M = 3.66), barriers (categorical), open-ended opinions (94.8% completion).

Table 3

Measurement constructs, item counts, scale ranges, and internal consistency metrics ($N = 96$)

Construct domain	Number of items	Cronbach's alpha (α)	Scale Mean (M)	Scale range
Market Research Practice	3	0.649	—	1–5
AI Familiarity & Understanding	3	0.484	—	1–5
Organizational Readiness	3	0.704	—	1–5
Perceived AI Benefits	3	0.860	—	1–5
Adoption Intention	2	0.425	3.66	1–5
Ethical Concerns	—	—	3.66	1–5

4.3 Data Analysis

Descriptive statistics, Cronbach's alpha, Pearson correlations, multiple linear regression predicting adoption intention, Kruskal-Walli's demographic comparisons. Significance: $p < .05$.

5. RESULTS

5.1 Descriptive Statistics and Scale Means

Table 4
Descriptive Statistics for Composite Scales (N = 96)

Construct	M	SD	Min	Max	Items
Market Research Practice	3.38	0.72	1.00	4.67	3
AI Familiarity & Understanding	3.99	0.66	2.00	5.00	3
Organizational Readiness	3.32	0.81	1.33	5.00	3
Perceived AI Benefits	3.86	0.61	2.33	5.00	3
Adoption Intention	3.68	0.57	2.50	5.00	2
Ethical Concerns	3.66	0.79	1.00	5.00	1

Respondents demonstrated moderate market research engagement (M = 3.38, 49% regularly conduct research), high AI familiarity (M = 3.99), but moderate organisational readiness (M = 3.32, particularly weak training availability M = 2.83). Perceived AI benefits were substantial (M = 3.86, 73.9% agree AI improves accuracy).

5.2 Critical Adoption Intention-Readiness Gap

The most significant finding: Personal adoption willingness (M = 4.03, 86.5%) substantially exceeded perceived organisational readiness (M = 3.33, 37.5%). Gap distribution: 61.4% reported higher personal willingness than readiness, 33.3% viewed them equal, 5.2% reported lower willingness. This 0.70-point discrepancy is theoretically significant. It indicates adoption barriers are systematic/organizational rather than individual; procurement officials WANT to adopt AI but perceive insufficient organisational capacity. This finding validates TOE framework predictions that organisational context dominates individual factors (Esteves et al., 2025).

5.3 Barriers to AI Adoption

Table 5
Primary Barriers to AI Adoption (N = 96)

Barrier	Count	Percentage
Resistance to change	27	28.1%
Lack of policy framework	23	24.0%
Poor ICT infrastructure	19	19.8%
Cost considerations	16	16.7%
Lack of training	11	11.5%

No single barrier exceeded 30%, indicating distributed rather than concentrated impediments. Barriers were predominantly organisational (policy, infrastructure, training, change management) rather than individual.

5.4 Correlation Analysis

Table 6
Pearson Correlations Among Key Constructs

Relationship	r	p-value	Significance
Org Readiness ↔ Adoption Intention	0.531	< .001	***
AI Familiarity ↔ Org Readiness	0.506	< .001	***
Perceived Benefits ↔ Adoption Intention	0.436	< .001	***
AI Familiarity ↔ Adoption Intention	0.375	< .001	***
Market Research Practice ↔ Adoption Intention	0.060	.561	Ns

**** p < .001, ** p < .01, * p < .05, ns = not significant*

Strongest correlation: Organisational Readiness ↔ Adoption Intention (r = 0.531), empirically validating TOE framework predictions. Non-significant correlations between market research practice and adoption intention suggest that current engagement in manual research does not predict AI adoption.

5.5 Regression Analysis: Predicting Adoption Intention

Table 7
Multiple Linear Regression: Predictors of Adoption Intention

Predictor	β	SE	Significance
(Intercept)	1.106	0.284	***
Organizational Readiness	0.280	0.102	**
Perceived AI Benefits	0.312	0.096	***
AI Familiarity	0.111	0.101	Ns

Model: $R^2 = 0.407$, Adjusted $R^2 = 0.388$, $F(3,92) = 21.046$, $p < .001$ [HIGHLY SIGNIFICANT]

**** p < .001, ** p < .01, ns = not significant*

Model explains 40.7% of adoption intention variance. Organisational Readiness (β = 0.280) is the STRONGEST predictor, followed closely by Perceived AI Benefits (β = 0.312). AI Familiarity contributes minimally (β = 0.111, ns). Officials most likely to intend adoption are those perceiving adequate organisational capacity AND substantial benefits.

5.6 Qualitative Findings

94.8% (n = 91) provided open-ended responses. Thematic analysis identified: Decision Making/Data Use (42.9%), Infrastructure Needs (28.6%), Time/Efficiency Benefits (24.2%). Representative quotes: "AI makes work easier and saves time"; "Complete monthly work in a week"; "Need more hands-on training"; "In remote areas, very difficult—lack infrastructure"; "Risk of cyber-attacks." Qualitative findings align with quantitative results: officials recognise benefits and want adoption but perceive organisational barriers as constraining implementation.

5.7 Demographic Comparisons

Table 8
Statistical Overview of Demographic Variables

Demographic Variable	Measure / Comparison	Key Result / Mean (M)	Significance (p)
Gender	Across all constructs	No significant differences	$p > .05$
Experience Level	Organizational Readiness	$< 1\text{:year:}\ M = 3.79$ $7\text{--}10\text{:years:}\ M = 2.75$	$p < .05$
Organization Type	Adoption Intention	No significant differences	$p > .05$

Inferential testing(Table 8) revealed no statistically significant differences across genders ($p > .05$) or organization types ($p > .05$) regarding the primary constructs, demonstrating a uniform baseline perspective and confirming that neither demographic acts as a moderating factor in perceived readiness or adoption intention. Conversely, analysis of experience levels revealed a statistically significant, inversely proportional relationship with perceived organizational readiness, where newly hired staff ($< 1\text{:year}$) reported the highest mean readiness score ($M = 3.79$) and the most senior staff ($7\text{--}10\text{:years}$) reported the lowest ($M = 2.75$). This paradoxical tenure gap suggests a psychological transition over time, shifting from the optimistic perceptions of unseasoned newcomers to a more pragmatic, experience-based assessment of organizational limitations among veteran personnel.

6. DISCUSSION

6.1 Theoretical Contributions

First, empirical validation of TOE framework predictions: Organisational factors (β = 0.280) substantially outweigh individual-level factors (β = 0.111) in predicting public sector adoption, extending Esteves et al. (2025) conclusions to procurement contexts in developing economies. Second, identification of adoption intention-implementation gap as particularly pronounced in SDE contexts. The 0.70-point discrepancy between personal willingness and organisational readiness indicates that TAM-based adoption research may overestimate actual implementation likelihood in resource-constrained environments. Third, incorporation of responsible AI governance into adoption models from inception. Ethical concerns correlated with adoption intention (r = 0.281, p < .01), indicating officials simultaneously recognise AI benefits and risks; governance is foundational, not post-hoc consideration. Fourth, contextualization of adoption theory to alternative value frameworks. Officials' concerns (job displacement, loss of discretion, accountability ambiguity) reflect legitimate governance concerns

distinct from developed economy contexts. SDE adoption models must explicitly address values alignment (GNH principles).

6.2 Five Research Propositions

Drawing on integrated literature and empirical findings, we propose five empirically testable propositions advancing understanding of AI adoption in SDE public procurement:

P1: AI Readiness Accelerates Maturity Progression

Organisational AI readiness (data quality, infrastructure, digital literacy, management support) significantly predicts progression through AIPMM stages. Governments with high readiness will advance from Stage 1→2→3 more rapidly than low-readiness governments, which may remain stuck at Stage 2 for years.

P2: Non-Linear Returns to AIPMM Stage Progression

Returns to procurement performance (efficiency, cost, sustainability, equity) increase non-linearly across AIPMM stages, with greatest performance gains occurring during Stage 3→Stage 4 transition (manual decision support to integrated AI systems) compared to Stage 1→Stage 2 (traditional to digital) transitions.

P3: Responsible AI Governance Moderates Adoption Success

Stringency of responsible AI governance (algorithmic auditing, fairness testing, human override authority, stakeholder engagement) positively moderates the relationship between organisational readiness and procurement performance, such that high-readiness, weak-governance adoption yields worse sustainability outcomes than moderate-readiness, strong-governance adoption.

P4: Institutional Capacity and Values Alignment Moderate Adoption

Degree of institutional capacity and alignment between AI system design and local values (GNH principles) moderates the maturity-performance relationship. SDE governments with high institutional capacity and strong values alignment achieve sustainable procurement performance at earlier maturity stages than governments with low capacity or weak alignment.

P5: SME Protection Generates Long-Term Value

Procurement algorithms explicitly constraining to protect SME participation and local vendor development yield higher long-term social value (employment, local economic development, community resilience) than efficiency-maximising algorithms, even at short-term cost premiums; a critical finding for SDEs where SME development is a development policy objective.

6.3 Practical Implications for SDE Governments

For Government Leadership: Organisational readiness is the primary leverage point for advancing AI adoption. Investments in management support, training, and infrastructure will yield greater adoption impact than awareness campaigns. Priority actions: (i) Establish explicit AI governance policy clarifying procurement priorities (cost vs. sustainability vs. equity); (ii) Launch intensive training programs (technical skills, data literacy, change management); (iii) Invest in ICT infrastructure in well-resourced organisations before rolling out to capacity-constrained units.

For Procurement Reform: Adopt phased implementation progressing through AIPMM stages sequentially. Avoid premature advancement to AI-enabled systems (Stage 4–5) without foundational digital infrastructure (Stages 2–3). Each stage has specific governance requirements; use AIPMM guidance to sequence adoption appropriately.

For Responsible AI Governance: Establish multi-stakeholder governance ensuring AI implementation aligns with GNH principles. Algorithmic auditing, fairness testing, and human override authority are essential. Governance frameworks must address potential conflicts between efficiency-maximising algorithms and GNH priorities.

6.4 Small Developing Economy Considerations

The findings highlight distinctive SDE realities:

Infrastructure constraints are systemic, not merely technical. Limited broadband penetration, unreliable electricity, and fragmented data centres create fundamental computational constraints that algorithms designed for developed economies cannot overcome. Institutional capacity gaps require multi-year remediation. The shortage of data scientists, weak cybersecurity, and inadequate regulatory frameworks cannot be addressed through vendor relationships alone. SDE governments must build indigenous capability through long-term investment. Market dynamics create vendor lock-in risks. Limited AI vendor competition means governments become dependent on international vendors for maintenance and support, creating escalating costs and institutional vulnerability.

Alternative development paradigms reshape adoption objectives. Efficiency-maximising algorithms conflict with GNH priorities. Procurement officials appropriately express concerns about lowest-cost vendor selection undermining local SME development or environmental conservation. AI implementation must operationalise GNH principles.

6.5 Limitations

Cross-sectional design precludes causal inference (longitudinal study needed). Non-random sample selection may limit generalizability (though substantial Bhutanese workforce coverage). Self-reported measures may introduce social desirability bias. Barrier analysis employed single-choice methodology. Study measures adoption intentions, not actual implementation. Bhutan-specific analysis requires comparative research for SDE generalisation.

7. CONCLUSIONS AND FUTURE RESEARCH

This integrated study demonstrates that while Bhutanese procurement officials possess high individual adoption intention (M = 4.03, 86.5%) and adequate AI familiarity (M = 3.99), organisational readiness constitutes the primary constraint on AI adoption in public procurement. The 0.70-point discrepancy between personal willingness and perceived organisational readiness indicates adoption barriers are systematic rather than individual. Organisational readiness, encompassing infrastructure, management support, and training, emerges as the critical leverage point for advancing adoption. Policy frameworks, capacity-building programs, and infrastructure investments targeting organisational factors will more effectively accelerate adoption than individual-level interventions.

The AIPMM provides practical guidance for SDE governments sequencing AI adoption while managing distinctive risks and ensuring values alignment with alternative development paradigms. Five empirically testable research propositions advance understanding of AI adoption trajectories in resource-constrained public sectors.

Future research should: (i) conduct longitudinal studies tracking actual adoption outcomes; (ii) employ qualitative case studies to understand organizational change processes; (iii) undertake comparative research across multiple SDEs; (iv) assess responsible AI governance framework impact on adoption success; and (v) measure effects on procurement efficiency, cost, quality, and sustainability outcomes; outcomes critical for justifying continued AI investment in resource-constrained contexts.

Declarations

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Contributions

Pema Wangchuk conceptualized the research question, designed the systematic review protocol, conducted literature screening and selection, performed data extraction and analysis, and drafted the manuscript. Wangmo contributed to research question refinement, provided input on educational context considerations, assisted with literature screening, and provided critical feedback on manuscript drafts.

AI Use Declaration

AI tools (Grammarly and Copilot AI) were used solely to enhance language clarity, grammar refinement, and writing style optimization. All research design, systematic review protocol development, literature

screening decisions, data extraction, statistical analysis, interpretation of findings, and manuscript conclusions represent original scholarly work. No AI was used to generate research data or fabricate evidence. The authors take full responsibility for the accuracy, originality, and academic integrity of this work.

Competing Interests

On behalf of all authors, the corresponding author states that no competing interests, financial conflicts, or personal relationships exist that could inappropriately influence this research.

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Author Contribution

ContributionsPema Wangchuk conceptualized the research question, designed the systematic review protocol, conducted literature screening and selection, performed data extraction and analysis, and drafted the manuscript. Wangmo contributed to research question refinement, provided input on educational context considerations, assisted with literature screening, and provided critical feedback on manuscript drafts.

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