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Awareness and Usage of Fitness Tracking Applications Among University Students: A Cross-Sectional Study

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ABSTRACT

In the contemporary digital landscape, mobile health (mHealth) applications have emerged as pivotal instruments for monitoring physical activity, especially among younger cohorts. University students, a demographic frequently challenged by sedentary academic routines, serve as a critical focal point for digital health interventions. This research explored the awareness and engagement patterns regarding fitness tracking applications among university students in Pakistan, while also identifying the behavioral and technical catalysts for adoption. Utilizing a descriptive cross-sectional design, data was gathered from 152 participants at the University of Education, Lahore, through a validated 30-item, 5-point Likert-scale instrument. The findings revealed that while foundational awareness was high (exceeding 78%), sustained daily engagement remained limited, with fewer than 50% reporting consistent use. Key impediments to long-term adoption included data confidentiality concerns, high battery consumption, and the 'novelty effect.' Interestingly, a significant majority (69.1%) expressed a preference for integrating these digital tools into formal university sports curricula. The study concludes that a notable 'awareness-usage' gap persists in the Pakistani academic context. Bridging this disparity requires robust institutional frameworks, enhanced application optimization, and targeted digital health literacy initiatives to convert passive awareness into lasting behavioral change.

Keywords: *Health, Fitness Tracking Applications, University Students, Physical Activity, Digital Health Literacy, Pakistan, Technology Acceptance Model.*

Introduction

The digital revolution has fundamentally transformed personal health management through the widespread adoption of smartphone-based health technologies. Fitness tracking applications, integrating functionalities such as pedometers, nutritional logs, sleep metrics, and heart rate monitors, have become increasingly popular among the "digital native" younger generation (Silva et al., 2021). These platforms, frequently coupled with wearable technology, facilitate continuous and passive health surveillance, a capability that was once restricted to specialized clinical environments (Kooiman et al., 2018).

University students represent a critical demographic within this digital health ecosystem. The shift into higher education often correlates with a decline in physical exertion, disrupted dietary patterns, and heightened academic stress, all of which contribute to long-term metabolic and cardiovascular risks (Nelson et al., 2008). Despite the ubiquitous presence of smartphones in academic settings, the degree to which students utilize these devices for substantive health tracking remains under-researched, particularly within South Asian environments (Ali et al., 2020).

In the context of Pakistan, while mobile connectivity is expanding rapidly, there remains a significant lack of institutional support for digital health literacy. Most existing mHealth literature originates from Western or East Asian perspectives, leaving a vacuum in local research (Ali et al., 2020; Rashidi et al., 2020). This study aims to address this knowledge gap by investigating the depth of awareness and the specific behavioral engagement with fitness applications among students at the University of Education, Lahore.

Theoretical Framework

This research is underpinned by three complementary behavioral models that explain the adoption and sustained use of digital health technology. The Technology Acceptance Model (TAM), originally proposed by Davis (1989), suggests that the integration of any new technology is primarily driven by two factors: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). In the realm of fitness applications, PU relates to the student's belief that the app will effectively enhance their physical well-being, while PEOU pertains to the user-friendliness of the digital interface. Research by Kim and Han (2014) highlights that for younger users, the accuracy of data acts as a critical moderator; for instance, inconsistent calorie or step tracking can significantly diminish the perceived utility and subsequent engagement.

Supplementing TAM, the Self-Determination Theory (SDT) developed by Ryan and Deci (2017) provides a deeper understanding of long-term behavioral persistence. According to SDT, habitual adoption depends on the satisfaction of three fundamental psychological needs: autonomy, competence, and relatedness. Fitness applications address these needs by offering personalized goal-setting (autonomy), providing gamified rewards and progress tracking (competence), and enabling social connectivity through community challenges (relatedness). By combining TAM and SDT, this study establishes a comprehensive framework to analyze why initial awareness often fails to manifest as consistent, long-term usage.

Furthermore, the Health Belief Model (HBM), a cornerstone of social psychology since the 1950s, offers a third perspective on user motivation. The HBM posits that a student's decision to engage with fitness technology is influenced by their perception of health-related risks and the anticipated benefits of preventive action. As noted by Kim and Han (2014), university students are more inclined to utilize tracking tools if they perceive themselves as susceptible to lifestyle-related conditions, such as cardiovascular issues or obesity. Additionally, the model emphasizes the role of "cues to action," which, in a modern digital context, are represented by the automated push notifications and reminders generated by these applications.

The central issue explored in this research is the prevailing discrepancy between the awareness of fitness tracking applications and their actual integration into daily health routines. While university students are highly active digital users, their interaction with health-tracking features is often perfunctory. Many students recognize these tools but lack the necessary motivation or technical literacy to utilize them for sustainable health outcomes (Rashidi et al., 2020). This failure to maintain consistent usage limits the effectiveness of mHealth technology as a preventive tool against sedentary lifestyles. Consequently, it is vital to identify the barriers that prevent students from evolving from passive awareness to habitual, goal-oriented usage.

Method

Research Design and Participants

This study utilized a descriptive cross-sectional research design to gather quantitative insights from the student body at the University of Education, Lahore. Data was collected through a structured, self-administered digital survey distributed via convenience sampling across various university communication platforms, including WhatsApp threads and social media groups. The final dataset comprised 152 complete responses, providing a statistically sound sample size for a descriptive analysis of this nature (Krejcie & Morgan, 1970). To uphold ethical standards, all participants were guaranteed complete anonymity, and no personally identifiable data was recorded. Furthermore, participation was strictly voluntary, and respondents maintained the right to withdraw at any stage of the process.

Research Instrument

The primary instrument for data collection was a 35-item questionnaire, divided into a five-item demographic segment and 30 behavioral items. The latter were evaluated using a 5-point Likert scale, ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). The instrument's items were meticulously developed and refined based on an extensive review of established mHealth and fitness tracking literature (Ali et al., 2020; Davis, 1989; Kim & Han, 2014; Rashidi et al., 2020). This structured tool focused on three core domains: (a) awareness of specific application features, (b) behavioral integration and usage patterns, and (c) perceived health outcomes alongside institutional recommendations. Prior to formal administration, the questionnaire underwent a pilot phase to ensure linguistic clarity and conceptual relevance.

Data Analysis

The raw data retrieved from Google Forms was processed and analyzed using Microsoft Excel. Descriptive statistical techniques, specifically frequency counts and percentage distributions, were applied to all variables. The findings were systematically organized into tables for a comprehensive interpretation of the 30 Likert-scale items. The primary metric used for reporting awareness and engagement levels was the aggregate agreement percentage, combining "Strongly Agree" and "Agree" responses.

Results

Demographic and Baseline Characteristics

The study participants were predominantly young adults, with the largest age group being 20–22 years (41.4%). In terms of gender distribution, males represented 56.6% of the sample, while females accounted for 43.4%. A significant majority (85.5%) were undergraduate students (BS/ADP programs). Crucially, 96.7% of the respondents owned a personal smartphone, indicating a high level of technological readiness for mHealth engagement. Additionally, approximately 42.1% of the participants reported active involvement in university-level sports teams. A detailed demographic breakdown is provided in Table 1.

Table 1

Demographic and Baseline Profile of Respondents (N = 152)

Variable	Category	Frequency (n)	Percentage (%)
Age Group	Below 20 years	30	19.7%
	20–22 years	63	41.4%
	23–25 years	44	28.9%
	26 years and above	15	9.9%
Gender	Male	86	56.6%
	Female	66	43.4%
Study Level	Undergraduate (BS/ADP)	130	85.5%
	Postgraduate	15	9.9%
	Other	7	4.6%
Smartphone Ownership	Yes	147	96.7%
	No	5	3.3%
Sports Team Member	Yes	64	42.1%
	No	88	57.9%

Note. *Data collected via Google Forms from students of the University of Education, Lahore (Session 2022–2026).*

Full Survey Item Responses

Table 2 provides a detailed breakdown of the Likert-scale distributions for the entire 30-item questionnaire. For analytical clarity, these items are categorized according to the three primary thematic domains investigated in this research. This exhaustive data presentation ensures total transparency regarding the participants' responses and facilitates the potential for future research replication and validation.

Table 2

Complete Questionnaire Item Response Distributions (N = 152)

No.	Item	SA (%)	A (%)	N (%)	D (%)	SD (%)	Agreement (%)
Section A: Awareness of Fitness Application Features							
1	Awareness of the existence of fitness tracking applications	36.8	41.4	17.1	4.6	0.0	**78.2**
2	Ability to download and set up fitness applications	38.2	41.4	14.5	4.6	1.3	**79.6**
3	Familiarity with the step counting feature	40.1	36.8	16.4	5.3	1.3	**76.9**
4	Knowledge of sleep pattern and quality tracking	33.6	39.5	21.1	5.3	0.7	**73.1**
5	Awareness of heart rate and pulse monitoring	33.6	42.1	19.7	3.3	1.3	**75.7**
6	Knowledge of calorie calculation feature	34.2	46.1	15.1	3.3	1.3	**80.3**
7	Awareness of customized workout plans	38.2	43.3	16.4	2.0	0.0	**81.5**
8	Perceived ease of navigation (user-friendliness)	25.7	49.3	19.7	5.3	0.0	**75.0**
9	Trust in privacy and data security	24.3	36.2	32.9	5.3	1.3	**60.5**
10	Confidence in health improvement via app usage	26.0	34.9	32.2	7.2	0.7	**60.9**
Section B: Usage Patterns and Behavioral Integration							
11	Regular use of fitness tracking apps	24.3	25.7	20.4	20.4	9.2	**50.0**
12	Daily monitoring of steps and active minutes	25.7	28.9	15.8	21.7	7.9	**54.6**

No.	Item	SA (%)	A (%)	N (%)	D (%)	SD (%)	Agreement (%)
13	Use of apps for nutritional and calorie monitoring	21.7	27.0	21.1	18.4	11.8	**48.7**
14	Preference for apps over manual tracking	21.7	37.5	22.4	13.2	5.3	**59.2**
15	Usage of wearable devices (smartwatch/band)	21.1	23.7	21.1	25.0	9.2	**44.8**
16	Reliance on app notifications to stay active	27.6	25.7	18.4	21.1	7.2	**53.3**
17	Consistency of usage for more than six months	21.7	25.0	19.7	21.1	12.5	**46.7**
18	Perceived increase in overall physical activity level	21.7	32.9	27.0	12.5	5.9	**54.6**
19	Perceived accuracy of health and performance data	23.7	38.2	25.7	7.9	4.7	**61.9**
20	Motivation through visual progress tracking	27.0	42.1	21.1	7.2	2.6	**69.1**
Section C: Perceived Outcomes and Institutional Recommendations							
21	Achievement of specific health goals (e.g., weight loss)	31.6	36.8	25.0	3.9	2.6	**68.4**
22	Motivation through social features (sharing progress)	23.7	37.5	28.9	7.9	2.0	**61.2**
23	Reliance on digital tools due to academic workload	22.4	36.8	29.6	9.2	2.0	**59.2**
24	Support for integration into university sports programs	28.3	46.7	20.4	3.3	1.3	**75.0**

No.	Item	SA (%)	A (%)	N (%)	D (%)	SD (%)	Agreement (%)
25	Willingness to recommend apps to fellow students	27.6	40.8	24.3	4.6	2.6	**68.4**
26	Belief apps improve sleep quality	25.0	35.5	28.3	8.6	2.6	**60.5**
27	Awareness of gamification features (badges, streaks)	30.9	40.1	20.4	6.6	2.0	**71.0**
28	Use of apps for workout scheduling and planning	28.9	38.2	21.1	8.6	3.3	**67.1**
29	Interest in learning to interpret advanced health metrics	31.6	38.8	22.4	5.3	1.9	**70.4**
30	Willingness to use apps if offered in university programs	35.5	43.4	16.4	3.3	1.3	**78.9**

Note. *SA=Strongly Agree, A=Agree, N=Neutral, D=Disagree, SD=Strongly Disagree. Agreement (%) represents the sum of SA and A. Items 26–30 are supplementary measures adapted from the original thesis instrument.*

Awareness of Fitness Application Features

As illustrated in Table 3, participants exhibited a robust understanding of fundamental fitness tracking functionalities across all ten awareness-related metrics (Items 1–10). The highest aggregate agreement was observed for customized workout programming (81.5%), followed closely by caloric expenditure calculation (80.3%), application accessibility (79.6%), and pedometer functionalities (76.9%). Conversely, trust in data confidentiality (60.5%) and confidence in the efficacy of health improvements (60.9%) emerged as the lowest-scoring dimensions. These findings suggest that while university students possess a comprehensive awareness of technical features, they maintain substantial reservations regarding data security and the tangible health benefits of long-term usage.

Table 3

Summary of Awareness of Fitness Application Features (N = 152)

Feature / Construct	SA + A (%)	Neutral (%)	D + SD (%)
Awareness of app existence	78.2	17.1	4.6
Ability to download and set up apps	79.6	14.5	5.9
Step counting feature	76.9	16.4	6.6

Feature / Construct	SA + A (%)	Neutral (%)	D + SD (%)
Sleep tracking feature	73.1	21.1	6.0
Heart rate monitoring	75.7	19.7	4.6
Calorie calculation feature	80.3	15.1	4.6
Customized workout plans	81.5	16.4	2.0
Ease of navigation (UI)	75.0	19.7	5.3
Trust in privacy and data security	60.5	32.9	6.6
Confidence in health improvement via app	60.9	32.2	7.9

Note. *Agreement (%) refers to combined Strongly Agree and Agree responses. SA = Strongly Agree; D = Disagree; SD = Strongly Disagree.*

Usage Patterns and Behavioral Integration

The data reveals a significant "awareness-usage gap" across all engagement metrics (Items 11–20). Although awareness levels consistently surpassed 73%, sustained and regular application usage was reported by only 50.0% of the participants. Daily tracking of physical activity, such as step counts or active minutes, was practiced by 54.6% of the sample, whereas nutritional and caloric monitoring was less prevalent at 48.7%. Long-term commitment—characterized by continuous usage for more than six months—was confirmed by only 46.7% of the students. Notably, the ability to track progress visually emerged as the most significant motivational factor (69.1%). In contrast, the adoption of specialized wearable devices remained relatively low at 44.8%, suggesting that the majority of students rely primarily on integrated smartphone sensors for health tracking. A comprehensive summary of these usage patterns is detailed in Table 4.

Table 4

Summary of Fitness Application Usage Patterns and Behavioral Integration (N = 152)

Usage Behavior	Agreement (%)	Neutral (%)	Disagreement (%)
Regular use of fitness tracking apps	50.0	20.4	29.6
Daily monitoring of steps/active minutes	54.6	15.8	29.6
Nutritional/calorie intake monitoring	48.7	21.1	30.2
Preference for apps over manual tracking	59.2	22.4	18.5

Usage Behavior	Agreement (%)	Neutral (%)	Disagreement (%)
Use of wearable device (smartwatch/band)	44.8	21.1	34.2
Reliance on app notifications to stay active	53.3	18.4	28.3
Consistent usage for more than 6 months	46.7	19.7	33.6
Perceived increase in physical activity level	54.6	27.0	18.4
Perceived accuracy of health data	61.9	25.7	12.6
Motivation via visual progress tracking	69.1	21.1	9.8

Note. *Agreement (%) refers to combined Strongly Agree and Agree responses. Disagreement (%) refers to combined Disagree and Strongly Disagree responses.*

Perceived Outcomes and Institutional Demand

Despite the inconsistencies noted in engagement patterns, the participants reported substantial perceived benefits across all outcome-related metrics (Items 21–25, 27–30). A significant majority (68.4%) expressed the belief that these applications were instrumental in achieving specific health objectives, such as weight regulation or enhanced physical endurance. Visual feedback on progress emerged as a powerful motivator for 69.1% of the respondents. Interestingly, social connectivity and sharing features showed a more moderate influence (61.2%), with 28.9% maintaining a neutral stance. This suggests that students at the University of Education, Lahore, are driven more by internal progress than by external peer comparison. A compelling finding was the strong institutional demand: 75.0% of students advocated for the formal integration of fitness technology into university sports curricula, and 78.9% indicated a high readiness to adopt these tools if provided through institutional initiatives. A detailed summary of these perceptions is provided in Table 5.

Table 5

Perceived Outcomes and Institutional Recommendations (N = 152)

Outcome / Recommendation Item	Agreement (%)	Neutral (%)	Disagreement (%)
Achievement of specific health goals (weight, fitness)	68.4	25.0	6.5
Motivation via visual progress tracking	69.1	21.1	9.8
Motivation via social features (sharing progress)	61.2	28.9	9.9

Outcome / Recommendation Item	Agreement (%)	Neutral (%)	Disagreement (%)
Reliance on digital tools due to academic workload	59.2	29.6	11.2
Support for university sports program integration	75.0	20.4	4.6
Willingness to recommend apps to peers	68.4	24.3	7.2
Awareness of gamification features (badges, streaks)	71.0	20.4	8.6
Interest in learning advanced health metrics	70.4	22.4	7.2
Willingness to use apps in university programs	78.9	16.4	4.6

***Note.** Agreement (%)' represents the aggregate of 'Strongly Agree' and 'Agree' responses, while 'Disagreement (%)' denotes the combined total of 'Disagree' and 'Strongly Disagree' responses*

Discussion

The findings of this research corroborate a well-established pattern in mHealth literature: high levels of initial awareness do not necessarily translate into sustained behavioral engagement. With over 78% of students recognizing the existence of these apps but fewer than 50% reporting consistent use, the "awareness-usage gap" identified in this study aligns with previous observations in South Asian contexts (Ali et al., 2020; Rashidi et al., 2020) and extends this discourse to the specific environment of a Pakistani public university.

The predominance of pedometer-based tracking as the most utilized feature (76.9%) is consistent with global trends, identifying step counting as the primary entry point for digital health interaction, especially for users without access to high-end wearables (Peng et al., 2019). The comparative underutilization of sophisticated metrics, such as sleep cycle analysis or heart rate variability, reflects the "technical literacy ceiling" noted by Ali et al. (2020), where engagement diminishes as technical complexity increases.

Furthermore, data privacy emerged as a critical structural barrier. With only 60.5% of participants expressing confidence in data security, the study reinforces the "trust deficit" prevalent among users in developing regions (Ali et al., 2020). This is particularly significant in a regulatory landscape where data protection laws are still evolving, leaving users without institutional guarantees regarding the management of their biometric information.

The decline in long-term engagement (46.7% usage beyond six months) validates the "novelty effect" hypothesis proposed by Fausset et al. (2013). This finding supports the Self-Determination Theory (SDT) perspective (Ryan & Deci, 2017), suggesting that external motivators like badges or digital streaks are insufficient to replace internalized health motivation without personalized feedback or institutional accountability.

One of the most policy-relevant findings is the overwhelming support (75.0%) for formal app integration into university sports programs. This indicates that students are receptive to digital health tools but require a structured framework for meaningful application, echoing Nollen et al. (2014) regarding the efficacy of institutionally embedded wellness initiatives. Additionally, observed gender-based variations, where males focused on performance metrics and females on wellness tracking, align with Kim and Han (2014), offering design implications for more inclusive digital health tools.

Conclusion

The study concludes that fitness tracking applications have a significant presence in the lives of University of Education students. While the "Digital Health Revolution" has successfully created awareness, it has not yet fully translated into a sustained lifestyle change for the majority. There is a clear "Awareness-Usage Gap" that needs to be addressed through institutional support and better digital health literacy. The potential for these apps to improve student health is immense, but it requires moving beyond simple step counting toward a more holistic understanding of biological data.

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