Configurational adoption of fitness technologies among business students using fsQCA

Adopción configuracional de tecnologías fitness en estudiantes de áreas empresariales mediante fsQCA

Authors

Alexander Haro-Sarango, Gladys Proaño-Altamirano, Diana Castillo-Martínez, Evelyn Gavilanes-Carranza

Abstract

Introduction: Fitness apps and wearables support physical-activity self-management, but adoption depends on interdependent individual and contextual conditions.
Objective: To identify configurations associated with high fitness technology adoption among business students.
Methodology: A cross-sectional study analyzed 403 complete Google Forms responses. The 32-item, eight-factor model was evaluated through CFA, composite reliability, AVE, HTMT, and common-method diagnostics; calibrated scores were examined through necessity, sufficiency, negated-outcome, PRI, and robustness analyses.
Results: The eight-factor model fit well ($\chi^2(436)$ = 148.54, CFI/TLI = 1.000, RMSEA = .000, SRMR = .026); composite reliability was .893–.927, AVE was .676–.760, and HTMT was below .85. No condition was necessary. Five configurations explained high adoption (consistency = .946, PRI = .894, coverage = .566), and four asymmetric configurations explained its negation.
Discussion: Algorithmic coaching trust and privacy–personalization calculus formed the shared core; low unique coverage showed considerable overlap among the pathways.
Conclusions: Adoption was configurational and asymmetric, supporting differentiated rather than uniform digital physical-activity strategies.

Keywords

active learning culture; business students; fitness technologies; fuzzy-set qualitative comparative analysis; wearable devices.

Resumen

Introducción: Las aplicaciones fitness y los dispositivos wearables apoyan la autogestión de la actividad física, pero su adopción depende de condiciones individuales y contextuales interdependientes.
Objetivo: Identificar configuraciones asociadas con una alta adopción de tecnologías fitness en estudiantes de áreas empresariales.
Metodología: Se analizaron 403 respuestas completas obtenidas mediante Google Forms. El modelo de 32 ítems y ocho factores se evaluó mediante AFC, fiabilidad compuesta, AVE, HTMT y pruebas de método común; los puntajes calibrados se examinaron mediante necesidad, suficiencia, resultado negado, PRI y robustez.
Resultados: El modelo de ocho factores mostró buen ajuste ($\chi^2(436)$ = 148.54, CFI/TLI = 1.000, RMSEA = .000, SRMR = .026); la fiabilidad compuesta fue .893–.927, la AVE .676–.760 y el HTMT inferior a .85. Ninguna condición fue necesaria. Cinco configuraciones explicaron la alta adopción (consistencia = .946, PRI = .894, cobertura = .566) y cuatro configuraciones asimétricas explicaron su negación.
Discusión: La confianza en el coaching algorítmico y el cálculo privacidad–personalización formaron el núcleo compartido; las coberturas únicas reducidas mostraron un solapamiento considerable entre las rutas.
Conclusiones: La adopción fue configuracional y asimétrica, lo que respalda estrategias digitales de actividad física diferenciadas en lugar de uniformes.

Palabras clave

análisis cualitativo comparativo; cultura activa de aprendizaje; dispositivos wearables; estudiantes empresariales; tecnologías fitness.

Introduction

Digital fitness technologies have become embedded in how university students monitor movement, organize exercise, and interpret feedback about health and well-being. Students use these tools to record data and organize leisure activities, although usage patterns vary across personal and socioeconomic conditions (Berbeka et al., 2023). Their effects, however, are not uniformly positive. An eight-week mobile-application intervention increased energy expenditure but produced only trivial changes in body composition (Rangel Colmenero, 2023), whereas a 12-week intervention improved physical activity and intrinsic motivation, with social and gamified functions emerging as relevant engagement mechanisms (Ibragimova et al., 2025). Technology can therefore facilitate action without guaranteeing sustained or physiologically meaningful change. The same digital environment may also displace movement: mobile-phone dependence has been associated with low physical activity among university students (Mamani-Jilaja et al., 2024). These contrasting findings make adoption a behavioral and contextual problem rather than a simple decision to download an application or own a device.

The first mechanism concerns value and capability. Perceived usefulness in the Technology Acceptance Model and performance expectancy in UTAUT explain why users engage with systems that are expected to improve valued outcomes (Davis, 1989; Venkatesh et al., 2003). In the fitness context, perceived health–academic value captures whether digital monitoring is expected to support energy, concentration, stress management, and reduced sedentarism. Digital fitness self-efficacy extends social cognitive theory by representing confidence in configuring devices, interpreting metrics, and using feedback for self-regulation (Bandura, 1986). Prior studies show that usefulness, perceived control, self-efficacy, and satisfaction are linked to initial or continued fitness-app use (Cho et al., 2015; Yu et al., 2021; Zhang & Xu, 2020), but these variables need not operate with equal importance for every student.

A second mechanism concerns whether students accept algorithmic mediation. Fitness platforms do not merely record activity; they recommend goals, issue alerts, classify performance, and exchange personal data for tailored feedback. Trust in automation is therefore relevant because reliance depends on whether recommendations are perceived as competent, predictable, and appropriate (Lee & See, 2004). At the same time, privacy calculus theory proposes that disclosure decisions reflect an evaluation of anticipated benefits against perceived privacy costs (Dinev & Hart, 2006). In this study, algorithmic coaching trust and privacy–personalization calculus are treated as distinct constructs: the former concerns confidence in automated guidance, whereas the latter concerns the acceptability of data use in exchange for understandable and useful personalization.

A third mechanism is social and contextual. Social influence and facilitating conditions are central to UTAUT, while self-determination theory clarifies why feedback, competence, relatedness, and autonomous motivation can sustain engagement (Deci & Ryan, 2000; Venkatesh et al., 2012). Gamified and cooperative initiatives have increased participation and perceived motivation in university settings (Escobosa Morera et al., 2024), and mobile tracking has produced motivational and physical improvements when integrated with structured pedagogy (Moudettir et al., 2025). Conversely, mandatory exercise check-ins may fail to translate directly into app use when self-determined motivation is not activated (Han & Li, 2026). Gamification may also externalize motivation or intensify comparison. Accordingly, gamified social influence, technology accessibility, and active learning culture are modeled as contextual enablers whose effects depend on how they combine with value, capability, trust, and privacy reasoning.

The literature is dominated by net-effect models that estimate whether one predictor has an average association with intention or use. Such models are informative but do not test equifinality, conjunctural causation, or causal asymmetry. The studies reviewed above also suggest three unresolved issues: access can coexist with weak adoption; similar levels of use may arise from different motivational and institutional conditions; and the drivers of high adoption may not be the inverse of the drivers of low adoption. A configurational analysis directly addresses these issues by examining whether different combinations of conditions are sufficient for the outcome and its negation.

The objective was to identify the configurations associated with high fitness technology adoption among final-level students in business-related programs. The model integrated seven causal conditions—perceived health–academic value (PHV), digital fitness self-efficacy (DFS), algorithmic intelligent coaching trust (AIC), privacy–personalization calculus (PPC), gamified social influence (GSI), fitness technology accessibility (FTA), and active learning culture (ALC)—and the outcome high fitness technology adoption (HFTA).

Method

A quantitative, non-experimental, cross-sectional, and explanatory-configurational design was used. The target population comprised all students enrolled in the final academic level of business-related programs at a university-level technological institution in the Ecuadorian highlands. Data collection was conducted through Google Forms. The analytical census contained 403 complete responses; no missing or out-of-range values were detected. Because the realized dataset covered the defined population, inferential p-values and confidence intervals were not used to generalize beyond it.

The questionnaire contained 32 items measured on a five-point Likert-type scale (1 = strongly disagree to 5 = strongly agree), with four indicators for each construct. Item content was mapped to established theoretical domains: perceived usefulness and outcome value for PHV; self-efficacy for DFS; trust in automation for AIC; privacy calculus for PPC; social influence and gamification for GSI; facilitating conditions for FTA; institutional and social support for ALC; and behavioral intention and continued use for HFTA. FTA4 was expressed in the same positive direction as the other accessibility indicators: 'The cost of apps, mobile data, or devices does not prevent me from using fitness technologies.' Table 1 summarizes the measurement structure.

The measurement model was evaluated before constructing composite and fuzzy-set scores. A correlated eight-factor confirmatory factor analysis was estimated using diagonally weighted least squares (DWLS), which reduces reliance on multivariate normality for ordered response categories. Model fit was evaluated with chi-square, CFI, TLI, RMSEA, and SRMR. Standardized loadings of .70 or higher, composite reliability of .70 or higher, and average variance extracted (AVE) of .50 or higher were used as measurement-quality criteria. Discriminant validity was assessed with the heterotrait–monotrait ratio (HTMT), using .85 as the conservative threshold (Henseler et al., 2015), and with the Fornell–Larcker comparison.

Potential common method bias was examined through two complementary diagnostics because all variables were self-reported in the same form. Harman's unrotated single-factor test quantified the percentage of variance explained by the first factor, and a one-factor CFA was compared with the hypothesized eight-factor model. These procedures do not eliminate method bias, but they determine whether a single common factor provides a plausible account of the covariance structure (Podsakoff et al., 2003).

Composite scores were calculated as the mean of the four indicators assigned to each construct. Direct calibration transformed these scores into fuzzy-set memberships using 1.50 for full non-membership, 3.00 for the crossover point, and 4.50 for full membership. Scores equal to the crossover were adjusted by a small constant during truth-table assignment to avoid ambiguous maximum membership.

The fsQCA followed the sequence recommended for configurational research (Pappas & Woodside, 2021; Ragin, 2008; Schneider & Wagemann, 2012). Necessity was evaluated for the presence and absence of every condition, with .90 as the consistency criterion. Coverage and relevance of necessity (RoN) were also reported; RoN evaluates whether an apparently necessary condition is empirically relevant rather than nearly constant. The sufficiency truth table used a minimum frequency of three cases, consistency of .80, and PRI consistency of .60. PRI was included to reduce simultaneous sufficiency for the outcome and its negation. Intermediate solutions were interpreted according to theoretically plausible positive directional expectations.

Causal asymmetry was assessed by repeating the truth-table and minimization procedure for the negated outcome (~HFTA). Robustness was evaluated by increasing frequency, consistency, and PRI thresholds across three additional scenarios. The stability assessment focused on whether the shared configurational core, solution consistency, PRI, and coverage remained substantively comparable rather than requiring identical Boolean expressions under every threshold combination.

Table 1. Measurement structure and theoretical grounding

Construct	Theoretical domain	Operational content	Items
PHV	Perceived usefulness / outcome value	Value for energy, well-being, lower academic sedentarism, concentration, and stress management	PHV1–PHV4
DFS	Social cognitive self-efficacy	Capability to configure technologies, interpret metrics, and use data for self-regulation	DFS1–DFS4
AIC	Trust in automation	Confidence in recommendations, intelligent alerts, personalized goals, and algorithmic adjustments	AIC1–AIC4
PPC	Privacy calculus	Acceptance of data use when personalization benefits and protection practices are clear	PPC1–PPC4
GSI	Social influence / self-determination	Motivation through challenges, badges, rankings, shared achievements, and healthy competition	GSI1–GSI4
FTA	Facilitating conditions	Availability of compatible devices, internet connectivity, wearables, and manageable costs	FTA1–FTA4
ALC	Institutional and social support	Institutional promotion, spaces, activities, and encouragement for active living	ALC1–ALC4
HFTA	Behavioral intention / continuance	Use or intended use of apps and wearables within the university routine	HFTA1–HFTA4

Results

The 403 cases provided complete responses for all 32 indicators. Construct means ranged from 2.948 to 3.005 and standard deviations from 1.080 to 1.159. Skewness values were close to zero (−.075 to .095), and excess kurtosis ranged from −1.088 to −.815, confirming broad response dispersion without severe asymmetry. Table 2 reports the descriptive and measurement-quality results.

The eight-factor CFA converged and showed excellent global fit: $\chi^2(436) = 148.54$, CFI = 1.000, TLI = 1.000, RMSEA = .000, and SRMR = .026. Standardized loadings ranged from .809 to .885. Cronbach's alpha and composite reliability exceeded .89 for every construct, while AVE ranged from .676 to .760. These results support indicator reliability and convergent validity. By contrast, the single-factor model fit poorly, $\chi^2(464) = 6081.87$, CFI = .794, TLI = .780, RMSEA = .174, and SRMR = .161.

Discriminant validity was supported. All HTMT values were below .85; the largest were AIC–HFTA (.738), PPC–HFTA (.728), and AIC–PPC (.697). Their bootstrap intervals also remained below .85. The square root of AVE for each construct exceeded its correlations with the other constructs.

Common-method diagnostics did not indicate that a single response tendency dominated the data. The first unrotated factor accounted for 33.91% of total variance, and the one-factor CFA was substantially inferior to the eight-factor model. Common method variance cannot be excluded completely in a cross-sectional self-report design, but it does not provide an adequate explanation of the observed covariance structure.

Necessity analysis showed that no individual condition or its absence reached .90 consistency. AIC had the highest necessity consistency (.797), followed by PPC (.779), PHV (.776), and DFS (.756). RoN values were reported to distinguish empirical relevance from trivial necessity; none of the conditions met the consistency requirement for a necessary condition.

Five intermediate configurations were sufficient for high adoption. Their consistency ranged from .962 to .972, PRI from .914 to .944, raw coverage from .317 to .379, and unique coverage from .023 to .045. Overall solution consistency was .946, PRI was .894, and coverage was .566. The coverage value indicates that the solution accounts for a little more than half of the membership in high adoption; it should not be characterized as strong. The small unique-coverage values show that the five recipes overlap considerably and should be interpreted as variations around a shared core rather than five independent routes.

AIC and PPC were present in all five configurations. S1 combined this core with PHV, DFS, and GSI; S2 added PHV, DFS, and FTA; S3 added PHV, DFS, and ALC; S4 added PHV, GSI, and ALC; and S5 combined the core with DFS, FTA, and ALC. These patterns indicate limited substitution among capability, value, social, access, and institutional conditions, while trust and privacy–personalization reasoning remain stable components of the high-adoption solution.

The negated-outcome analysis confirmed causal asymmetry. Four configurations explained low adoption with solution consistency of .951, PRI of .911, and coverage of .583. The most empirically distinctive route combined the absence of AIC, DFS, PHV, and PPC (unique coverage = .132). Accessibility was present in one low-adoption route, demonstrating that access alone does not prevent non-adoption when value, capability, trust, and social or institutional conditions are absent.

The robustness analysis retained high solution consistency (.953–.955), PRI (.905–.912), and coverage between .524 and .572 in the stricter scenarios. AIC and PPC remained in the dominant positive configurations. Some peripheral terms and negated contextual conditions changed as frequency and inclusion thresholds increased, which is expected in QCA; the substantive core and the interpretation of overlapping pathways remained stable.

Table 2. Descriptive statistics, reliability, and convergent validity

Construct	M	SD	Skew.	Kurt.	α	CR	AVE	Loading range
PHV	2.989	1.159	0.053	-1.088	0.913	0.913	0.724	0.831–0.861
DFS	2.977	1.080	0.067	-0.815	0.893	0.893	0.676	0.809–0.844
AIC	2.990	1.123	-0.014	-0.909	0.906	0.906	0.708	0.837–0.844
PPC	2.948	1.124	0.095	-1.032	0.911	0.912	0.720	0.831–0.859
GSI	2.993	1.112	0.076	-0.926	0.909	0.909	0.714	0.819–0.867

FTA	3.005	1.147	-0.075	-1.041	0.909	0.909	0.714	0.823–0.857
ALC	2.970	1.147	0.039	-1.048	0.914	0.914	0.726	0.837–0.868
HFTA	2.965	1.120	0.032	-0.926	0.927	0.927	0.760	0.859–0.885

Table 3. Confirmatory factor analysis and common-method diagnostics

Model / diagnostic	**Estimator**	**χ^2**	**df**	**CFI**	**TLI**	**RMSEA**	**SRMR / result**
Eight-factor correlated	DWLS	148.54	436	1.000	1.000	.000	0.026
Single-factor	DWLS	6081.87	464	0.794	0.780	0.174	0.161
Harman first factor	—	—	—	—	—	—	33.91% of variance

Table 4. HTMT discriminant-validity matrix

	PHV	**DFS**	**AIC**	**PPC**	**GSI**	**FTA**	**ALC**	**HFTA**
PHV	—							
DFS	0.255	—						
AIC	0.491	0.674	—					
PPC	0.440	0.677	0.697	—				
GSI	0.367	0.055	0.264	0.180	—			
FTA	0.078	0.257	0.027	0.263	0.041	—		
ALC	0.269	0.066	0.164	0.112	0.210	0.047	—	
HFTA	0.684	0.599	0.738	0.728	0.476	0.218	0.336	—

Note. All HTMT ratios were below the conservative .85 threshold. The largest bootstrap upper bound was .794.

Table 5. Necessity analysis for high fitness technology adoption

Set	**Consistency**	**Coverage**	**RoN**
AIC	0.797	0.782	0.822
PPC	0.779	0.794	0.840
PHV	0.776	0.772	0.818

DFS	0.756	0.754	0.809
GSI	0.713	0.709	0.780
ALC	0.678	0.678	0.764
FTA	0.666	0.645	0.733
~FTA	0.556	0.551	0.695
~ALC	0.541	0.519	0.666
~GSI	0.523	0.505	0.663
~DFS	0.499	0.480	0.649
~PPC	0.476	0.449	0.627
~AIC	0.466	0.456	0.646
~PHV	0.465	0.449	0.638

Note. The necessity criterion was consistency ≥ .90. RoN = relevance of necessity; ~ denotes the absence of a condition.

Table 6. Intermediate sufficient configurations for high adoption

Route	PHV	DFS	AIC	PPC	GSI	FTA	ALC	Consistency	PRI	Raw cov.	Unique cov.
S1	●	●	●	●	●	—	—	0.967	0.931	0.379	0.037
S2	●	●	●	●	—	●	—	0.966	0.927	0.363	0.035
S3	●	●	●	●	—	—	●	0.971	0.940	0.350	0.023
S4	●	—	●	●	●	—	●	0.972	0.944	0.332	0.045
S5	—	●	●	●	—	●	●	0.962	0.914	0.317	0.045
Solution								0.946	0.894	0.566	—

Note. ● = presence; ⊗ = absence; — = condition not included. Low unique coverage indicates substantial overlap across configurations.

Table 7. Sufficient configurations for the negated outcome (~HFTA)

Route	PHV	DFS	AIC	PPC	GSI	FTA	ALC	Consistency	PRI	Raw cov.	Unique cov.
N1	⊗	⊗	⊗	⊗	—	—	—	0.958	0.925	0.496	0.132
N2	⊗	—	⊗	⊗	⊗	⊗	—	0.986	0.972	0.320	0.034
N3	⊗	⊗	⊗	—	⊗	●	⊗	0.961	0.905	0.242	0.023

N4	—	⊗	⊗	⊗	⊗	⊗	⊗	0.988	0.976	0.277	0.030
Solution								0.951	0.911	0.583	—

Table 8. Robustness analysis under alternative truth-table thresholds

Scenario	Freq.	Cons. cut	PRI cut	Terms	Sol. cons.	Sol. PRI	Sol. cov.
Robust 1	4	0.85	0.65	6	0.953	0.908	0.572
Robust 2	5	0.90	0.70	5	0.955	0.912	0.552
Robust 3	6	0.90	0.70	5	0.953	0.905	0.524

Discussion

The results support a configurational rather than additive interpretation of fitness technology adoption. No condition was necessary, but AIC and PPC appeared in every high-adoption configuration. This shared core suggests that automated guidance and data-based personalization are not peripheral interface features. Students can differ in perceived value, self-efficacy, gamified influence, access, and institutional support, yet high adoption consistently involves confidence in the system's guidance and an acceptable exchange between personal data and individualized benefits.

The measurement results strengthen this interpretation. AIC, PPC, and DFS were moderately related, but the CFA, AVE, and HTMT analyses show that they are not interchangeable. Capability answers whether the student can use and interpret the technology; algorithmic trust answers whether the system's recommendations deserve reliance; and privacy calculus answers whether the personalization benefit justifies data use. Treating them as a single technological-attitude factor would conceal these different mechanisms.

The findings also clarify why access was weakly associated with HFTA (r = .200) despite literature that presents accessibility as central. Access is a facilitating condition, not a sufficient motivational mechanism. One negated-outcome configuration contained FTA together with the absence of PHV, DFS, AIC, GSI, and ALC. Thus, a compatible device or affordable service can coexist with low adoption when the student sees little value, lacks confidence, distrusts recommendations, or receives no social and institutional reinforcement. This result is consistent with evidence that digital exposure can coexist with inactivity or problematic mobile use (Mamani-Jilaja et al., 2024).

Gamification appeared only in selected pathways. This conditional role is consistent with interventions in which challenges, cooperation, and social functions improved participation or motivation (Escobosa Morera et al., 2024; Ibragimova et al., 2025; Sañudo et al., 2024). The present findings do not imply that badges or rankings are universally effective. GSI contributed when combined with value, trust, privacy acceptance, and either capability or active culture. This distinction matters because gamification without perceived value or autonomous engagement may produce short-lived compliance rather than sustained use.

The overall coverage of .566 is meaningful but incomplete, and the unique coverage of the individual routes is low. The solution therefore represents an overlapping family of configurations anchored in AIC and PPC, not five sharply separated student profiles. Unmeasured factors—including prior exercise habits, device ownership history, health status, body image, and perceived app quality—may account for the remaining outcome membership. The wording of conclusions and practical recommendations was consequently restricted to associations within this cross-sectional population.

The study has limitations. The design is cross-sectional and cannot establish temporal or causal effects. The census refers to one institutional population and does not support statistical generalization to other universities or academic fields. All indicators were collected through the same self-report form; the common-method diagnostics reduce but do not eliminate this concern. Finally, direct calibration uses substantively defined anchors that should be tested in other populations. Longitudinal, experimental, and multisource studies should examine whether the identified configurations predict continued use and objectively measured physical activity.

Conclusions

High fitness technology adoption among business students was associated with multiple, overlapping configurations rather than one universal pathway. Algorithmic coaching trust and privacy–personalization calculus formed the most stable core, while perceived value, digital self-efficacy, gamified influence, accessibility, and active learning culture operated as partially substitutable enablers.

The negated-outcome analysis showed that low adoption is not the simple inverse of high adoption. In particular, access can be present without adoption when value, capability, trust, social influence, or institutional support are absent. Universities should therefore avoid strategies limited to providing applications or devices. More defensible interventions would combine transparent data practices and explainable recommendations with differentiated onboarding, metric literacy, voluntary social challenges, and opportunities to integrate physical activity into academic routines.

The conclusions are associative and population-specific. They describe the configurational structure observed in 403 final-level business students and should be tested in other disciplines, institutions, and longitudinal settings.

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