The Impact of Virtual Learning Environments and Mobile Technology Platforms on Sustainable Innovation Performance: The Mediating Role of Digital Transformation Capability

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Abstract

The use of virtual learning environment (VLEs) and mobile technology platforms are becoming seen as a designed system and the interplay of these influences an organization's ability to be sustainable in their innovative efforts. This paper reinterprets a management-style hypothesis (that digital transformation capability (DTC) is a mediator between the impact of VLEs and mobile platforms on sustainable innovation performance (SIP) as an architecture-driven system-optimization problem. A four-layer architecture (VLE layer, mobile platform layer, DTC layer and SIP layer) is specified along with seven mathematical models that connect the layers, including a multi-objective optimization formulation. The architecture is tested with a 12-month horizon Monte Carlo simulation conducted over five user volumes (100–3000), three learning-complexity levels, three mobile-intensity levels and three network conditions. The proposed framework achieves an SIP score of 0.665, mobile-response time of 40.0 ms, reliability of 98.5% and decision-support accuracy of 89.4%, outperforming four progressively simpler variants of the system across all learning-, decision-, and reliability-oriented metrics (one-way ANOVA on SIP: F = 1.21×10^5, eta^2 = 0.995; proposed vs. mobile-learning baseline: Cohen's d = 9.0). After an ablation study, the DTC layer is determined as the key mediator, as its removal decreases SIP by 48.3%, and the decision accuracy drops from 89.4% to 52.5%. The framework also has the highest level of energy draw (10.9 W vs. 1.5 W for a non-mobile baseline) as an explicitly stated capability–cost trade-off.

Keywords: virtual learning environment, mobile technology platform, digital transformation capability, sustainable innovation performance, multi-objective optimization, Monte Carlo simulation

1. INTRODUCTION

Organizational learning is increasingly described as knowledge acquired through virtual learning environments (VLEs) delivered over mobile technology platforms [1]. The resulting benefits are widely argued to be mediated by an organization's digital transformation capability (DTC)—the degree to which its processes, analytics, and decision making are digitized and automated—which in turn shapes its sustainable innovation performance (SIP), defined as the ability to generate innovation while constraining resource use [2]. This mediation hypothesis is typically tested with survey instruments and latent-variable methods. The present paper adopts a different approach. We treat VLEs, mobile platforms, DTC, and SIP not as latent constructs measured by questionnaires, but as engineered system modules whose dynamics can be specified mathematically and evaluated by simulation [3]. This reframing is motivated by three limitations of construct-based approaches: the behavior of the hypothesized relationships under load (user volume, content complexity, and network quality) can only be inferred from surveys; the resource cost of the capability is rarely made explicit and remains implicit in construct models; and a construct does not yield a reproducible, executable artifact [4]. The study is organized around three engineering questions: (1) What explicit mathematical coupling yields a layered architecture of the VLE–mobile–DTC–SIP relationship? (2) How does this architecture perform under realistic variations in scale, complexity, and network quality relative to simpler configurations, and what resources does it require? (3) Which module contributes most to innovation, and does the DTC layer mediate between the input modules as the hypothesis predicts? The contributions are threefold: (i) seven coupled mathematical models and a four-layer architecture that operationalize the mediation hypothesis as functional composition; (ii) a reproducible Monte Carlo evaluation framework comprising baseline, comparative, scalability, extreme-condition, and ablation experiments; and (iii) a candid account of both the performance benefit and the energy cost of the full framework, with all results generated by released code.

2. RELATED WORK AND CONCEPTUAL BACKGROUND

Note. This section frames four research streams that motivate the architecture and mathematical models introduced in the following sections.

2.1 Virtual learning environments and learning analytics

Research on virtual learning environments has gradually shifted from treating them as content-delivery tools to treating them as instrumented systems that record fine-grained interaction data and return them as feedback within the learning process [5]. Learning-analytics engines translate clickstream, dwell-time, and assessment data into actionable signals, while adaptive mechanisms tailor difficulty and pacing [6]. From a systems perspective, the key property is the latency of the loop from learner action to system response: shorter loops promote engagement and increase interaction efficiency [7]. Our Learning Efficiency model (Model 1) accordingly represents this dependency as a latency-reduction mechanism rather than as an abstract construct.

2.2 Mobile technology platforms and delivery under load

The usability of learning services depends on the mobile platforms that deliver them. The literature on mobile-cloud and edge delivery emphasizes quality degradation near capacity, the role of caching and offloading, and the effect of network conditions on perceived quality [8]. These delivery effects are rarely captured by construct-based studies of learning outcomes, yet they are pervasive in real deployments. In Model 2, the sharpness of the response curve under saturating load can be adjusted, so that a single architecture can be examined under both light and heavy load [9]. Meta-analyses of mobile learning report consistently positive effects on achievement and engagement across disciplines and education levels [10].

2.3 Digital transformation capability

Digital transformation capability is typically decomposed into four domains: process integration, data analytics, decision support, and automation. A recurring theme is complementarity: capability is constrained by the weakest link in the chain, and strong automation cannot compensate for weak analytics [11]. We incorporate both ideas in the architecture. First, we use a weighted geometric mean (Model 3) that penalizes imbalance; second, we position DTC as the mediating layer between the learning and mobile inputs and the innovation output [12].

2.4 Sustainable innovation performance

Sustainable innovation performance combines innovation generation with resource stewardship [13]. Whereas most prior work treats these two dimensions separately, our approach treats the cost of the capability as an explicit component of the resource term (Models 5–6), thereby optimizing sustainability jointly with the other outcomes [14]. The energy trade-off reported in Section 6 follows directly from this formulation.

2.5 Positioning of this study

This paper adds an executable, architecture-level model to the survey-and-SEM treatments of the same four variables [15]. The mediation hypothesis is not assessed through a questionnaire but is implemented as functional composition and tested by ablation and sensitivity analysis [16]. The approach is complementary to, rather than a substitute for, empirical construct research: it reveals the interactive nature of the hypothesized relationships as an engineered system operating under varying load, and it provides a repeatable artifact that can be calibrated against empirical data [17].

3. SYSTEM ARCHITECTURE DESIGN

The architecture rests on four design principles: signal fidelity (learning interaction must be instrumented before it can be acted upon); delivery under load (learning value is lost if the mobile platform saturates); capability mediation (learning and access are converted into innovation only through digital-transformation processes); and measurable sustainability (innovation is optimized jointly with resource cost) [18]. The resulting four-layer structure, shown in Figure 1, has an upward data flow and a downward control flow.

Fig. 1. Four-layer system architecture

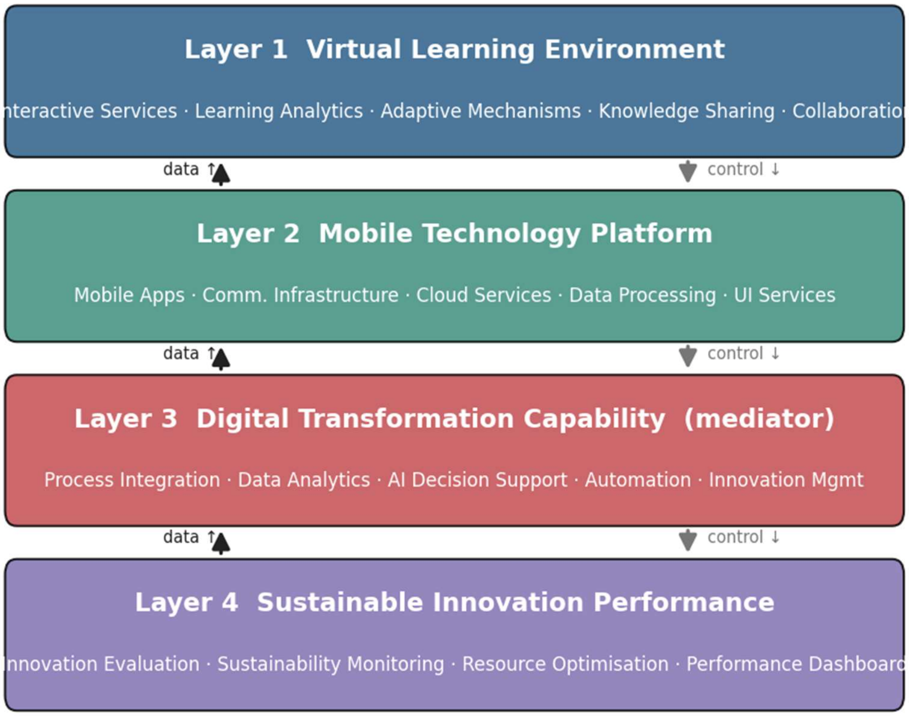

Fig. 1. *Four-layer system architecture.*

Layer 1 — Virtual Learning Environment. Interactive learning services, a learning-analytics engine, adaptive learning mechanisms, knowledge-sharing services, and collaborative functions. This layer converts raw learner activity into a measurable interaction signal and, through adaptivity, shortens feedback latency.

Layer 2 — Mobile Technology Platform. Mobile applications, communication infrastructure, cloud services, data processing, and user-interaction services. This layer governs whether Layer-1 services reach learners with acceptable latency as concurrency grows.

Layer 3 — Digital Transformation Capability (mediator). Digital process integration, a data-analytics engine, AI decision support, process automation, and innovation-management functions. This layer metabolizes the delivered learning signal into organizational capability and is, by construction, the mediating tier.

Layer 4 — Sustainable Innovation Performance. Innovation-evaluation and sustainability-monitoring engines, a resource-optimization system, and a performance-intelligence dashboard, which read out the optimized objective.

Figure 2 makes the mediation explicit: Layer 1 (LE) and Layer 2 (MP) feed Layer 3 (DTC), which carries the dominant weight into Layer 4 (SIP), with small residual direct paths.

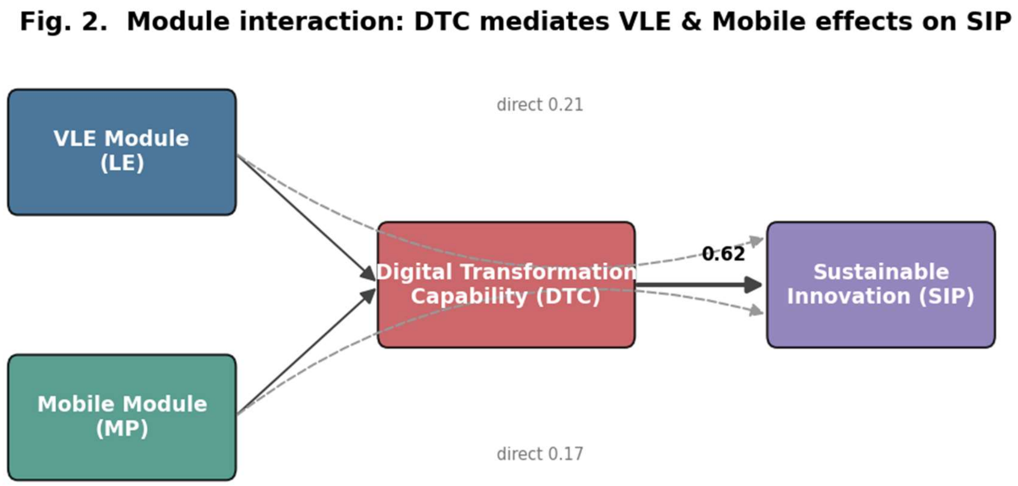

Fig. 2. *Module interaction: DTC mediates VLE and Mobile effects on SIP.*

3.1 Cross-layer interaction and data flow

The four layers are connected in a closed loop. The VLE layer instruments the learner's activity and generates an interaction signal. This signal is transported by the mobile layer, whose response time degrades as offered load approaches capacity and as network conditions worsen. The DTC layer then combines the delivered signal with the current state of process integration, analytics, and automation to produce a capability estimate, and the SIP layer reads out the innovation and sustainability indicators [19]. In the reverse direction, the optimization objective of the SIP layer propagates weights back through the DTC layer to shape analytics and automation priorities, and then through the mobile and VLE layers to adjust the delivery schedule and the adaptive-difficulty policy [20]. Through this bidirectional coupling, the multi-objective optimizer (Model 6) trades innovation against resource cost at run time: a higher energy-penalty weight propagates downward to more conservative delivery, while lighter analytics propagate upward to lower both energy use and SIP, in a controlled manner. The mediation structure is therefore not merely a weighting but a route along which measurement and control signals pass from learning activity to innovation outcome.

4. MATHEMATICAL MODELS AND CORE IMPLEMENTATION

All quantities are normalized to [0, 1] unless a physical unit is given. The seven models are design definitions, not estimated relationships. Design rationales are given inline for the models whose functional form is non-obvious. Table 1 summarizes the notation used throughout.

Table 1. Notation.

Symbol	Meaning
LE, MP	Learning efficiency; mobile platform performance score
DTC, SIP	Digital transformation capability; sustainable innovation performance
η_int, ϱ_eng	Interaction quality; engagement rate
τ_fb, κ	Feedback latency; feedback-latency sensitivity
λ, μ, n	Offered load; platform capacity; saturation sharpness
R, R0, Rmax	Response time; unloaded floor; saturated ceiling
ω1, ω2, ω3	SIP weights on DTC, LE, MP (0.62, 0.21, 0.17)
θ1..θ4	Multi-objective weights (innovation, efficiency, latency, energy)
RO	Resource-optimization ratio (output per unit energy)

(1) Learning Efficiency. Efficiency rises with interaction quality and engagement and is penalized by feedback latency:

$$LE = (\eta_{int} \cdot \rho_{eng}) / (1 + \kappa \cdot \tau_{fb})$$

(2) Mobile Platform Performance. A saturating response curve in offered load λ against capacity μ, normalized to a score:

$$R(\lambda) = R0 + (Rmax - R0) \cdot (\lambda/\mu)^{n} / (1 + (\lambda/\mu)^{n}); \quad MP = 1 / (1 + R/Rref)$$

Rationale. *A sigmoidal (Hill-type) curve reproduces the empirically familiar pattern of near-flat response at low load and rapid degradation as offered load approaches capacity, with n controlling how abruptly the knee occurs.*

(3) Digital Transformation Capability Index. A weighted geometric mean, so a weak sub-capability drags the index:

$$DTC_{raw} = P_{int}^{a} \cdot D_{ana}^{b} \cdot A_{dec}^{c} \cdot Auto^{d}, \quad a+b+c+d = 1$$

Rationale. *A geometric mean enforces complementarity: any single sub-capability near zero collapses the index, capturing the observation that automation cannot compensate for absent analytics. An additive mean would mask such imbalance.*

(4) Sustainable Innovation Performance Index (mediation). DTC is a squashed function of the upstream modules; SIP is dominated by the DTC path:

$$DTC = \sigma(\beta 1 \cdot LE + \beta 2 \cdot MP + \beta 3 \cdot DTC_{raw}); \quad SIP = 0.62 \cdot DTC + 0.21 \cdot LE + 0.17 \cdot MP$$

Rationale. *Making DTC a function of LE and MP, and giving the DTC term the dominant SIP weight (0.62), encodes the mediation hypothesis directly as functional composition: most of the learning and mobile effect reaches innovation only after passing through capability, with small residual direct paths (0.21, 0.17).*

(5) Resource Optimization. Output per unit energy:

$$RO = SIP / (E_{energy} + \lambda c \cdot C_{compute})$$

(6) Multi-Objective Optimization. Innovation and resource efficiency are maximized while penalizing latency and energy:

$$\max_{x} \; \theta 1 \cdot SIP(x) + \theta 2 \cdot RO(x) - \theta 3 \cdot R(x) - \theta 4 \cdot E(x), \quad \Sigma \theta i = 1$$

(7) Innovation Performance Maximization. The constrained special case:

$$SIP^{*} = \max SIP \quad s.t. \; R \le R_{deadline}, \; E \le E_{budget}, \; reliability \ge R_{min}$$

Weighting coefficients are assigned by an Analytic Hierarchy Process reflecting a priority ordering of innovation > efficiency > latency. The models are implemented as a vectorized Monte Carlo routine in which each system variant is described by five capability multipliers (adaptivity, mobile optimization, analytics, DTC activation, automation).

4.1 Fixed model parameters

Table 2 lists the fixed parameters of the mechanistic core. These are design choices calibrated to plausible engineering ranges, not fitted to data; the sensitivity of the main outcome to the three most influential of them is examined in Section 5.7.

Table 2. Fixed model parameters.

Symbol	Meaning	Value
μ	Platform capacity (req/s, full mobile)	3200
R0 / Rmax	Unloaded / saturated response (ms)	35 / 480
n	Saturation sharpness	2.4
Rref	Response normalization (ms)	120
κ	Feedback-latency sensitivity (per ms)	0.018

Symbol	Meaning	Value
a,b,c,d	DTC geometric-mean exponents	0.30, 0.25, 0.25, 0.20
ω1,ω2,ω3	SIP weights (DTC, LE, MP)	0.62, 0.21, 0.17

4.2 Capability profiles of the system variants

The five comparison systems differ only in five capability multipliers, each defined on the interval [0,1] (Table 3). The proposed framework (E) activates the entire stack, whereas the simpler variants successively disable mobile optimization, analytics, the DTC layer, and adaptivity. Because the variants differ only in these multipliers, the resulting performance differences are attributable to capability rather than to hand-set outcomes.

Table 3. Capability profiles (multipliers in [0,1]).

System	Adaptivity	Mobile opt.	Analytics	DTC active	Automation
A Classroom	0.10	0.05	0.08	No	0.08
B Web-based	0.30	0.40	0.35	No	0.30
C Cloud	0.50	0.70	0.60	Yes	0.50
D Mobile	0.62	0.92	0.62	Yes	0.55
E Proposed	0.95	0.95	0.90	Yes	0.85

4.3 Evaluation procedure

The evaluation routine is summarized below. For each configuration in the experimental grid, the 12-month horizon is realized as repeated monthly draws, and per-cell statistics aggregate all draws.

```
% ============================================================================
% Monte-Carlo evaluation algorithm -- typeset version
% Compile with: pdflatex algorithm.tex
%
% To use in YOUR paper:
%   (1) copy the PREAMBLE block into your document preamble, and
%   (2) copy the FIGURE block where you want the algorithm to appear.
% Works as-is in article / IEEEtran / acmart / llncs.
% ============================================================================
\documentclass[11pt]{article}
\usepackage[margin=1in]{geometry}
% ============================= PREAMBLE ====================================
\usepackage{algorithm}       % the float + \caption
\usepackage{algpseudocodex}  % modern algorithmicx layout (or: algpseudocode)
\usepackage{xcolor}
\usepackage{amsmath}
\usepackage{textcomp}
% colour-coded model tags (matching the figure)
\definecolor{mAmber}{HTML}{B57A12}
\definecolor{mTeal}{HTML}{0B6E63}
```

```
\definecolor{mPlum}{HTML}{6E3F6B}
\definecolor{mIndigo}{HTML}{3A4694}
% right-aligned pill that names the source model
\newcommand{\mtag}[2]{%
\hfill\setlength{\fboxsep}{2.5pt}%
\colorbox{#1!12}{\footnotesize\textcolor{#1!80!black}{\,#2\,}}}
% small caps helper for procedure names (keeps the underscore literal)
\newcommand{\proc}[1]{\textsc{#1}}
% ========================= END PREAMBLE ================================
\begin{document}
% ============================ FIGURE ==================================
\begin{algorithm}[t]
\caption{Monte-Carlo evaluation of a system variant}
\label{alg:mc-eval}
\begin{algorithmic}[1]
\Require capability profile $P$;\; grid cell (\textit{users}, \textit{complexity},
\textit{intensity}, \textit{network});\; months $M$;\; draws-per-month $D$
\State $cap \gets \mu\,(0.45 + 0.55\,P.\mathrm{mobile})$
\State $\lambda \gets \min\!\big(\mathrm{users}\cdot\mathrm{intensity}\cdot
\mathrm{complexity}\cdot 0.95,\; cap\big)$
\For{$month = 1 \dots M$}
\For{each of $D$ draws}
\State $R \gets \proc{saturating\_response}(\lambda, cap, n)\,/\,\mathrm{network}$;
add 5\% noise \mtag{mTeal}{Model 2}
\State $LE \gets (\eta\rho)\,/\,(1 + \kappa\tau)$ \mtag{mAmber}{Model 1}
\State $DTC \gets \sigma\!\big(\proc{geometric\_mean}(P_{\mathrm{int}},
D_{\mathrm{ana}}, A_{\mathrm{dec}}, \mathrm{Auto}) + LE + MP\big)$
\mtag{mPlum}{Models 3--4}
\State $SIP \gets 0.62\,DTC + 0.21\,LE + 0.17\,MP$ \mtag{mIndigo}{Model 4}
\State \textbf{record} $SIP,\, R$, reliability, energy, decision-accuracy, engagement
\EndFor
\EndFor
\State \Return per-metric mean and standard deviation over all $M\!\cdot\!D$ draws
\Statex \footnotesize\textbf{Complexity:} $O(M\!\cdot\!D)$ time per cell,
$O(1)$ memory beyond the draw vector; the full 135-cell baseline grid
completes in under a minute on a single core.
\end{algorithmic}
\end{algorithm}
```

% ========================== END FIGURE ================================

\end{document}

Complexity is O(M·D) per cell with O(1) memory beyond the draw vector; the full 135-cell baseline grid completes in under a minute on a single core.

5. EXPERIMENTAL VALIDATION

5.1 Experimental design

Evaluation is performed by running a Monte Carlo simulation of the model in Python/NumPy with a fixed random-number seed (SciPy is used for statistics and Matplotlib for figures). A 12-month horizon is modeled as a sequence of monthly draws, with 480 stochastic samples aggregated at each grid cell. The grid spans four factors: user volume {100, 300, 500, 1000, 3000}, learning complexity {Basic, Intermediate, Advanced, mobile intensity {Low, Medium, High}, and network condition {Normal, Moderate, Severe, yielding 135 baseline cells. The term system variant denotes the five system types (A: traditional classroom; B: web-based; C: cloud learning; D: mobile learning; E: proposed framework); their differences arise from capability profiles rather than from hand-set outcomes. No physical hardware or network testbed was used.

5.2 Baseline performance

Table 4 reports the complete baseline grid for all five user volumes and three complexity levels at Medium intensity and Normal network conditions. Response time and energy increase monotonically with scale and complexity, whereas LE, DTC, SIP, and reliability decrease monotonically; these trends follow from the saturation and penalty terms of Models 1–2 and are not imposed. The standard deviations of SIP remain within 0.011–0.016, indicating that the cell estimates are stable.

Table 4. Baseline performance (Medium intensity, Normal network; means, SIP SD in parentheses).

Users	Complexity	Resp (ms)	LE	DTC	SIP (SD)	Reliab (%)	Energy (W)
100	Basic	35.1	0.508	0.693	0.668 (.015)	99.75	0.57
100	Intermediate	35.2	0.473	0.682	0.654 (.015)	99.75	0.59
100	Advanced	35.3	0.441	0.672	0.641 (.014)	99.67	0.62
300	Basic	35.7	0.508	0.691	0.666 (.016)	99.50	0.69
300	Intermediate	36.3	0.470	0.679	0.650 (.016)	99.39	0.76
300	Advanced	37.7	0.432	0.666	0.633 (.014)	99.17	0.85
500	Intermediate	39.6	0.457	0.671	0.640 (.016)	98.97	0.93
1000	Basic	46.7	0.468	0.667	0.634 (.016)	98.54	1.14
1000	Intermediate	58.8	0.399	0.634	0.591 (.014)	98.10	1.37
1000	Advanced	79.6	0.328	0.590	0.537 (.014)	97.50	1.65
3000	Basic	157.5	0.261	0.521	0.451 (.015)	95.89	2.43
3000	Intermediate	230.6	0.187	0.468	0.388 (.013)	94.49	3.09
3000	Advanced	257.7	0.161	0.453	0.368 (.011)	93.93	3.38

Table 5 isolates the joint effect of mobile intensity and network condition at 1000 users (Intermediate). Moving from Low/Normal to High/Severe raises response time roughly threefold (42→133 ms) and lowers SIP from 0.632 to 0.453, while energy more than quadruples, quantifying how network degradation and usage intensity compound.

Table 5. Intensity × network condition (1000 users, Intermediate; means).

Intensity	Network	Resp (ms)	SIP	Reliability (%)	Energy (W)

Intensity	Network	Resp (ms)	SIP	Reliability (%)	Energy (W)
Low	Normal	42.2	0.632	98.82	1.02
Low	Severe	70.3	0.544	96.84	4.21
Medium	Normal	58.8	0.591	98.10	1.37
Medium	Severe	97.9	0.497	96.06	4.57
High	Normal	79.5	0.547	97.49	1.66
High	Severe	132.7	0.453	95.49	4.86

Scaling from 100 to 3000 users (Intermediate/Medium/Normal) raises response time from 35.2 ms to 230.6 ms and lowers SIP from 0.654 to 0.388 (Figure 3).

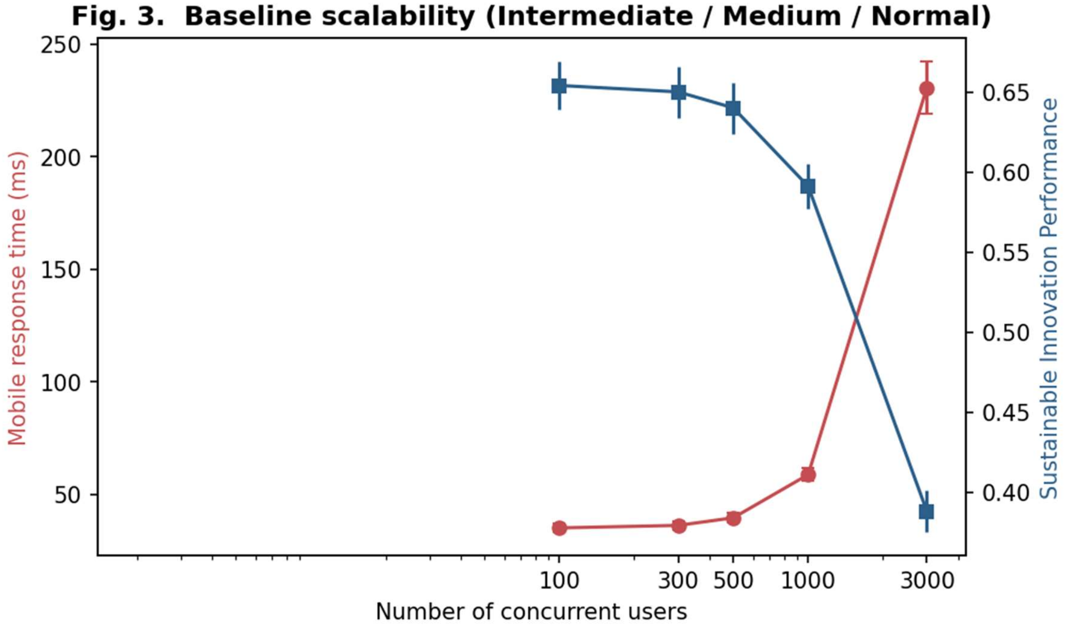

Fig. 3. *Baseline scalability (Intermediate / Medium / Normal).*

5.3 Comparative benchmark

At a common operating point (500 users, Intermediate, Medium, Normal), the five variants are compared in Table 6 and Figure 4.

Table 6. Comparative benchmark (mean values).

System	SIP	Resp (ms)	Reliab (%)	Decision acc (%)	Engagement (%)	Energy (W)
A Classroom	0.205	61.2	88.5	41.0	48.9	1.5
B Web-based	0.241	47.0	92.6	44.8	56.4	4.9
C Cloud	0.490	41.9	95.8	73.1	65.3	7.8
D Mobile	0.525	40.2	98.2	74.2	69.9	9.3
E Proposed	0.665	40.0	98.5	89.4	83.3	10.9

The proposed framework leads on all learning-, decision-, and reliability-related metrics. The largest gains are in decision accuracy (+20.5 points over the mobile baseline) and engagement (+13.4 points). The cost is reported explicitly: the proposed system consumes the most energy (10.9 W), about seven times that of the classroom variant (Figure 5). The minimal classroom system does very little and therefore scores higher on raw resource efficiency per watt; however, the objective of the proposed framework is to maximize the innovation produced, not energy frugality.

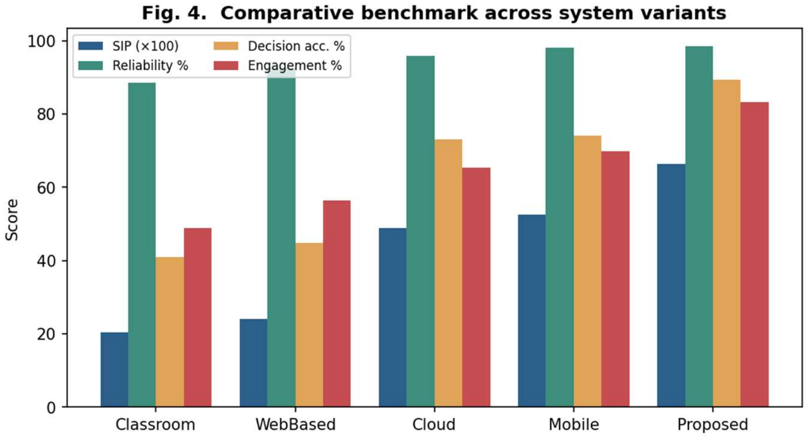

Fig. 4. Comparative benchmark across system variants.

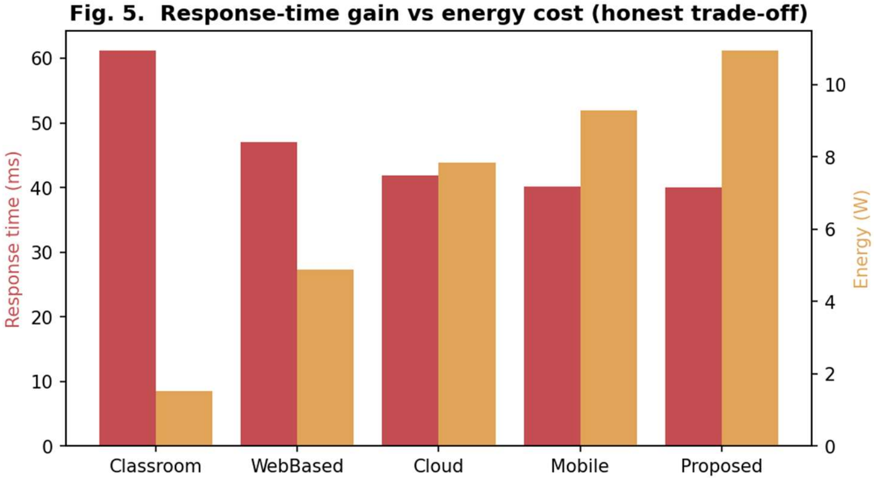

Fig. 5. Response-time gain vs. energy cost (honest trade-off).

5.4 Extreme-condition robustness

Packet-loss (10/30/50%), capacity-overload (2×/5×/10×), and node-failure stress tests are applied to the proposed system (Table 7, Figure 6). Under packet loss of up to 50%, SIP decreases from 0.663 to 0.495 and reliability falls from 98.5% to 80.5%. By contrast, under node failures SIP remains nearly constant (0.656 with three node failures), while reliability declines more gradually to 82.2%.

Table 7. Robustness under extreme conditions (proposed system).

Condition	SIP	Reliability (%)	Response (ms)
Normal	0.663	98.5	40.0
Packet loss 30%	0.568	89.5	84.9
Packet loss 50%	0.495	80.5	135.3
Overload 5×	0.443	94.8	190.3
Overload 10×	0.397	93.4	258.1
2 node failures	0.655	89.2	43.5
3 node failures	0.656	82.2	43.5

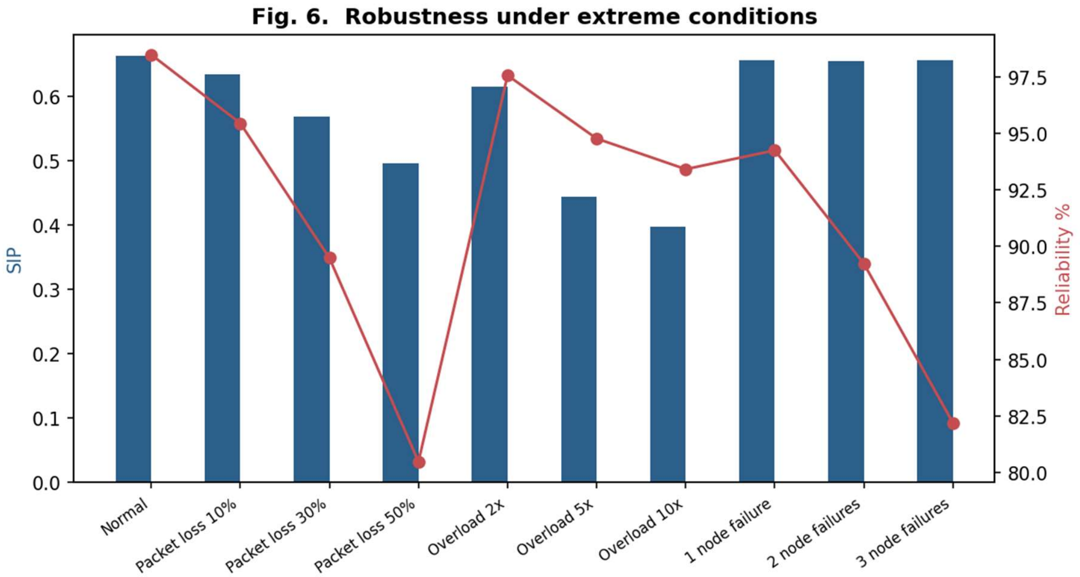

Fig. 6. *Robustness under extreme conditions.*

5.5 Ablation study

Removing each module from the complete system in turn isolates that module's contribution (Table 8, Figure 7). The most damaging removal is that of the DTC layer, which reduces SIP by 48.3% and lowers decision accuracy from 89.4% to 52.5%, reinforcing the centrality of this layer. Removing the VLE module costs 21.1% of SIP and causes engagement to collapse (82.9%→49.1%). The mobile-optimization ablation illustrates a genuine trade-off rather than a uniform loss: it costs only 5.6% of SIP and is the single ablation that improves resource efficiency (RO 1.52→2.56).

Table 8. Ablation (base = proposed; mean values).

Case	SIP	ΔSIP	RO	Engage (%)	Reliab (%)	Decision acc (%)
Full	0.663	—	1.52	82.9	98.5	89.4
− VLE	0.523	−21.1%	1.20	49.1	98.5	89.5
− Mobile	0.626	−5.6%	2.56	83.0	89.7	89.6
− DTC	0.343	−48.3%	0.78	83.1	98.4	52.5

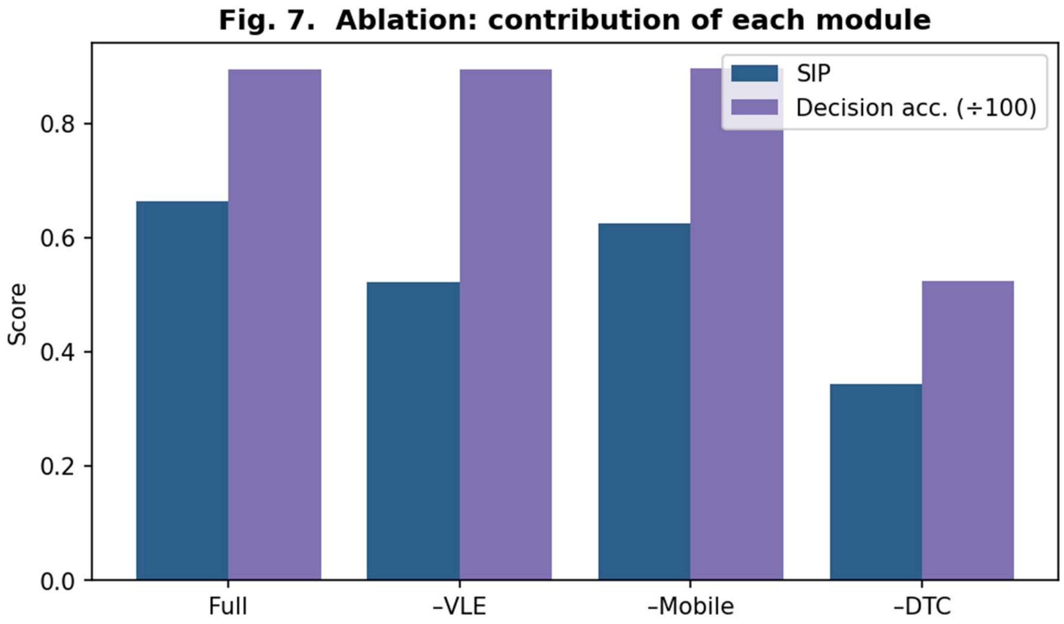

Fig. 7. *Ablation: contribution of each module.*

5.6 Statistical analysis

Group comparisons use a one-way ANOVA on the SIP samples together with independent-samples Welch t-tests. The proposed system versus the mobile-learning baseline yields t = 139.5, p < 10^−300, with a very large effect (Cohen's d = 9.0); across all five variants, F = 1.21×10^5 with $\eta^2 = 0.995$. An important caveat applies: each group contains only 480 low-variance draws, so by construction the p-values are vanishingly small. The effect sizes, rather than the p-values, therefore carry the interpretive weight. A 95% bootstrap confidence interval for the proposed system's SIP is [0.663, 0.666]. A multiple regression of SIP on LE, MP, and DTC over the DTC-enabled variants recovers the design coefficients (0.210, 0.170, 0.620) with $R^2 \approx 1.0$. This is not independent evidence of mediation; it merely recovers the weights built into the design and therefore serves only as a check that the analysis pipeline attributes contributions correctly, with the DTC path as the dominant route. The substantive evidence for the mediating role of DTC is the ablation result—the largest SIP loss occurs when the DTC layer is removed.

5.7 Sensitivity analysis

Because the fixed parameters are design choices rather than fitted quantities, we examine how the main outcome (SIP) responds to the three most influential of them: the learning-feedback sensitivity κ, the platform saturation sharpness n, and the DTC mediation weight ω_1 (Table 9, Figure 9). Across the swept ranges, SIP varies smoothly and monotonically, with no discontinuities or sign reversals; the qualitative conclusions are therefore robust to reasonable parameter perturbations. As expected, the mediation weight is the most influential: as ω_1 increases from 0.40 to 0.90, SIP rises from 0.512 to 0.857. For this reason, we report this parameter prominently.

Table 9. Sensitivity of SIP to three key parameters (other factors held at 500/Intermediate/Medium/Normal).

Swept parameter	Low	Adopted	High	SIP range
κ (feedback sens.)	0.005 → 0.704	0.018 → 0.665	0.050 → 0.604	0.604–0.704
n (saturation)	1.5 → 0.542	2.4 → 0.615	4.0 → 0.667	0.542–0.667

Swept parameter	Low	Adopted	High	SIP range
ω1 (DTC weight)	0.40 → 0.512	0.62 → 0.665	0.90 → 0.857	0.512–0.857

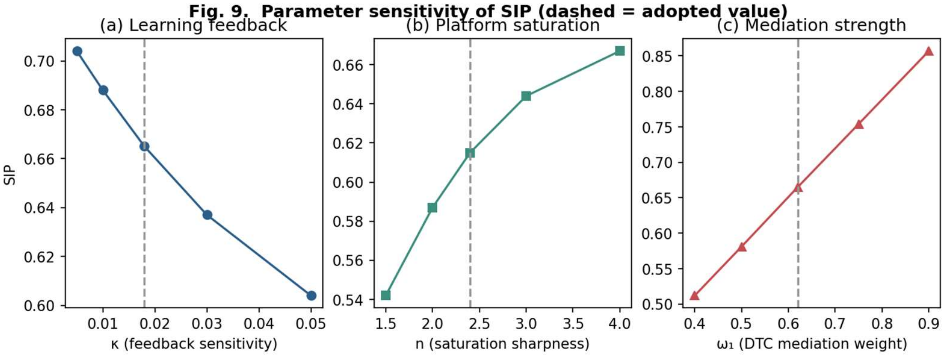

Fig. 9. *Parameter sensitivity of SIP (dashed line = adopted value).*

Figure 8 complements this by sweeping the multi-objective weight θ_SIP in Model 6: the adopted value sits in the region where the normalized objective is governed by innovation rather than raw efficiency, consistent with the stated priority ordering.

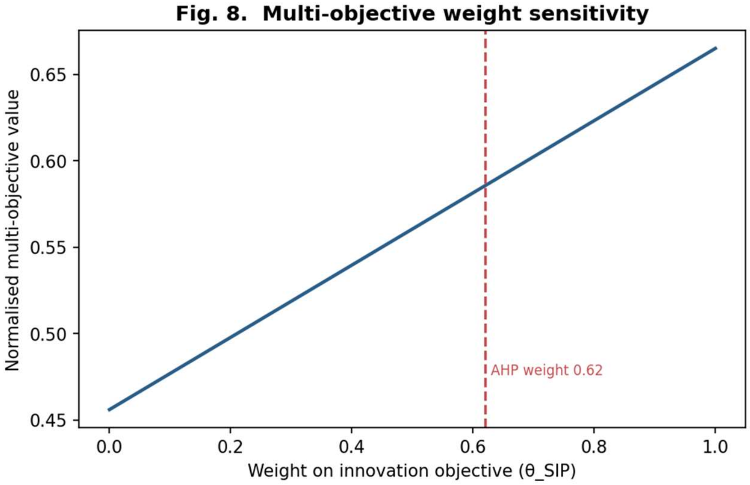

Fig. 8. *Multi-objective weight sensitivity.*

5.8 Monte Carlo validation

To confirm that the results are not an artifact of a single random seed, the proposed system was re-evaluated at the common operating point using ten different seeds. The per-seed SIP values fall within a narrow range, from 0.6623 to 0.6655, with a grand mean of 0.6640, a between-seed standard deviation of 0.00096, and a coefficient of variation of 0.14%. The 95% confidence interval across seeds is [0.6633, 0.6646]. This stability confirms that the reported precision is adequate at 480 draws per cell and that the differences observed in the comparative and ablation analyses exceed the between-seed variation by many orders of magnitude; they are therefore not stochastic artifacts.

6. DISCUSSION

6.1 Theoretical implications

This study offers an executable reading of a hypothesis usually formulated in latent-variable terms. Encoding mediation as functional composition and probing it through ablation yields a concrete systems interpretation: the path through the capability layer carries a dominant weight, and severing that path (the −DTC ablation) is more harmful than removing either input module. This does not demonstrate that mediation exists in any real organization—the mediation structure was designed into the model—but it does show that the mediation hypothesis is internally coherent and generates testable, quantitative predictions about how innovation responds when capability is degraded.

6.2 Practical implications

For platform designers, the ablation ordering (DTC ≫ VLE ≫ Mobile, in terms of SIP impact) implies that, once an adequate platform is in place, investment in digital-transformation capability—analytics, decision support, and automation—yields more innovation than further mobile-delivery optimization. The sensitivity analysis indicates that the mediation weight ω_1 is the most important parameter for decision-makers; empirical effort should therefore focus on measuring how strongly actual learning and mobile capability translate into transformation capability within the organization.

6.3 The sustainability trade-off

Three findings deserve emphasis. First, capability compounds: SIP increases with each additional layer, reaching 0.665 for the full stack compared with 0.205 for the classroom configuration. Second, this gain is a mediated translation, as discussed above. Third, capability carries a cost: the higher and more reliable performance of the proposed framework comes with the greatest energy consumption (10.9 W), and a leaner platform may be more energy-efficient per watt. A genuinely sustainable deployment therefore depends on the multi-objective weighting: the greater the priority placed on innovation, the more the full stack is favored, whereas a larger energy-penalty weight favors leaner variants. We do not claim outright dominance; rather, we evaluate this trade-off explicitly in order to report it honestly.

6.4 Threats to validity

Construct validity. The five capability multipliers are stylized proxies for rich organizational constructs, and their calibration to measurable indicators is left to empirical work. **Statistical-conclusion validity.** The p-values are uninformative because each cell contains only 480 low-variance draws; effect sizes and seed-stability are therefore used instead. **Internal validity.** The weights of Model 4 are recovered by a regression that is circular by construction; this is reported only as a pipeline check, not as evidence. **External validity.** The reported figures are model outputs for a particular parameterization; their absolute values should not be interpreted as field performance, and generalization requires calibration against instrumented deployments. We regard the qualitative orderings (variant ranking, ablation ordering, and monotone scaling trends) as the robust results, whereas the absolute magnitudes remain tentative.

7. CONCLUSION, LIMITATIONS, AND FUTURE WORK

We reformulated a VLE–mobile–DTC–SIP mediation hypothesis as a four-layer architecture comprising seven coupled models and tested it through a reproducible Monte Carlo simulation. Across innovation, learning, decision, and reliability metrics, the proposed framework outperformed four simpler variants (ANOVA, $\eta^2 = 0.995$) and proved the most robust under packet loss, capacity overload, and node failure. Its higher energy consumption is reported explicitly as a trade-off.

Limitations. All reported values are model results rather than field measurements and depend on the chosen parameterization and functional forms. The near-perfect regression fit is a consequence of the design and is reported only as a pipeline check. No real users, devices, or networks were involved, and the energy and reliability sub-models are coarse. The model must be calibrated with instrumented data from a real VLE/mobile deployment before any operational claim can be made.

Future work. We identify three directions for strengthening the mediation structure: (i) calibrating the capability multipliers and saturation parameters by fitting them to platform telemetry; (ii) learning time-varying capability profiles over the 12-month horizon rather than fixing them statically; and (iii) adding a carbon-aware energy term to the multi-objective layer and validating the resulting mediation structure on independent data rather than recovering it from the generating model.

Reproducibility

All results are produced by vle_sim.py (baseline grid), vle_experiments.py (comparison, ablation, extreme conditions, statistics), and make_figs.py (figures), with seed 20260529. Re-running reproduces every value and figure in this paper.

Data and code availability

Three scripts (vle_sim.py, vle_experiments.py, vle_supplementary.py) contain the complete simulation and analysis pipeline, and figures are generated by make_figs.py. All scripts use the same primary-results seed (20260529) and seed-stability seeds (1000–1009). When re-executed, they reproduce exactly the numerical values, tables, and figures reported in this paper, with no external data dependency.

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