

Beyond the intention-behavior gap: A mixed-methods UTAUT study of physical education teachers' technology adoption in Morocco

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Abstract

Problem Statement: Technology adoption in education depends on teachers' perceptions and structural conditions. Physical education (PE) remains underexplored in adoption research, particularly in Global South contexts where infrastructure deficits are substantial. The Unified Theory of Acceptance and Use of Technology (UTAUT) has been extensively validated in high-income settings, but its applicability to in-service PE teachers in North Africa has not been empirically examined. **Purpose:** This study explores technology adoption among Moroccan PE teachers and inspectors using UTAUT, examining construct hierarchies, moderation effects, and structural barriers. **Approach:** A convergent parallel mixed-methods design integrated survey data (N = 104, six Moroccan regions) with reflexive thematic analysis of semi-structured interviews (N = 5; maximum variation sampling). The 24-item UTAUT instrument showed excellent internal consistency ($\alpha = .878-.910$). Quantitative analyses included descriptive statistics, confirmatory factor analysis (MLR estimator), multiple regression, and ANOVA. Qualitative analysis followed Braun and Clarke's (2022) six-phase procedure ($\kappa = .78$). **Results:** Performance Expectancy (M = 3.94) and Behavioral Intention (M = 3.85) were the highest-rated constructs; Facilitating Conditions was the lowest (M = 2.76, $\Delta = -0.37$ below meta-analytic benchmarks). Performance Expectancy ($\beta = .432, p < .001$) and Social Influence ($\beta = .276, p = .004$) predicted Behavioral Intention ($R^2 = .385$). ICT training significantly moderated Facilitating Conditions ($F(2, 101) = 7.45, p = .001, \eta^2 p = .129$). Four qualitative themes emerged: infrastructural constraints, digital inequalities, gamification concerns, and institutional training gaps. A clear intention-behavior gap was observed (usage M = 2.81). **Conclusions:** Moroccan PE teachers report strong adoption intentions but face structural barriers that create a substantial intention-behavior gap. Facilitating conditions, not psychological readiness, constitute the primary adoption bottleneck. For Morocco Digital 2030 and comparable initiatives, infrastructure investment and discipline-specific professional development must precede technology deployment.

Key Words; facilitating conditions; mixed methods; Morocco; physical education; technology adoption; UTAUT

Introduction

Digital technologies have fundamentally altered the conditions under which teaching and learning occur. A cumulative body of evidence positions technology adoption as a structural feature of contemporary educational practice, not an exceptional event (Scherer et al., 2019). Meta-analytic work synthesizing decades of research shows that technology integration consistently predicts improvements in student engagement, instructional efficiency, and learning outcomes (Blut et al., 2022). Yet these aggregate effects conceal a critical asymmetry. Gains materialize only when adoption is genuine, sustained, and pedagogically grounded rather than imposed by policy mandates alone (Venkatesh et al., 2003).

Teachers occupy the decisive position in this process. They are not passive conduits through which technology flows into classrooms. They are active agents whose beliefs, competencies, and institutional conditions determine whether technological potential is realized or quietly abandoned (Ertmer, 1999). Research consistently documents that perceived usefulness, self-efficacy, and access to support predict technology use more powerfully than equipment availability alone. The Technological Pedagogical Content Knowledge framework formalizes this insight (Mishra & Koehler, 2006). Effective technology-enhanced teaching requires the simultaneous integration of technological, pedagogical, and disciplinary knowledge. Professional development systems in many countries have yet to address this triple competency systematically. Absent this integration, teachers may hold favorable attitudes toward technology while remaining structurally unable to translate those attitudes into sustained practice.

These general dynamics assume distinctive forms within physical education. Physical education differs fundamentally from academic subjects taught in fixed classroom settings. It unfolds in gymnasias, outdoor fields, and sports facilities. Connectivity there is intermittent and session durations are compressed (Bodsworth & Goodyear, 2017). The discipline carries a historically grounded tension between corporeal engagement, the primacy of embodied movement, and digital mediation. Some scholars characterize this tension as epistemologically incongruent with physical education's core identity (Jastrow et al., 2022). Alongside these tensions, specific affordances have emerged: wearable sensors, gamified applications, and video analysis tools have demonstrated tangible value in PE, from real-time biometric feedback to peer-assisted skill refinement (Wallace et al., 2022). Evidence for these benefits, however, derives almost exclusively from high-income contexts with stable infrastructure, raising fundamental questions about generalizability.

Despite this expanding evidence base, three converging gaps limit both theoretical progress and policy relevance. The first concerns the distribution of research attention across educational actors. Existing studies disproportionately examine how students respond to technology-enriched environments. Teachers' adoption perceptions and the structural conditions enabling or obstructing their practice remain substantially undertheorized (Scherer et al., 2019; Ertmer & Ottenbreit-Leftwich, 2010). This asymmetry matters: teachers are gatekeepers whose adoption decisions mediate every downstream student-level effect. A second gap concerns geographic representation. The predominant theoretical frameworks for technology adoption were developed primarily in high-income, high-connectivity contexts. The Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al., 2003) and its extensions exemplify this pattern. Applications to sub-Saharan African and MENA educational systems remain sparse (Agyei, 2021; Hennessy et al., 2015). This scarcity risks producing transplanted solutions disconnected from the infrastructural, institutional, and cultural realities that teachers in these regions face daily (El-Masri & Tarhini, 2017).

A third gap is disciplinary and methodological. Physical education has received systematically less attention than academic subjects within the educational technology literature (Jastrow et al., 2022). The discipline's specific constraints, particularly its outdoor and movement-centered character, require theoretical treatment distinct from that applied to mathematics or language instruction. Concurrently, the dominant research design in this literature remains quantitative and cross-sectional. Such designs produce adoption scores that describe what teachers report but cannot explain why intentions fail to translate into practice, or why structurally similar teachers diverge in their adoption trajectories. Convergent mixed-methods designs address this limitation by integrating statistical patterns with the contextual meaning teachers assign to those patterns, generating explanatory meta-inferences unavailable to either method alone (Creswell & Creswell, 2018).

These gaps converge with particular force in Morocco. The country's National Digital Strategy and the longstanding GENIE programme signal sustained political commitment to technology integration across educational sectors (UNESCO, 2022). Yet empirical data on the adoption experiences of in-service physical education teachers remain absent from the international literature. Wibowo et al. (2025) explicitly called for UTAUT applications among PE teachers, a gap the present study addresses in the Moroccan context. Critical questions remain unanswered. How do in-service teachers perceive the four UTAUT constructs? What structural conditions obstruct the conversion of high adoption intentions into classroom practice? How does the near-complete absence of formal ICT training, a systemic feature of Moroccan public schooling (Berbar et al., 2021), interact with teachers' self-directed learning strategies? Answering these questions is prerequisite to designing effective, contextually grounded policy under Morocco Digital 2030.

The present study addresses these intersecting gaps. Using a convergent mixed-methods design, it integrates UTAUT-based survey data (N = 104 EPS teachers and inspectors) from six Moroccan regions with reflexive thematic analysis of semi-structured interviews (N = 5; Braun & Clarke, 2022). Four research questions organize the inquiry, examining construct hierarchies relative to meta-analytic benchmarks, technology use frequency patterns, moderation effects of ICT training, school setting, and professional experience, and the structural obstacles and enabling conditions that qualitative accounts reveal and that quantitative patterns cannot access alone. This study generates the first empirical UTAUT dataset for in-service EPS teachers in Morocco and North Africa and models a convergent mixed-methods approach replicable across Global South settings.

Material & Methods

Research Design

A convergent parallel mixed-methods design integrated quantitative and qualitative data collected simultaneously and analyzed independently before merging (Creswell & Creswell, 2018). Survey data mapped adoption perceptions across a professionally diverse sample; interviews excavated the contextual mechanisms that statistical summaries cannot reach. Merging both strands through a joint display matrix enabled meta-inferences that neither dataset could support alone (Creamer, 2018). This integration logic, rather than sequential elaboration, distinguishes the present design from prior single-method work on teacher technology adoption in PE contexts (Mears & Hansen, 2020; Scherer et al., 2019).

Participants

Participant selection followed a four-stage eligibility and recruitment protocol; Fig 1 displays the complete flow. Of 503 in-service EPS professionals registered across six AREF databases as of October 2024,

110 met five inclusion criteria (active teaching or inspection status, secondary-level post, minimum two years' seniority, personal device ownership, and an active sports federation certification affiliated with the Comité National Olympique Marocain (CNOM), attesting to discipline-specific expertise beyond initial STAPS/ENSEP training) and two exclusion criteria (administrative-only PE staff; pilot study participants). Of 110 questionnaires distributed, 108 were returned (98.2%); four were excluded at quality review, yielding $N = 104$ (overall inclusion rate: 94.5%; population coverage: 20.7% of the estimated national population).

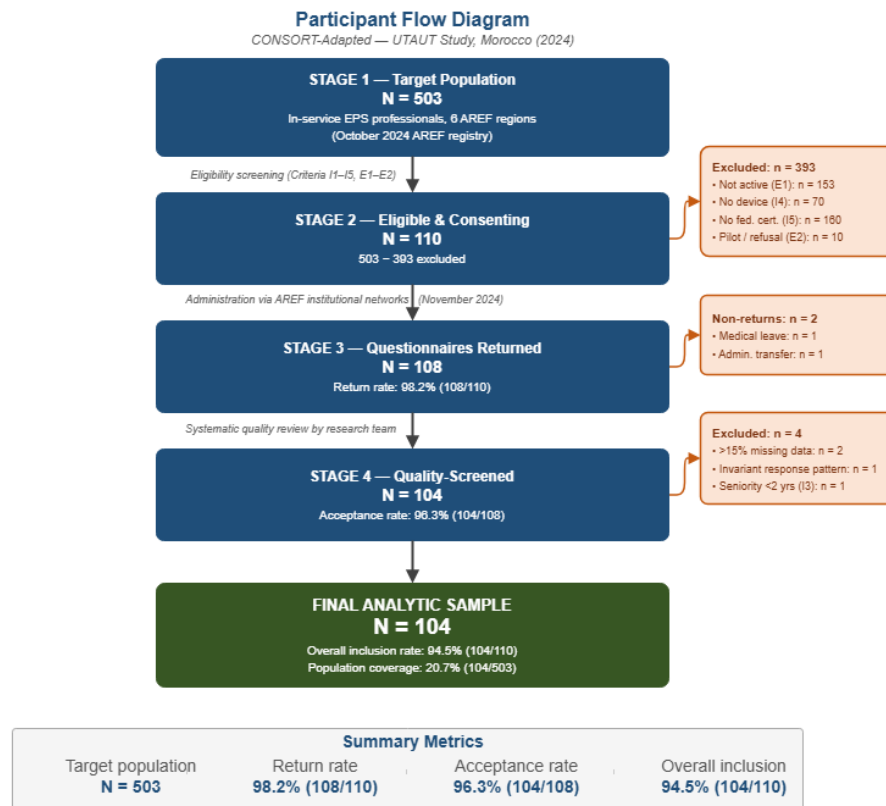


Fig 1. CONSORT-Adapted Participant Flow Diagram ($N = 503 \rightarrow 104$).

The final sample comprised 88 classroom teachers (84.6%) and 16 inspectors (15.4%), with 66 men (63.5%) and 38 women (36.5%). Mean age was 37.8 years ($SD = 7.2$, range: 25-56) and mean experience 12.2 years ($SD = 6.2$, range: 2-28). Regional distribution spanned Casablanca-Settat (23.1%), Rabat-Salé-Kénitra (19.2%), Beni Mellal-Khénifra (17.3%), Tanger-Tétouan-Al Hoceima (15.4%), Marrakech-Safi (13.5%), and Souss-Massa (11.5%), with urban (55.8%), semi-urban (27.9%), and rural (16.3%) settings. Public institutions predominated (78.8%). Regarding ICT training, 48.1% ($n = 50$) reported none, 34.6% ($n = 36$) partial, and 17.3% ($n = 18$) complete, making the untrained majority a defining feature of this sample. Personal device ownership was high: 90.4% held smartphones and 77.9% laptops.

Alongside the quantitative strand, five participants were selected from this sample using maximum variation sampling (Patton, 2015) to anchor the qualitative strand. Selection prioritized diversity across gender, professional experience, school sector, and region. Profiles were: T01 (male, 42, 14 years' experience, public, Casablanca-Settat, 63 min), T02 (female, 28, 4 years, private, Casablanca-Settat, 47 min), T03 (male, 52, 24 years, public, Rabat-Salé-Kénitra, 82 min), T04 (female, 35, 9 years, private, Marrakech-Safi, 54 min), and T05 (male, 38, 12 years, public, Tanger-Tétouan-Al Hoceima, 58 min), yielding 304 minutes of total interview data. This purposive logic prioritized informational richness over representativeness, consistent with reflexive thematic analysis conventions (Braun & Clarke, 2022). The decision to interview five participants was informed by the concept of information power: samples with high information density, defined by a specific study aim, dense participant information, and a well-established theoretical framework, require fewer participants to achieve analytical quality (Malterud et al., 2016).

Instruments

Technology adoption perceptions were assessed with a 24-item instrument (adapted from Venkatesh et al., 2003) for PE teaching contexts. Four constructs were operationalized. Performance Expectancy (4 items; e.g., "Digital technologies improve my PE teaching quality"), Effort Expectancy (4 items; e.g., "I become quickly competent with a new PE application"), Social Influence (3 items; e.g., "My administration encourages technology integration"), and Facilitating Conditions (4 items; e.g., "WiFi and necessary equipment are available in my school"). Behavioral Intention (3 items; e.g., "I plan to integrate more technologies into my

teaching sequences") served as the criterion construct. All items used 5-point Likert scales (1 = *Strongly disagree*, 5 = *Strongly agree*). Five additional items assessed technology use frequency across pedagogical contexts, and seven binary items catalogued specific tools used. The instrument underwent bilingual translation-back-translation into Arabic and French, expert review by six PE specialists, and cognitive piloting with 10 teachers prior to deployment. Pilot feedback led to rewording of three items to better reflect the physical education context; no items were dropped.

The final instrument preserved all original UTAUT constructs while embedding PE-specific examples within item stems. Internal consistency was excellent across all constructs ($\alpha = .878-.910$, $\omega = .879-.911$; global $\alpha = .92$). Factorial validity was assessed via confirmatory factor analysis (CFA) using the lavaan, semTools, and semPlot packages (Rosseel, 2012) in R (version 4.3.2). The CFA was conducted on the 18 Likert-scale items constituting the five UTAUT constructs (PE: 4 items, EE: 4, SI: 3, FC: 4, BI: 3). The remaining six items assessed technology use frequency (five items) and binary tool usage (one composite item) and were excluded from the measurement model. Given that all 18 items exhibited non-normal score distributions (Shapiro-Wilk $p < .05$), a maximum likelihood strong estimator (MLR) was applied (Satorra & Bentler, 1994). The hypothesized five-factor structure (PE, EE, SI, FC, BI) demonstrated acceptable fit: $\chi^2(125) = 183.331$, $p = .001$; CFI = .956; TLI = .946; RMSEA = .067 [90% CI: .045, .087]; SRMR = .052. The five-factor model substantially outperformed the single-factor alternative ($\Delta CFI = +.416$, $\Delta AIC = 545.2$), providing the primary evidence of factorial validity for this exploratory sample. All standardized factor loadings were statistically significant (all $p < .001$) and ranged from .743 to .922, all above the .70 threshold (Hair et al., 2019). Average variance extracted (AVE) exceeded .50 for all constructs (range: .646-.750) and composite reliability (CR) exceeded .70 (range: .879-.911; Fornell & Larcker, 1981). Discriminant validity was confirmed as the square root of each construct's AVE exceeded its inter-construct correlations across all pairs (Fornell-Larcker criterion). Replication with larger probability samples is recommended for confirmatory purposes (Wolf et al., 2013).

The semi-structured interview guide covered three domains: past and current technology experiences in PE, perceived obstacles and facilitators of adoption, and professional aspirations for future integration. Open-ended probes were designed to elicit narrative accounts rather than confirmatory responses, allowing participants to surface dimensions of experience not anticipated by the UTAUT framework. Interviews were conducted in French or Arabic according to participant preference, audio-recorded with consent, and transcribed verbatim. Transcripts were returned to participants for member checking; no substantive modifications were requested.

Five participants were purposively selected from the quantitative sample using a maximum variation strategy (Patton, 2015; Campbell et al., 2020). Selection ensured diversity across gender (3M/2F), teaching sector (3 public, 2 private), and professional experience (4-24 years). Geographic diversity spanned 4 of the 6 sampled regions. One regional inspector (T05) was included to capture the institutional supervisory perspective. Semi-structured individual interviews averaged 60.8 min ($SD = 13.2$; range = 47-82 min). A total of 39 coded extracts were distributed across four deductive themes aligned with the UTAUT framework. The maximum variation sampling strategy yielded analytically rich and diverse accounts. Code saturation was reached at T04; T05, included for his institutional inspector perspective, confirmed existing themes without generating new codes, providing cross-thematic triangulation rather than novel content. This pattern is consistent with informational sufficiency for the study's exploratory aims, where analytical depth rather than representative saturation is the appropriate criterion (Braun & Clarke, 2022). No new sub-codes emerged after T04, confirming saturation for small purposive samples (Fugard & Potts, 2015).

Procedure

Quantitative data were collected via Google Forms distributed through AREF networks across six regions in November 2024. Participation was voluntary, with anonymity guaranteed through participant codes. Semi-structured interviews were conducted by videoconference in November 2024, with written informed consent obtained prior to each session. Both strands ran in parallel across October-November 2024, preserving dataset independence. Neither strand was analyzed until both collection phases were complete, ensuring quantitative findings did not influence qualitative coding prior to the designated integration stage. Following completion of both collection phases, findings were merged through a joint display procedure described in the Data Analysis section.

Data Analysis

All quantitative analyses were conducted in R (version 4.3.2; R Core Team, 2023) using the *psych* and *lavaan* packages. Preliminary screening assessed outliers via standardized scores ($|z| > 3.29$) and distributional normality via Shapiro-Wilk tests and Q-Q plot inspection. Descriptive statistics (M , SD , frequencies, $\% \geq 4$) characterized all constructs and usage variables. Reliability was estimated jointly with Cronbach's alpha and McDonald's omega to provide complementary perspectives on scale functioning (McNeish, 2018). Bivariate associations among constructs were examined with Pearson correlations and 95% confidence intervals via Fisher's Z transformation. ICT training level (none, partial, complete) was tested as a moderator of each UTAUT construct via one-way ANOVAs with Tukey HSD post-hoc comparisons. Partial eta-squared (η^2p) indexed effect sizes (.01, .06, .14 = small, medium, large; Cohen, 1988). Multiple regression identified independent predictors of Behavioral Intention, with standardized coefficients (β), t -statistics, 95% confidence intervals, and variance inflation factors (VIF < 10) reported. Effects of school setting and professional experience were examined via

ANOVA and Pearson correlations respectively, with Bonferroni correction applied across multiple comparisons. The significance threshold was set at $\alpha = .05$, with exact p -values reported to three decimal places.

Qualitative analysis followed the six-phase reflexive thematic analysis procedure (Braun & Clarke, 2022): data familiarization, initial code generation, theme construction, theme review, definition and naming, and report production. NVivo 12 supported data management throughout. An independent researcher double-coded 40% of the corpus; Cohen's kappa of .78 indicated substantial agreement (Landis & Koch, 1977). Researcher positionality as PE practitioners was acknowledged and documented to sustain reflexivity across analytic phases. All three authors are trained PE practitioners with experience in the Moroccan public education system. This insider positioning facilitated participant rapport and interpretation but carried out the risk of confirming expected findings. To mitigate this, the lead researcher maintained a reflexive journal throughout analysis, and theme definitions were reviewed by an external researcher unfamiliar with the UTAUT framework prior to finalization.

Following independent analyses of both strands, findings were merged through a joint display matrix that juxtaposed quantitative statistics with corresponding qualitative themes and prevalence estimates (Creamer, 2018). Meta-inferences were constructed exclusively at this stage, identifying patterns of convergence, complementarity, and expansion across strands rather than within either dataset individually. (Fetters et al., 2013).

Ethical approval was granted by the Hassan II University research ethics committee. All participants provided written informed consent and were assured of voluntary participation, anonymity through coded identifiers (Q001-Q104; T01-T05), and the right to withdraw at any stage without consequence. Data are stored on university-encrypted servers with access restricted to the research team.

Results

Preliminary Analyses

Of the 110 eligible participants contacted, 108 returned questionnaires (return rate: 98.2%), of which 104 met quality criteria for analysis (acceptance rate: 96.3%). No significant differences emerged between early (Wave 1) and late (Wave 2) respondents on any UTAUT construct (all $p > .05$; Armstrong & Overton, 1977). The final sample of $N = 104$ included 66 men (63.5%) and 38 women (36.5%). Mean age was 37.8 years ($SD = 7.2$, range = 25-56) and mean teaching experience was 12.2 years ($SD = 6.2$). Teachers ($n = 88$, 84.6%) and inspectors ($n = 16$, 15.4%) were distributed across six Moroccan regions, with a concentration in urban settings ($n = 58$, 55.8%). Regarding ICT training, 50 participants (48.1%) reported no formal training, 36 (34.6%) partial training, and 18 (17.3%) complete training. Smartphones were the most common personal device ($n = 94$, 90.4%), followed by laptops ($n = 81$, 77.9%) and tablets ($n = 43$, 41.3%). Full participant characteristics are presented in Table 1.

Table 1. Sociodemographic and Continuous Characteristics of Participants (N = 104)

Variable	Category	<i>n</i>	%
Gender	Male	66	63.5
	Female	38	36.5
Function	PE Teacher	88	84.6
	Inspector	16	15.4
School sector	Public	82	78.8
	Private	22	21.2
School setting	Urban	58	55.8
	Semi-urban	29	27.9
	Rural	17	16.3
ICT training	None	50	48.1
	Partial	36	34.6
	Complete	18	17.3
Digital equipment	Smartphone	94	90.4
	Laptop	81	77.9
	Tablet	43	41.3
Region	Casablanca-Settat	24	23.1
	Rabat-Salé-Kénitra	20	19.2
	Béni Mellal-Khénifra	18	17.3
	Tanger-Tétouan-Al Hoceima	16	15.4
	Marrakech-Safi	14	13.5
	Souss-Massa	12	11.5
Continuous variable	<i>M</i> <i>SD</i> <i>Min</i> <i>Max</i>		
Age (years)	37.8 7.2 25 56		
Teaching experience (years)	12.2 6.2 2 29		

Statistical assumptions were examined prior to main analyses. The Shapiro-Wilk test indicated non-normal distributions for PE, EE, and BI ($p < .05$). SI and FC met normality ($p \geq .15$). Regression residuals were normally distributed (SW $W = .985$, $p = .272$) and showed constant variance (Breusch-Pagan $\chi^2(4) = 8.465$, $p = .076$). The Durbin-Watson statistic ($DW = 1.611$) indicated mild positive autocorrelation. In this cross-sectional survey design, temporal dependence is implausible; the more likely explanation is geographic clustering across AREF regions. Variance inflation factors ranged from 1.44 to 2.00, confirming the absence of problematic collinearity. The correlation between Performance Expectancy and Effort Expectancy ($r = .626$) was the highest

inter-construct correlation observed. Although VIF = 2.00 remained well below the conventional threshold of 5.0 (Hair et al., 2019), this correlation reflects structural overlap between the two expectancy constructs consistent with prior UTAUT research (Blut et al., 2022) and does not bias the regression estimates. Justifications for analytical decisions regarding regional clustering, multilevel modelling, and statistical power are detailed in the **Data Analysis section**.

UTAUT Construct Profiles

Internal consistency across all five constructs was excellent before inspection of means (Cronbach's α range = .878-.910; McDonald's ω range = .879-.911). The hierarchy of construct means established a clear ordering. Performance Expectancy was the highest-rated construct ($M = 3.94$, $SD = 0.76$), followed by Behavioral Intention ($M = 3.85$, $SD = 0.87$), Effort Expectancy ($M = 3.66$, $SD = 0.86$), and Social Influence ($M = 3.00$, $SD = 1.04$). Facilitating Conditions obtained the lowest mean ($M = 2.76$, $SD = 0.93$). FC was the only construct below the scale midpoint (3.00) and showed the largest deviation from its meta-analytic benchmark ($\Delta = -0.37$; ref = 3.13; Tamilmani et al., 2021). Deviations for the remaining constructs were smaller: PE ($\Delta = -0.13$), SI ($\Delta = -0.17$), EE ($\Delta = -0.08$), and BI ($\Delta = -0.10$). Negative skewness was detected for PE (-0.960), EE (-0.619), and BI (-0.437), indicating score concentration at the upper end. Descriptive statistics, reliability indices, and benchmark comparisons are presented in Table 2.

Table 2. Descriptive statistics and reliability of UTAUT Constructs (N = 104)

Construct	Items	<i>M</i>	<i>SD</i>	Min	Max	Skewness	SW <i>p</i>	α^a	ω^b	<i>M</i> _{ref}
PE	4	3.94	0.76	2.00	5.00	-0.960	<.001	.878	.910	4.10
EE	4	3.66	0.86	1.00	5.00	-0.60	.011	.881	.882	3.79
SI	3	3.00	1.01	1.00	5.00	0.11	.150	.897	.881	3.18
FC	4	2.76	0.93	1.00	5.00	-0.02	.206	.905	.896	3.13
BI	3	3.85	0.86	1.67	5.00	-0.42	.005	.878	.879	3.95

Note. ^a α = Cronbach's alpha; ω = McDonald's omega. *M*_{ref} = meta-analytic benchmark mean (Tamilmani et al., 2021). SW *p* = Shapiro-Wilk normality test *p*-value. PE = Performance Expectancy; EE = Effort Expectancy; SI = Social Influence; FC = Facilitating Conditions; BI = Behavioral Intention.

The profile displayed in Fig 2 makes the construct hierarchy and benchmark gaps visible simultaneously. Four constructs cluster at or above the midpoint, while FC stands apart as the only construct below the scale midpoint, with a deviation of $\Delta = -0.37$ from its meta-analytic benchmark.

Figure 2. UTAUT Construct Profiles: Morocco EPS vs. Benchmarks

Global Benchmark: Tamilmani et al. (2021); MENA estimates: Al-Emran et al. (2020)

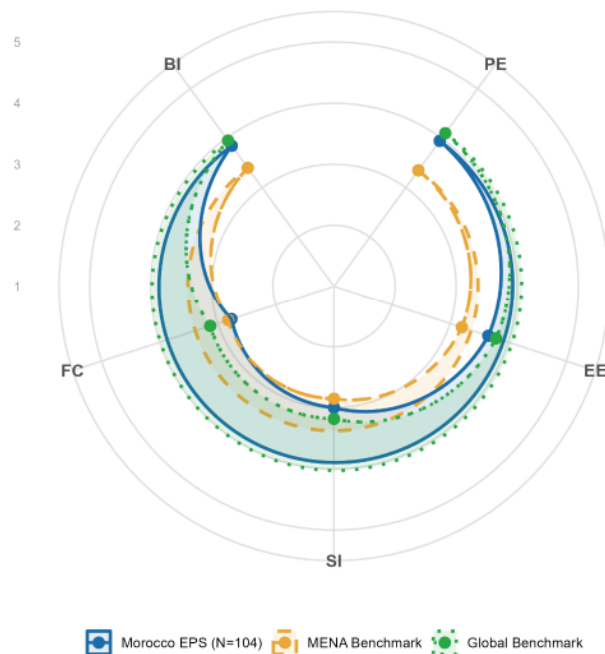


Fig 2. UTAUT construct profile with meta-analytic benchmark comparisons (N = 104).

All 10 inter-construct correlations were positive and statistically significant ($p < .001$). The strongest association was between PE and EE ($r = .626$, $p < .001$, 95% CI [.493, .731]). Among correlations with BI, PE showed the highest bivariate correlation ($r = .562$, $p < .001$, 95% CI [.414, .681]). SI showed the second-strongest association ($r = .490$, $p < .001$, 95% CI [.328, .624]). EE ($r = .364$, $p < .001$, 95% CI [.184, .520]) and FC ($r = .350$, $p < .001$, 95% CI [.169, .509]) showed weaker associations. The full correlation matrix is presented in Table 3.

Table 3. Zero-Order Correlation Matrix for UTAUT Constructs (N = 104)

	PE	EE	SI	FC	BI
PE	-				
EE	.626***	-			
SI	.471***	.409***	-		
FC	.418***	.390***	.433***	-	
BI	.562***	.364***	.490***	.350***	-
M	3.94	3.66	3.00	2.76	3.85
SD	0.76	0.86	1.01	0.93	0.86

Note. Pearson r coefficients. Confidence intervals (95%) for PE: EE [.493, .731], SI [.307, .609], FC [.245, .565], BI [.414, .681]. For EE: SI [.235, .558], FC [.213, .542], BI [.184, .520]. For SI: FC [.262, .577], BI [.328, .624]. FC-BI [.169, .509]. * $p < .05$. ** $p < .01$. *** $p < .001$.

Predictors of Behavioral Intention

The overall regression model was statistically significant ($R^2 = .385$, $R^2_{adj} = .360$, $F(4, 99) = 15.48$, $p < .001$), accounting for 38.5% of variance in behavioral intention. This $R^2 = .385$ is consistent with the explanatory power typically reported in UTAUT educational studies (Tamilmani et al., 2021), supporting the model's contextual validity despite the constrained sample size. Two predictors reached significance. Performance Expectancy was the strongest predictor ($\beta = .432$, $t(99) = 4.023$, $p < .001$, 95% CI [.0250, 0.738], $sr^2 = .101$), accounting for 10.1% of unique variance beyond the other predictors. Social Influence was the second significant predictor ($\beta = .276$, $t(99) = 2.925$, $p = .004$, 95% CI [0.075, 0.394], $sr^2 = .053$), contributing 5.3% of unique variance. Together, PE and SI accounted for 15.4% of unique variance in BI ($sr^2_{total} = .154$). Full regression coefficients, standard errors, and confidence intervals are presented in Table 4.

Table 4. Multiple Regression Analysis: Predictors of Behavioral Intention (N = 104)

$R^2 = .385$, $R^2_{adj} = .360$, $F(4, 99) = 15.48$, $p < .001$. Residual diagnostics: SW $W = .985$, $p = .272$; Breusch-Pagan $\chi^2(4) = 8.465$, $p = .076$; Durbin-Watson = 1.611.

Predictor ^a	B	SE	β	95% CI	t	p	r(BI)	sr ²	VIF
PE	0.494	0.123	.432	[0.250, 0.738]	4.023	<.001	.562	.101	2.00
EE	-0.047	0.103	-.047	[-0.252, 0.159]	-0.456	.654	.364	.001	1.92
SI	0.235	0.080	.276	[0.075, 0.394]	2.925	.004	.490	.053	1.48
FC	-0.038	0.125	+.064	[-0.290, 0.213]	0.748	.456	.350	.001	1.44

Note. ^aB = unstandardized coefficient; SE = standard error; β = standardized coefficient; $r(BI)$ = bivariate correlation with BI; sr^2 = squared semi-partial correlation. Bold = significant ($p < .05$). EE non-significant due to collinearity with PE ($r = .626$; $sr^2 = .001$). FC: $r(BI) = .350$ (positive zero-order); $\beta = +.064$ (non-significant in regression).

Effort Expectancy was not a significant predictor ($\beta = -.047$, $t(99) = -0.456$, $p = .654$, $sr^2 = .001$). Its high zero-order correlation with PE ($r = .626$, $VIF = 1.86$) indicates substantial overlap with an already-included predictor. Facilitating Conditions was also not significant ($\beta = +.064$, $t(99) = 0.748$, $p = .456$, $sr^2 = .003$). Its positive but non-significant coefficient reflects shared variance with PE and SI. Its positive bivariate correlation with BI ($r = .350$) confirms a meaningful zero-order association. This pattern is consistent with shared variance between FC and PE ($r = .418$) and between FC and SI ($r = .433$), which together absorbed FC's predictive contribution. Fig 3 displays the tool adoption profile and frequency-of-use patterns across pedagogical contexts.

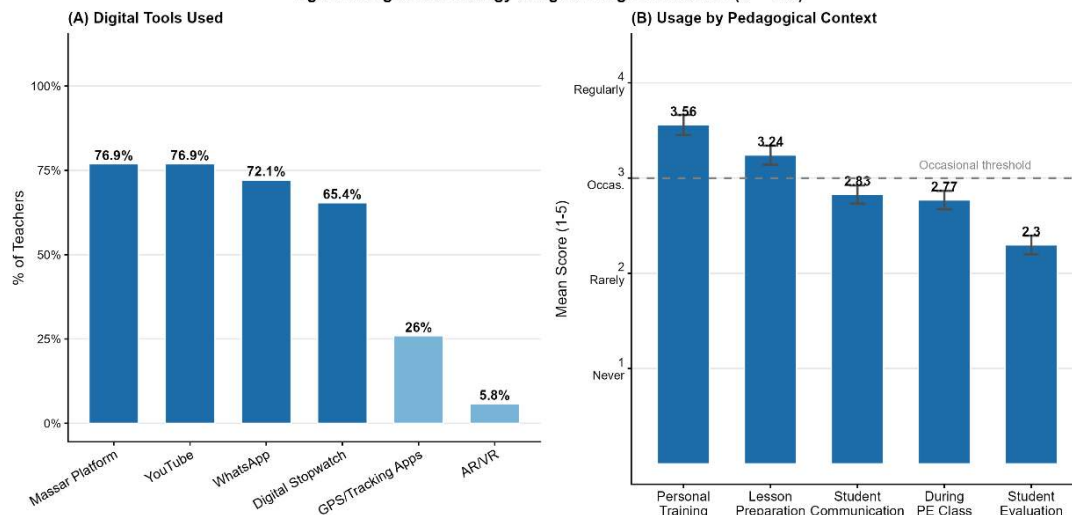
Figure 3. Digital Technology Usage among PE Teachers (N = 104)

Fig 3. Technology tool adoption rates and frequency of use across pedagogical contexts (N = 104).

Moderator Analyses

Three sets of moderator analyses examined whether ICT training level, exercise environment, and gender differentiated construct means. Across the 15 comparisons, one effect reached statistical significance. ICT training level moderated Facilitating Conditions ($F(2, 101) = 7.45, p = .001, \eta^2p = .129$). Training level showed a clear gradient on FC. Complete-training participants scored higher than those with no training (Complete: $M = 3.39, SD = 0.57$; None: $M = 2.54, SD = 1.05$). The complete-versus-none difference was significant ($\Delta M = 0.926, p = .001$). Partial-versus-none comparison was not significant ($\Delta M = 0.287, p = .295$). Complete exceeded Partial ($\Delta M = 0.639, p = .034$). The no-training group showed greater variability ($SD = 1.05$) than the complete-training group ($SD = 0.57$). *ICT training did not significantly moderate PE, EE, SI, or BI (all $p \geq .826$).* Moderator results are reported in Table 5.

Table 5. Moderator Analyses: ICT Training, Exercise Environment, and Gender on UTAUT Constructs (N = 104)

Construct	ICT Training			Exercise Environment			Gender		
	$F(2, 101)$	p	η^2p	$F(2, 101)$	p	η^2p	$t(df)$	p	d
PE	0.17	.848	.007	0.64	.529	.026	-1.31 (49.9)	.196	0.35
EE	0.02	.911	.001	0.41	.665	.017	0.14 (38.5)	.887	0.04
SI	0.19	.826	.008	2.01	.139	.038	-0.32 (35.8)	.748	0.09
FC	7.45	.001*	.129	0.43	.655	.017	-0.44 (41.4)	.660	0.12
BI	0.06	.910	.003	2.22	.114	.042	-0.58 (37.8)	.567	0.17

Note. η^2p = partial eta-squared: small $\geq .01$, medium $\geq .06$, large $\geq .14$ (Cohen, 1988). d = Cohen's d . Welch df for t -tests. FC $\times$ ICT Training post-hoc Tukey HSD: Complete > None ($\Delta M = 0.926, p = .001$); Partial vs. None ($\Delta M = 0.287, p = .295, ns$); Complete vs. Partial ($\Delta M = 0.639, p = .034$). Marginal effects: SI $\times$

Exercise Environment $F(2, 101) = 2.01, p = .096, \eta^2p = .038$; BI $\times$ Exercise Environment $F(2, 101) = 2.22, p = .105, \eta^2p = .042$. Both non-significant at $N = 104, p^* < .05, ** p < .01, *** p < .001$.

Fig 4 displays the FC $\times$ ICT training interaction visually. The boxplot displays both the mean differences and the within-group dispersion contrast, with the no-training group showing the widest spread and the lowest median.

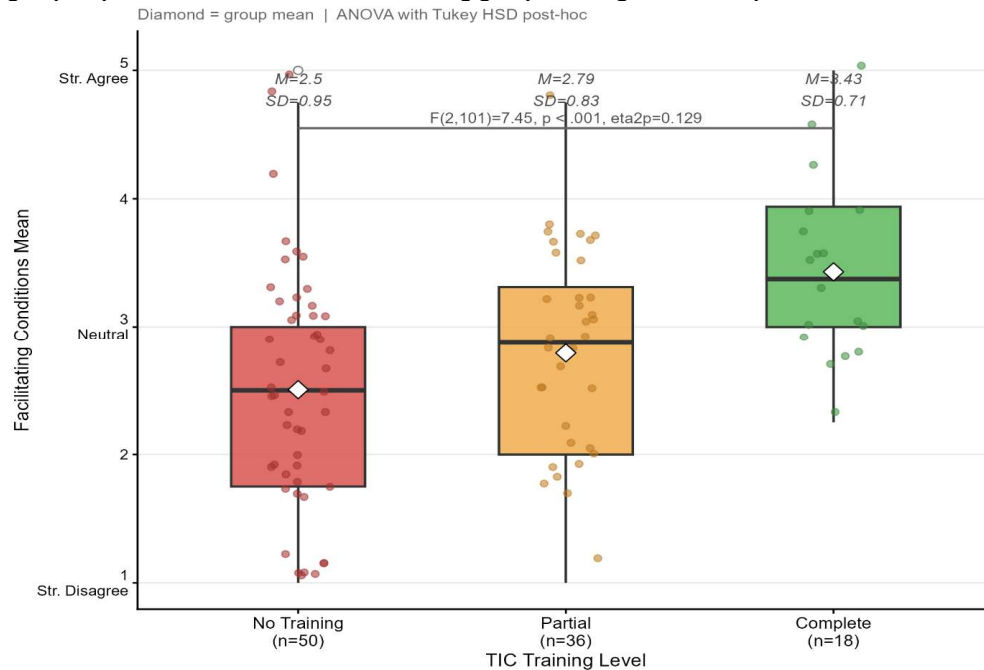


Fig 4. Facilitating Conditions means by ICT training level with Tukey HSD post-hoc comparisons (N = 104).

Exercise environment did not significantly moderate SI ($F(2, 101) = 2.01, p = .096, \eta^2p = .038$) and BI ($F(2, 101) = 2.22, p = .105, \eta^2p = .042$). Both are reported for descriptive purposes only. Observed power for these effects was approximately .40 given $N = 104$ (Faul et al., 2007). This low observed power ($\approx .40$) constitutes a central methodological limitation. The marginal SI and BI effects ($p = .096$ and $p = .105$) may reflect true medium-to-large effects ($\eta^2p \approx .09$) that the present sample was underpowered to detect. Absence of significance at $N = 104$ should not be interpreted as absence of effect. Replication with $N \geq 150$ is necessary before drawing definitive conclusions regarding these moderator effects (Maxwell et al., 2008). Gender did not moderate any construct significantly (all Welch t comparisons: $p \geq .196, d \leq 0.35$).

Qualitative Findings

Five participants were interviewed across four Moroccan regions using maximum variation sampling. Their socioprofessional profiles are presented in Table 6. The distribution of coded extracts is presented in Table 7. Code saturation details are reported in the Methods section (§Instruments). The full thematic codebook with verbatim extracts and analytical notes is presented in Supplementary Table S3.

Table 6. Socioprofessional Profiles of Interview Participants (N = 5)

ID	Gender	Age	Exp.a	Sector	Region	Duration (min)	Date	Extracts
T01	M	42	14	Public	Casablanca-Settat	63	08/11/2024	7
T02	F	28	4	Private	Casablanca-Settat	47	12/11/2024	7
T03	M	52	24	Public	Rabat-Salé-Kénitra	82	15/11/2024	9
T04	F	35	9	Private	Marrakech-Safi	54	18/11/2024	8
T05	M	38	12	Public	Tanger-Tétouan-Al Hoceima	58	20/11/2024	8
Total	3M/2F	M = 39.0	M = 12.6	3 Public/2 Private	4 regions	M = 60.8	Nov. 2024	39

Note. aExp. = teaching experience in years. M = Male; F = Female. Mean interview duration = 60.8 min (SD = 13.2). Individual semi-structured interviews recorded with participants' consent.

Table 6 displays the socioprofessional diversity of the five participants.

Table 7. Extract Distribution Matrix by Participant and Theme (N = 5, 39 Extracts)

Participant	Gender	Age	Exp.	Sector	T1 Infra.	T2 Inequal.	T3 Gamif.	T4 Training	Total
T01	M	42	14	Public	5	0	0	2	7
T02	F	28	4	Private	1	5	1	0	7
T03	M	52	24	Public	1	1	7	0	9
T04	F	35	9	Private	1	1	0	6	8
T05	M	38	12	Public	2	2	2	2	8
Total					10	9	10	10	39

Note. Each cell = number of extracts coded per participant per theme. T1 = Infrastructural Constraints; T2 = Digital Inequalities; T3 = Gamification and Motivation; T4 = Training and Institutional Support. T05 contributed equally across all four themes (n = 2 per theme).

Table 7 shows that Themes 1, 3, and 4 each obtained 10 extracts; Theme 2 obtained 9. No participant contributed exclusively to a single theme. T1 received contributions from all five participants; T2 from four; T3 and T4 from three each, reflecting the domain-specific focus of individual accounts. The participant-level distribution of extract counts by theme is displayed in Fig 5. The frequency distribution of sub-codes across all four themes is displayed in Fig 6.

Thematic Analysis

Theme 1: Infrastructural Constraints (n = 10 extracts). All five participants contributed to this theme; T01 was the most frequent contributor (n = 5). Structural obstacles consistently appeared in combination rather than isolation. Absent WiFi in outdoor sports areas was the most cited barrier (4/5 participants), compounded by compressed session time: distributing devices consumed up to ten of thirty-five available practice minutes. Device inequality within classes constituted an additional barrier, as incompatible hardware precluded standardized application use. T01 captured the cumulative weight of these constraints: "If we spend five minutes getting out phones... we lose ten minutes out of thirty-five. Sometimes I think it is not worth it" (INFRA_Time). Detailed verbatims and analytical notes are presented in Supplementary Table S3.

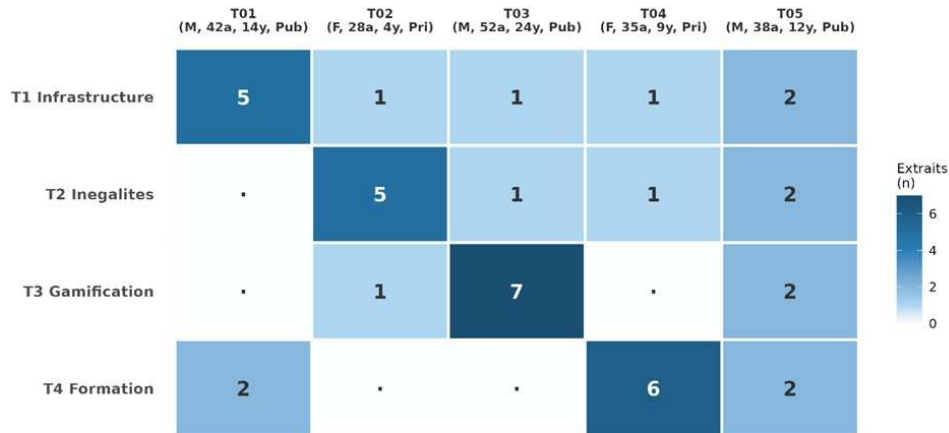
Theme 2: Digital Inequalities (n = 9 extracts). T02 was the dominant contributor (n = 5). The central pattern across accounts was that technology use widened existing student disparities rather than reducing them. Students from digitally resourced families required little support; those without that background demanded disproportionate teacher time, deepening the gap.

A hidden access barrier also emerged: some students avoided downloading recommended applications because mobile data allowances were insufficient, a form of invisible exclusion that only became apparent incidentally (INEQ_DataAccess). T02 summarized the ethical tension: "Instead of reducing differences, technology amplifies them" (INEQ_DigitalLiteracy). Detailed verbatims are presented in Supplementary Table S3.

Theme 3: Gamification and Motivation (n = 10 extracts). T03, the most experienced participant (24 years), contributed 7 of 10 extracts. Accounts described a consistent temporal arc: strong initial student engagement followed by habituation and behavioral distortion after three to four weeks. Two distortions were documented: students running with poor form to maximize step counts (GAMIF_QualityOverQuantity) and shaking phones to inflate counters artificially (GAMIF_SystemGaming). T03 identified the core concern: "My

goal is to develop the pleasure of moving [...] With these apps, I have the impression they run for points” (GAMIF_ExtrinsicConcern). Detailed verbatims are presented in Supplementary Table S3.

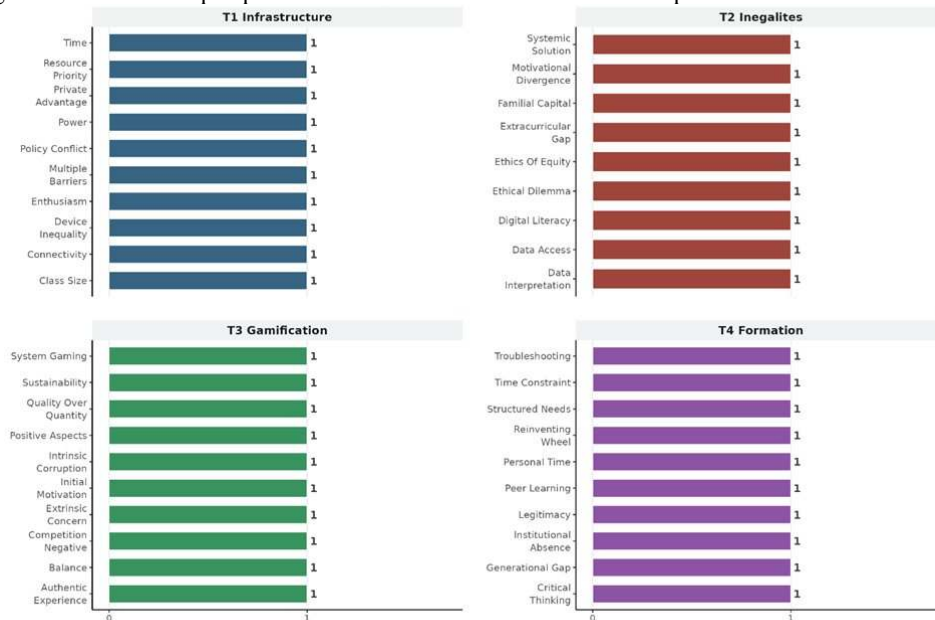
Theme 4: Training and Institutional Support (n = 10 extracts). T04 was the dominant contributor (n = 6). The consistent pattern was the complete absence of institutional training on technology integration, compensated through unrecognized personal time investment. Evening and weekend self-training via YouTube and teacher forums constituted a substantial hidden workload with no formal recognition (TRAIN_PersonalTime). Absence of shared platforms forced each teacher to develop solutions independently, generating redundant effort (TRAIN_ReinventingWheel). T04 stated: “On technologies, applications, how to integrate them concretely — there is nothing. We are left to figure it out ourselves” (TRAIN_InstitutionalAbsence). Detailed verbatims are presented in Supplementary Table S3.



Note. Participant labels: ID (Gender, Age, Exp., Sector). M = Male; F = Female; Pub = Public; Pri = Private. • = no extract. Dominant contributor per theme: T1 = T01 (n=5); T2 = T02 (n=5); T3 = T03 (n=7); T4 = T04 (n=6).

Fig 5. Distribution of coded extracts by participant and theme (N = 5, 39 extracts).

Fig 5 confirms the domain-specific concentration of extracts identified in Table 7. T01 dominated Theme 1 (5 extracts), T02 dominated Theme 2 (5 extracts), T03 dominated Theme 3 (7 extracts), and T04 dominated Theme 4 (6 extracts). T05 distributed contributions uniformly across all four themes (n = 2 each), reflecting the cross-thematic perspective characteristic of an institutional inspector role.



Note. Deductive thematic analysis (Braun & Clarke, 2022). T1 = 10 sub-codes; T2 = 9; T3 = 10; T4 = 10. All sub-codes carry equal weight (n=1) in this analysis.

Fig 6. Sub-code frequency distribution across four themes (N = 5, 39 extracts, 1 extract per sub-code).

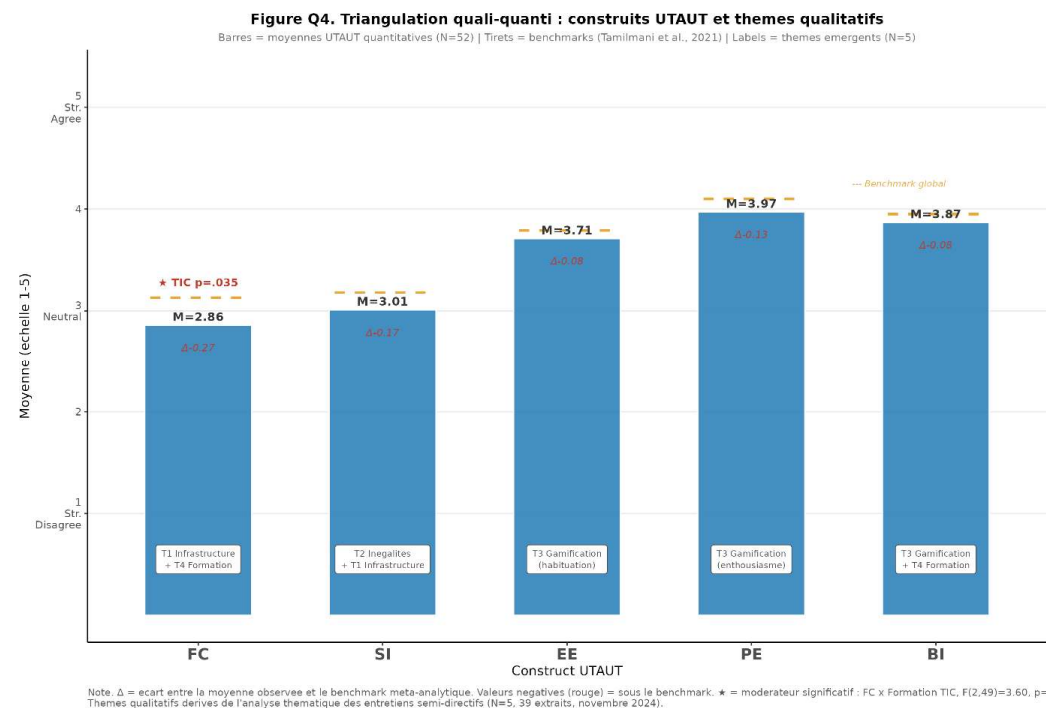
Fig 6 shows that each sub-code received exactly one extract, confirming equal analytical weight across all 39 sub-codes. T1 and T3 each yielded 10 sub-codes; T2 yielded 9; T4 yielded 10. This distribution is consistent with the deductive thematic structure, where each sub-code maps directly to one UTAUT-aligned construct.

Mixed-Methods Triangulation**Table 8. Joint Display: Qualitative Themes and UTAUT Constructs (Convergent Integration)**

Qualitative Theme	n extracts	UTAUT Constructs	Observed value	Reference	Δ	Moderating result	Convergence
T1: Infrastructural Constraints	10	FC	$M = 2.76$	3.13	-0.37	$FC \times TIC: F(2, 101) = 7.45, p = .001, \eta^2p = .129$	Strong
T2: Digital Inequalities	9	FC+SI	$SI: M = 3.00$	3.18	-0.17	$SI \times \text{Exercise Environment}: p = .096$ (trend)	Moderate
T3: Gamification and Motivation	10	BI+PE	$BI: M = 3.85$	3.95	-0.10	ns	Partial
T4: Training and Institutional Support	10	FC	None $M = 2.54$ / Complete $M = 3.39$	3.13	-0.37	$FC \times TIC: F(2, 101) = 7.45, p = .001, \eta^2p = .129$	Strong

Note. Reference = meta-analytic benchmark (Tamilmani et al., 2021). Δ = deviation between observed value and benchmark (negative values = below benchmark). η^2p = partial eta-squared (small $\geq .01$, medium $\geq .06$, large $\geq .14$; Cohen, 1988). Partial convergence for T3 reflects the tension between high BI/PE scores (confirmed adoption intention and perceived utility) and qualitative concerns about motivational quality (extrinsic vs. intrinsic engagement), a distinction that quantitative data alone cannot capture. FC = Facilitating Conditions; SI = Social Influence; BI = Behavioral Intention; PE = Performance Expectancy. T1 and T4 share the same moderating result because both map onto Facilitating Conditions; T1 captures physical infrastructure barriers while T4 captures training-related FC deficits, distinguished by ICT training sub-group means (None $M = 2.54$; Complete $M = 3.39$).

Table 8 organizes the four meta-inferences systematically: the UTAUT construct involved, the corresponding qualitative theme, the nature of the relationship (convergence or divergence-expansion), and the theoretical implication. Fig 7 visualizes the same relationships across the two data strands.

**Fig 7. Convergent integration of quantitative and qualitative findings across UTAUT constructs (N = 104).**

Convergence: Facilitating Conditions, Theme 1, and Theme 4 (strong). Quantitatively, FC was the only construct below the scale midpoint. It was also the only significant moderator in the study ($F(2, 101) = 7.45, p = .001, \eta^2p = .129$). The qualitative data named the conditions behind this quantitative result. Theme 1 documented absent WiFi, large classes, and compressed session time. Theme 4 documented the complete absence of formal institutional training. These qualitative accounts align directly with the quantitative finding that trained teachers perceived facilitating conditions as more favorable than untrained peers. Our findings align with those of Wibowo et al. (2025) among German PE teachers, where infrastructure deficits and absent training emerged as the dominant adoption barriers, suggesting these may reflect discipline-specific structural constraints rather than culturally idiosyncratic phenomena, though cross-national replication is needed. The sub-codes TRAIN_InstitutionalAbsence and TRAIN_PersonalTime documented the systematic gap between what teachers needed and what the institution provided.

Convergence: Social Influence and Theme 2 (moderate). SI showed the second-largest negative benchmark deviation ($\Delta = -0.17$). The exercise-environment pattern approached significance ($F(2, 101) = 2.01, p = .096, \eta^2p = .038$) without reaching the $\alpha = .05$ threshold. The qualitative data added context through sub-codes INEQ_FamilialCapital, INEQ_DigitalLiteracy, and INEQ_ExtracurricularGap. These documented unequal social conditions of technology exposure among students across the six sampled regions, providing a plausible account for the subdued SI scores.

Divergence-Expansion: Behavioral Intention, Performance Expectancy, and Theme 3. Quantitatively, PE ($M = 3.94$) and BI ($M = 3.85$) were the two highest-scoring constructs, both close to their respective benchmarks. This quantitative signal is accurate but incomplete. The qualitative data added a dimension absent from the UTAUT scales. High behavioral intention coexisted with three documented risks: extrinsic motivation displacing intrinsic motivation (GAMIF_IntrinsicCorruption, GAMIF_ExtrinsicConcern), declining engagement over time (GAMIF_Sustainability), and behavioral distortions linked to quantified objectives (GAMIF_SystemGaming, GAMIF_QualityOverQuantity). BI and PE scores captured teachers' intentions and perceived utility. The qualitative data captured teachers' accounts of what they observed in students once technology was deployed, namely motivational shifts and engagement patterns that UTAUT scales were not designed to measure. These are distinct phenomena that survey instruments alone cannot differentiate.

Discussion

Three convergent findings redirect attention from psychological readiness to structural constraint. Facilitating conditions, not motivation, constitute the primary adoption bottleneck. ICT training level moderated this construct significantly despite 48.1% of the sample reporting no formal training. And the intention-behavior gap, at over one scale point, is structurally produced.

The most theoretically consequential finding is the divergence between teachers' adoption intentions and their technology use during actual lessons. Behavioral intention reached $M = 3.85$, placing it among the higher values reported in UTAUT studies of educators (Tamilmani et al., 2021). Performance expectancy was higher still at $M = 3.94$. These scores indicate genuine psychological readiness. Yet technology use during physical education sessions registered $M = 2.81$, a gap of 1.06 scale points below behavioral intention. Evaluation-oriented use fell still lower at $M = 2.29$. Teachers believe in the technology, intend to use it, and then largely do not. This intention-behavior gap is theoretically predicted by the Theory of Planned Behavior (Ajzen, 1991). Even strong intentions fail to produce behavior when perceived behavioral control is insufficient. Facilitating conditions in UTAUT are directly analogous to this control construct (Sheeran & Webb, 2016). The present findings confirm this mechanism in a context where it had not previously been documented.

Crucially, the gap does not reflect motivational ambivalence. Teachers' qualitative accounts clarified why intentions stall at the classroom threshold. All five interview participants described infrastructural stacking: absent WiFi in outdoor facilities, electrical supply gaps, class sizes reaching forty students, and compressed session durations accumulated simultaneously. Of fifty session minutes, barely thirty-five involved active practice. Losing five minutes distributing devices is pedagogically prohibitive in this context. Evidence from sub-Saharan African educational settings documents nearly identical obstacle structures, where connectivity deficits and class size constraints interact to suppress effective technology use (Hennessy et al., 2015). The present accounts converge with the quantitative finding that resource availability and technical support were the weakest items in the entire instrument. The qualitative data explain the quantitative pattern. Quantitative data establish its prevalence.

The gap also illuminates tool selection patterns. Technologies adopted at high rates share a critical feature: independence from real-time connectivity. The digital stopwatch (86.5%), the Massar platform (84.6%), and YouTube (78.8%) all require minimal session-level coordination. Technologies demanding live infrastructure, such as GPS tracking applications (34.6%), and those requiring institutional procurement, such as augmented or virtual reality tools (3.8%), are near-absent. Teachers are not avoiding technology. They are selecting the subset compatible with their structural constraints. This adaptive strategy is consistent with affordance theory accounts of technology use in physical education contexts (Jastrow et al., 2022; Sargent & Calderón, 2021). Connectivity-light mobile tracking applications appear especially suited to these constraints, with prior intervention evidence showing measurable gains in adolescent fitness and motivation under similar infrastructural conditions (Moudettir et al., 2025). The high WhatsApp rate (73.1%) reflects asynchronous parent communication rather than in-session pedagogical integration. Aggregate adoption indices therefore erase qualitatively distinct categories of use.

The ICT training moderation effect on facilitating conditions is the study's most policy-relevant finding. Teachers reporting complete ICT training perceived facilitating conditions as significantly more favorable than those with no training ($\Delta M = 0.926, p = .001, \eta^2p = .129$). This effect size falls in the medium-to-large range and explains a meaningful proportion of variance in the construct most directly linked to behavioral enactment (Cohen, 1988). Training does not merely improve technical skills. It is associated with a reorientation of how teachers perceive and use available resources. Trained teachers reported extracting more affordance from identical physical environments, a pattern consistent with the hypothesis that competency shapes constraint perception (Ertmer, 1999), though causal direction cannot be established from cross-sectional data. Undertrained

teachers may experience identical infrastructure as more prohibitive than trained peers do. Lacking the competency to work around constraints creatively, they perceive the same context as more restrictive (Ertmer, 1999).

The policy significance of this moderation is sharpened by the training distribution. Fully 48.1% of the sample reported no formal ICT training. A further 34.6% described their training as partial. This means 82.7% of the sample operates below the threshold at which training shifts facilitating conditions perceptions meaningfully. This systemic training deficit has been documented in adjacent Moroccan EPS contexts: a study of 723 in-service PE teachers in online professional development found that despite high social presence and satisfaction, structural constraints substantially reduced perceived learning outcomes (Abaakil & Belhaj, 2023).

The TPACK framework identifies why generic ICT training is insufficient. Effective technology-enhanced PE requires the simultaneous integration of technological, pedagogical, and disciplinary knowledge (Mishra & Koehler, 2006). A teacher who understands a heart rate application technically but cannot embed its outputs in cooperative learning sequences lacks the pedagogical dimension. Professional development programs integrating all three dimensions consistently outperform discipline-agnostic alternatives (Voogt & Fisser, 2013; Moudettir et al., 2026b).

The qualitative accounts of digital inequality constitute a finding distinct from, though related to, the infrastructure and training themes. All five participants observed that technology integration amplified rather than reduced existing socioeconomic disparities among students. Students from digitally literate families proved immediately fluent with applications. Students without home digital exposure required sustained individual support. Class sizes of forty made that support structurally impossible to provide. This asymmetry extends to access itself: students whose mobile data plans were insufficient to download recommended applications faced a barrier visible only when they disclosed it incidentally. This invisibility exemplifies the second and third-level digital divides (van Dijk, 2020). Differential skills and usage outcomes persist even among individuals with nominal device access. Device ownership does not produce digital competence. Digital competence does not produce equitable benefit (Kummitha & Krishnamurthy, 2021). Physical education's student population, which typically spans a wider socioeconomic range than academic subjects, is particularly exposed to this gradient.

Four of five participants articulated explicit ethical concern about this dynamic. The tension between physical education's egalitarian pedagogical mandate and the stratifying effects of unmediated technology integration was a recurring theme. UTAUT and its variants measure adoption willingness but do not capture the reservations teachers hold about whether adoption serves all students equitably. This representational gap is not unique to physical education. Educational technology surveys across diverse contexts have consistently underestimated the ethical deliberation that experienced teachers exercise before integrating new tools into mixed-ability classrooms (Abbad, 2021). Social influence was the second-lowest construct in this study ($M = 3.00$). The qualitative findings suggest its scores may be further suppressed by teachers' principled reluctance to integrate tools perceived as pedagogically inequitable. This ethical friction is underrepresented in quantitative adoption research. Future UTAUT adaptations for physical education contexts should consider equity orientation as a distinct construct alongside the standard four (Granić, 2022).

The gamification findings introduce a theoretical complication that adoption frameworks have not adequately addressed. Four of five teachers reported initial motivational gains when gamified applications were introduced. These accounts align with meta-analytic evidence showing that game-based elements reliably produce short-term engagement increases (Sailer & Homner, 2020; Sotos-Martínez et al., 2024). Three participants described systematic motivational decline after three to four weeks. This temporal arc is consistent with habituation to extrinsic reward schedules documented in longitudinal gamification research (Hanus & Fox, 2015). Two behavioral distortions were documented: students shaking phones to inflate step counts and passing devices to more active peers to accumulate points. They appear to reflect a systematic response to quantified extrinsic reward structures rather than individual student dispositions (Van Roy & Zaman, 2019). Self-determination theory attributes this pattern to extrinsic contingencies undermining autonomous regulation (Ryan & Deci, 2000). The undermining effect is most pronounced when rewards are perceived as controlling rather than informational (Ntoumanis et al., 2021).

The implications for physical education are discipline-specific. Physical education's core goal is cultivating durable intrinsic motivation for physical activity. This goal is structurally vulnerable to the overjustification effect accompanying points-and-ranking gamification systems (Deci et al., 1999). Teachers in this study were alert to this risk in ways that adoption surveys cannot detect. Teachers believe these technologies can improve teaching while simultaneously holding reservations about the quality of motivation they generate. This coexistence of adoption readiness and pedagogical critical judgment exceeds what the standard UTAUT framework captures. This temporal erosion is particularly consequential given that evaluation-oriented technology use registered the lowest frequency in the sample ($M = 2.29$), suggesting that the very contexts where gamification is most deployed are those where motivational displacement is most advanced. Longitudinal study designs, rather than cross-sectional surveys, are needed to differentiate initial enthusiasm from sustained pedagogical integration (Sotos-Martínez et al., 2024).

Limitations

Several limitations constrain the inferences warranted by this study. First, the sample size ($N = 104$) was determined by the accessible population of physical education teachers and inspectors across six Moroccan regions, rather than by a priori power analysis. Post-hoc power analysis (G*Power 3.1; Faul et al., 2007) confirmed adequate power for the primary regression model (observed power = .99 at $f^2 = .15$, $\alpha = .05$, $N = 104$). Power for detecting small moderation effects was insufficient, however (observed power $\approx .40$ for $\eta^2 p \approx .09$ at $N = 104$), reinforcing the call for replication with $N \geq 150$. The present sample additionally precludes full latent variable structural equation modelling of construct relationships. The CFA reported here should be interpreted as an exploratory measurement validation rather than a definitive confirmatory test, given the sensitivity of fit indices to sample size below $N = 100$ (MacCallum et al., 1996). Future research should target larger probability samples to permit latent variable modelling and multigroup comparisons across career stages and regions. Second, cross-sectional design prohibits causal inference regarding the relationships between UTAUT constructs and behavioral intention. The direction of observed effects, while theoretically motivated, cannot be established without longitudinal or experimental designs. Cluster-randomized controlled trials targeting equivalent Moroccan adolescent populations have demonstrated the feasibility of such designs in the present infrastructural context (Moudettir et al., 2026a). Third, self-report measures are subject to social desirability bias, particularly for constructs tied to professional competence such as ICT training level and self-efficacy. Observational methods and objective measures of technology use, including application logs and lesson recordings, would strengthen future investigations. Fourth, qualitative findings derive from five interview participants selected through maximum variation sampling. While this sampling strategy maximises heterogeneity within a small purposive sample, transferability to other Moroccan regions or educational systems requires caution. Cross-cultural replication in comparable North African and Global South contexts remains a priority for the field. Fifth, the inclusion of inspectors ($n = 16$, 15.4%) alongside classroom teachers may have introduced role-specific variance in Social Influence and Facilitating Conditions perceptions, given inspectors' distinct institutional position. Future work should disaggregate these professional subgroups to examine whether construct hierarchies differ systematically by role. Sixth, Theme 3 (Gamification and Motivation) drew predominantly on T03's accounts (7 of 10 extracts), reflecting this participant's extensive pedagogical experience with gamification tools; transferability of this theme to less experienced teachers warrants caution.

Conclusion

Moroccan physical education teachers believe in digital technology. They see its value, intend to use it, and invest personal time mastering applications their training never covered. Yet when they step onto the gymnasium floor, those intentions encounter a reality that no amount of individual motivation can overcome. WiFi does not reach the outdoor fields. Classes of forty students make individualized support impossible. Fifty-minute sessions leave barely thirty-five minutes for active practice, and distributing devices consumes what little time remains. This is not a story of reluctant teachers. It is a story of structural constraint.

That complication matters theoretically. UTAUT, like most adoption frameworks, was designed to predict whether technology will be used, not how well, not for whom, and not at what cost. This study suggests that in physically active, socially heterogeneous, infrastructure-poor contexts, those distinctions are not secondary. They are central. The intention-behavior gap is not a failure of teacher motivation. It is a measure of the distance between policy ambition and classroom reality. It requires WiFi in gymnasias, technical support that arrives before lessons, and professional development that addresses not generic digital literacy but the specific pedagogical challenges of physical education.

What remains is this: Moroccan physical education teachers are not the problem. They are the solution, waiting for conditions that match their intentions. The policy architecture exists. The evidence now identifies where to build.

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References

- Abaakil, S., & Belhaj, L. (2023). Social presence and satisfaction in online professional development for physical education teachers during COVID-19: A Moroccan case study. *Journal of Research Administration*, 5(2), 3584-3596. <https://eric.ed.gov/?id=ED634359>
- Abbad, M. M. (2021). Using the UTAUT model to understand students' usage of e-learning systems in developing countries. *Education and Information Technologies*, 26(6), 7205-7224. <https://doi.org/10.1007/s10639-021-10573-5>
- Agyei, D. D. (2021). Integrating ICT into schools in Sub-Saharan Africa: From teachers' capacity building to classroom implementation. *Education and Information Technologies*, 26, 125-144. <https://doi.org/10.1007/s10639-020-10253-w>
- Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, 50(2), 179-211. [https://doi.org/10.1016/0749-5978\(91\)90020-T](https://doi.org/10.1016/0749-5978(91)90020-T)
- Armstrong, J. S., & Overton, T. S. (1977). Estimating nonresponse bias in mail surveys. *Journal of Marketing Research*, 14(3), 396-402. <https://doi.org/10.1177/002224377701400320>
- Berbar, H., Lotfi, S., & Talbi, M. (2021). Validation and development of a Moroccan school quality evaluation system. *Education Research International*, 2021, Article 1829259. <https://doi.org/10.1155/2021/1829259>
- Blut, M., Chong, A. Y.-L., Tsiga, Z., & Venkatesh, V. (2022). Meta-analysis of the unified theory of acceptance and use of technology (UTAUT): Making sense of contradictory findings. *MIS Quarterly*, 46(1), 13-54. <https://doi.org/10.25300/MISQ/2022/16136>
- Bodsworth, H., & Goodyear, V. A. (2017). Barriers and facilitators to using digital technologies in the cooperative learning model in physical education. *Physical Education and Sport Pedagogy*, 22(6), 563-579. <https://doi.org/10.1080/17408989.2017.1284672>
- Braun, V., & Clarke, V. (2022). *Thematic analysis: A practical guide*. SAGE Publications.
- Campbell, S., Greenwood, M., Prior, S., Shearer, T., Walkem, K., Young, S., Bywaters, D., & Walker, K. (2020). Purposive sampling: Complex or simple? Research case examples. *Journal of Research in Nursing*, 25(8), 652-661. <https://doi.org/10.1177/1744987120927206>
- Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum Associates.
- Creamer, E. G. (2018). *An introduction to fully integrated mixed methods research*. SAGE Publications.
- Creswell, J. W., & Creswell, J. D. (2018). *Research design: Qualitative, quantitative, and mixed methods approaches* (5th ed.). SAGE Publications.
- Deci, E. L., Koestner, R., & Ryan, R. M. (1999). A meta-analytic review of experiments examining the effects of extrinsic rewards on intrinsic motivation. *Psychological Bulletin*, 125(6), 627-668. <https://doi.org/10.1037/0033-2909.125.6.627>
- El-Masri, M., & Tarhini, A. (2017). Factors affecting the adoption of e-learning systems in Qatar and USA: Extending the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2). *Educational Technology Research and Development*, 65(3), 743-763. <https://doi.org/10.1007/s11423-016-9508-8>
- Ertmer, P. A. (1999). Addressing first- and second-order barriers to change: Strategies for technology integration. *Educational Technology Research and Development*, 47(4), 47-61. <https://doi.org/10.1007/BF02299597>
- Ertmer, P. A., & Ottenbreit-Leftwich, A. T. (2010). Teacher technology change: How knowledge, confidence, beliefs, and culture intersect. *Journal of Research on Technology in Education*, 42(3), 255-284. <https://doi.org/10.1080/15391523.2010.10782551>
- Faul, F., Erdfelder, E., Buchner, A., & Lang, A.-G. (2007). G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods*, 39(2), 175-191. <https://doi.org/10.3758/BF03193146>
- Fetters, M. D., Curry, L. A., & Creswell, J. W. (2013). Achieving integration in mixed methods designs: Principles and practices. *Health Services Research*, 48(6 Pt 2), 2134-2156. <https://doi.org/10.1111/1475-6773.12117>
- Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39-50. <https://doi.org/10.1177/002224378101800104>
- Fugard, A. J. B., & Potts, H. W. W. (2015). Supporting thinking on sample sizes for thematic analyses: A quantitative tool. *International Journal of Social Research Methodology*, 18(6), 669-684. <https://doi.org/10.1080/13645579.2015.1005453>
- Granić, A. (2022). Educational technology adoption: A systematic review. *Education and Information Technologies*, 27(7), 9725-9744. <https://doi.org/10.1007/s10639-022-10951-7>
- Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (8th ed.). Cengage Learning.
- Hanus, M. D., & Fox, J. (2015). Assessing the effects of gamification in the classroom: A longitudinal study on intrinsic motivation, social comparison, satisfaction, effort, and academic performance. *Computers & Education*, 80, 152-161. <https://doi.org/10.1016/j.compedu.2014.08.019>

- Hennessy, S., Onguko, B., Harrison, D., Ang'ondi, E. K., Namalefe, S., Naseem, A., & Wamakote, L. (2015). Developing the use of information and communication technology to enhance teaching and learning in East African schools: Review of the literature. *Journal of Educational Change*, 16(1), 69-95. <https://doi.org/10.1007/s10833-014-9243-4>
- Jastrow, F., Schul, J.-E., Bähr, I., Gröben, B., Herrmann, C., & Wegner, C. (2022). Digital media usage in physical education: A systematic review of empirical research. *German Journal of Exercise and Sport Research*, 52(2), 195-208. <https://doi.org/10.1007/s12662-022-00793-9>
- Kummitha, R. K. R., & Krishnamurthy, S. (2021). Smart city and the digital divide: A conceptual analysis of the digital divide in the context of Smart City. *Cities*, 116, Article 103286. <https://doi.org/10.1016/j.cities.2021.103286>
- Landis, J. R., & Koch, G. G. (1977). The measurement of observer agreement for categorical data. *Biometrics*, 33(1), 159-174. <https://doi.org/10.2307/2529310>
- MacCallum, R. C., Browne, M. W., & Sugawara, H. M. (1996). Power analysis and determination of sample size for covariance structure modeling. *Psychological Methods*, 1(2), 130-149. <https://doi.org/10.1037/1082-989X.1.2.130>
- Malterud, K., Siersma, V. D., & Guassora, A. D. (2016). Sample size in qualitative interview studies: Guided by information power. *Qualitative Health Research*, 26(13), 1753-1760. <https://doi.org/10.1177/1049732315617444>
- Maxwell, S. E., Kelley, K., & Rausch, J. R. (2008). Sample size planning for statistical power and accuracy in parameter estimation. *Annual Review of Psychology*, 59, 537-563. <https://doi.org/10.1146/annurev.psych.59.103006.093735>
- McNeish, D. (2018). Thanks coefficient alpha, we'll take it from here. *Psychological Methods*, 23(3), 412-433. <https://doi.org/10.1037/met0000144>
- Mears, D., & Hansen, L. (2020). Technology use in physical education: A review of literature from 2009-2019. *Quest*, 72(4), 395-414. <https://doi.org/10.1080/00336297.2020.1752817>
- Mishra, P., & Koehler, M. J. (2006). Technological pedagogical content knowledge: A framework for teacher knowledge. *Teachers College Record*, 108(6), 1017-1054. <https://doi.org/10.1111/j.1467-9620.2006.00684.x>
- Moudettir, Y., Ouhrir, S., & Lotfi, S. (2025). Impact of mobile tracking applications on adolescents' physical fitness and motivational outcomes in physical education. *Retos*, 73, 923-936. <https://doi.org/10.47197/retos.v73.117648>
- Moudettir, Y., Ouhrir, S., & Lotfi, S. (2026a). Mobile tracking ecosystem on motor engagement and physical performance: A cluster-randomized trial. *Retos*, 81, 1-16. <https://doi.org/10.47197/retos.v81.119074>
- Moudettir, Y., Ouhrir, S., & Lotfi, S. (2026b). The effects of digital technologies on physical education outcomes: A systematic review and meta-analysis. *Physical Education Theory and Methodology*, 26(2), 230-250. <https://doi.org/10.17309/tmf.v.2026.2.02>
- Ntoumanis, N., Ng, J. Y. Y., Prestwich, A., Quested, E., Hancox, J. E., Thøgersen-Ntoumani, C., Deci, E. L., Ryan, R. M., Lonsdale, C., & Williams, G. C. (2021). A meta-analysis of self-determination theory-informed intervention studies in health domain: Effects on motivation, health behavior, physical, and psychological health. *Health Psychology Review*, 15(2), 214-244. <https://doi.org/10.1080/17437199.2020.1718529>
- Patton, M. Q. (2015). *Qualitative research & evaluation methods: Integrating theory and practice* (4th ed.). SAGE Publications.
- R Core Team. (2023). *R: A language and environment for statistical computing* (Version 4.3.2) [Computer software]. R Foundation for Statistical Computing. <https://www.R-project.org/>
- Rosseel, Y. (2012). lavaan: An R package for structural equation modeling. *Journal of Statistical Software*, 48(2), 1-36. <https://doi.org/10.18637/jss.v048.i02>
- Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American Psychologist*, 55(1), 68-78. <https://doi.org/10.1037/0003-066X.55.1.68>
- Sailer, M., & Homner, L. (2020). The gamification of learning: A meta-analysis. *Educational Psychology Review*, 32(1), 77-112. <https://doi.org/10.1007/s10648-019-09498-w>
- Sargent, J., & Calderón, A. (2021). A critical review of digital technologies to support PE teachers' professional learning and curriculum innovation. *Physical Education and Sport Pedagogy*, 26(5), 480-493. <https://doi.org/10.1080/17408989.2020.1823946>
- Satorra, A., & Bentler, P. M. (1994). Corrections to test statistics and standard errors in covariance structure analysis. In A. von Eye & C. C. Clogg (Eds.), *Latent variables analysis* (pp. 399-419). SAGE Publications.
- Scherer, R., Siddiq, F., & Tondeur, J. (2019). The technology acceptance model (TAM): A meta-analytic structural equation modeling approach to explaining teachers' adoption of digital technology in education. *Computers & Education*, 128, 13-35. <https://doi.org/10.1016/j.compedu.2018.09.009>

-
- Sheeran, P., & Webb, T. L. (2016). The intention-behavior gap. *Social and Personality Psychology Compass*, 10(9), 503-518. <https://doi.org/10.1111/spc3.12265>
- Sotos-Martínez, V. J., Ferriz-Valero, A., García-Martínez, S., & Tortosa-Martínez, J. (2024). Gamification in physical education: Impact on self-determination and motivational climate. *Frontiers in Psychology*, 15, Article 1360985. <https://doi.org/10.3389/fpsyg.2024.1360985>
- Tamilmani, K., Rana, N. P., Wamba, S. F., & Dwivedi, R. (2021). The extended unified theory of acceptance and use of technology (UTAUT2): A systematic literature review and theory evaluation. *International Journal of Information Management*, 57, Article 102269. <https://doi.org/10.1016/j.ijinfomgt.2020.102269>
- UNESCO. (2022). *Programme GENIE: Bilan et perspectives pour l'intégration des TIC dans l'éducation au Maroc*. UNESCO Rabat Office.
- van Dijk, J. A. G. M. (2020). *The digital divide*. Polity Press.
- Van Roy, R., & Zaman, B. (2019). Unravelling the ambivalent motivational power of gamification: A basic psychological needs perspective. *International Journal of Human-Computer Studies*, 127, 38-50. <https://doi.org/10.1016/j.ijhcs.2018.04.009>
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425-478. <https://doi.org/10.2307/30036540>
- Voogt, J., & Fisser, P. (2013). Using collaborative design to prepare pre-service teachers for technology integration in their teaching practice. *Journal of Computer Assisted Learning*, 29(4), 290-302. <https://doi.org/10.1111/jcal.12018>
- Wallace, S., Mueller, J., & Strohmeyer, H. S. (2022). Digital competency in physical education: Development and validation of a teacher survey. *Curriculum Studies in Health and Physical Education*, 13(2), 131-150. <https://doi.org/10.1080/25742981.2022.2041785>
- Wibowo, J., Hofmann, R., Brand, T., & Wiese, H. (2025). Predicting the power of informal learning opportunities on technology use of physical education teachers. *Frontiers in Sports and Active Living*, 7, Article 1653809. <https://doi.org/10.3389/fspor.2025.1653809>
- Wolf, E. J., Harrington, K. M., Clark, S. L., & Miller, M. W. (2013). Sample size requirements for structural equation models. *Educational and Psychological Measurement*, 73(6), 913-934. <https://doi.org/10.1177/0013164413495237>