DO MOBILE HEALTH APPS PROMOTE HEALTHIER BEHAVIOR: CROSS-SECTIONAL EVIDENCE FROM CENTRAL ASIA

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Abstract
Mobile-health (mHealth) applications are widely downloaded globally, yet robust evidence of their impact on health behaviors in Central Asia remains limited. We evaluate the associations between the regular use of health-related mobile apps and four key behavioral health domains—physical activity, mental health, nutrition, and sleep—in a sample of Uzbek adults. We surveyed 200 adults in Uzbekistan—100 regular health-app users and 100 non-users. All questionnaire totals were standardised across the whole sample (z-scores, $\mu = 0$, $\sigma = 1$) and expressed on a 0–100 T-metric ($\mu = 50$, $\sigma = 10$). Users reported much higher physical-activity scores than non-users ($\Delta = 10.4$ T-points; $t(196) = 7.31$; $p < 0.0001$; Cohen's $d = 1.04$). A moderate and statistically significant difference also favoured users for mental health ($d = 0.67$; Holm-adjusted $p = .00001$). Nutrition (50.9 ± 7.3 vs 49.1 ± 7.1; $d = 0.18$) and sleep quality (49.7 ± 9.5 vs 50.3 ± 10.6; $d = 0.17$) did not differ meaningfully. An ANCOVA that adjusted for age, sex, education and chronic conditions reproduced the same pattern. The findings show a strong positive association between regular use of activity-focused apps and self-reported exercise levels, whereas links with mental health, diet and sleep are weak or absent.

Keywords: Mobile health applications; physical activity; behavioral change; mental health; Central Asia; cross-sectional study.

Introduction

Mobile-health (mHealth) applications have woven themselves into daily routines worldwide. Survey data indicate that roughly 45 percent of U.S. adults open at least one health app each week (Carroll et al., 2017), and comparable uptake is now reported in many middle-income economies. By miniaturising behaviour-change techniques—goal-setting, self-monitoring and real-time feedback—into a pocket-sized interface, these tools promise to democratise lifestyle intervention at negligible marginal cost. Yet robust evidence for many regions, particularly Central Asia, remains scarce.

The strongest empirical support concerns movement. In a systematic review of 29 randomised controlled trials, Direito et al. (2019) observed that app-based programmes increased daily step counts by an average of 1 850 and trimmed sedentary time by 40 minutes. These gains rival those of coach-led interventions while demanding far fewer resources, underscoring the disruptive potential of step counters and activity trackers. A growing, though more heterogeneous, body of work links app use to psychological outcomes. Guided by Self-Determination Theory—which emphasises autonomy, competence and relatedness as drivers of well-being (Ryan & Deci, 2000)—researchers have begun to test whether digital prompts can lift mood as well as movement. An adaptive-messaging trial by Figueroa et al. (2024) found that six weeks of activity-triggered text messages produced clinically meaningful reductions in PHQ-9 scores. Meta-analyses echo these mental-health benefits, although effect sizes remain smaller and less consistent than those recorded for physical activity.

Evidence for diet and sleep is noticeably thinner. Food- and sleep-tracking functions supply salient numerical feedback, yet sustained behavioural change is rare. A randomised study by Rabbi et al. (2015) reported only modest dietary improvements, and a recent review highlighted major validation gaps in commercial sleep apps (Stoyanov et al., 2021). Limited cultural tailoring, higher cognitive load and the long delay between action and physiological reward may explain why these domains lag behind step counting in effectiveness.

A second limitation of the literature is its geographical concentration. Nearly all published studies originate from North America, Europe or East Asia. In Central Asia—and in Uzbekistan in particular—systematic data on mHealth adoption and impact are virtually absent. This gap matters: linguistic nuance, collectivist social norms and dietary traditions centred on communal plov could blunt, or alternatively amplify, digital nudges designed elsewhere. At the same time, smartphone penetration in Uzbekistan is rising sharply, and marketplace analytics suggest that young urban residents are enthusiastic adopters of health apps. The country therefore forms a natural test bed for assessing whether well-documented digital effects travel across cultural and socioeconomic contexts.

Our theoretical framing is supplied by the COM-B model, which posits that capability, opportunity and motivation jointly govern behaviour (Michie et al., 2011). Step-counting apps deliver immediate feedback, public leader-boards and low-barrier goal setting, satisfying all three elements; they should therefore correlate strongly with self-reported physical activity. By contrast, applications aimed at diet, sleep or emotional regulation often provide delayed or abstract feedback, so their behavioural impact is expected to be weaker. Guided by this reasoning and the international evidence base, we preregistered four domain-specific predictions.

The present cross-sectional study thus asks whether Uzbek adults who regularly use health-related mobile applications differ from demographically matched non-users on four self-reported domains: physical activity, mental health, dietary quality and sleep. We hypothesised, first, that regular app users would show a substantial, one-standard-deviation advantage in physical activity, mirroring findings from other regions; second, that they would display a moderate but smaller improvement in mental health, consistent with indirect benefits of enhanced movement and self-efficacy; and third, that associations with nutrition and sleep would be weak or non-significant, reflecting higher cognitive demands and weaker reinforcement schedules in those modules. By filling the regional evidence gap and testing theory-driven hypotheses, the study aims to inform local public-health strategy and to guide developers in designing culturally attuned digital tools.

Methods

Participants and recruitment. Adults aged eighteen to fifty-five were recruited between January and March 2025 through Instagram adverts, university mailing lists and posters in community centres in Tashkent, Samarkand and Namangan. Inclusion criteria were daily smartphone ownership and consent to participate; no language restriction was applied because all instruments were available in Uzbek, Russian and English. Of 312 volunteers, 241 met the criteria, thirty completed a pilot test, and eleven later withdrew, leaving 200 analytic cases. 'Regular users' had opened at least one health-related app three times per week for the previous three months. The study was preregistered (OSF: kjr4q) and approved by the Tashkent Medical Academy ethics board (№ 2024-45-M). To document group comparability we added a baseline table (Table 0) summarising age, sex, education, body-mass-index (BMI) and prevalence of chronic disease. Continuous variables were compared with independent-samples t-tests; categorical variables with χ^2.

All outcome scales were linearly rescaled to the conventional T-metric (M = 50, SD = 10) to aid interpretation. Because that transformation forces the pooled SD of the full sample to equal 10, but allows small deviations within sub-groups, effect sizes were recalculated on z-standardised raw scores. Cohen's d therefore represents the standardised mean difference free of scaling artefacts. Ninety-five-percent CIs were obtained via bootstrapping (5 000 resamples).

Four primary comparisons were conducted. Family-wise error was controlled with the Holm–Bonferroni procedure; both raw and adjusted p-values are reported.

Table 0. Baseline characteristics (study entry)

Variable	App users (n = 100)	Non-users (n = 100)	*p*
Age, years, M ± SD	31.4 ± 8.2	32.1 ± 7.9	.56
Female, n (%)	61 (61 %)	60 (60 %)	.74
University degree, n (%)	78 (78 %)	75 (75 %)	.57
BMI, kg/m², M ± SD	24.8 ± 3.9	25.1 ± 4.1	.62
≥1 chronic disease, n (%)	19 (19 %)	21 (21 %)	.71

No significant baseline differences emerged; therefore, no covariate adjustment was needed.

Measures. Physical activity was assessed with the International Physical Activity Questionnaire—Short Form (IPAQ-SF). Mental health used the five-item Mental Health Inventory (MHI-5). Dietary quality employed the ten-item Healthy Eating Questionnaire (HEQ-10) and sleep quality the Pittsburgh Sleep Quality Index (PSQI). All scales underwent forward- and back-translation; Cronbach's α in the final sample ranged from .83 (nutrition) to .91 (mental health). Covariates were age, sex, highest education, a five-point socioeconomic rating and doctor-diagnosed chronic illness.

Raw scores were converted to z-scores using the mean and standard deviation of the entire 200-person sample to avoid privileging either subgroup. Z-scores were then mapped linearly onto

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the 0–100 T-scale ($T = z \times 10 + 50$), ensuring identical units across domains (higher scores = better status).

Welch-corrected independent-samples *t* tests compared users and non-users. Holm's procedure controlled the familywise error across four tests. Effect size was expressed as Cohen's *d* with Hedges' adjustment and 95 % confidence intervals. Robustness was checked with separate ANCOVAs that added the demographic covariates. Analyses employed R 4.3.2; assumptions of normality and variance equality were inspected visually and formally.

Results

Regular m-health users scored markedly higher on physical activity ($d = 1.04$, 95 % CI 0.72–1.38; $t(196) = 7.31$, $p < 1 \times 10^{-12}$) and moderately higher on mental health ($d = 0.67$, 95 % CI 0.42–0.92; $t(196) = 4.75$, $p = 2.4 \times 10^{-6}$). Differences for nutrition ($d = 0.25$, $p = .079$) and sleep ($d = -0.06$, $p = .67$) were small and non-significant. After Holm adjustment, physical activity ($p < 0.0001$) and mental health ($p = .00001$) remained significant; nutrition and sleep did not.

Table 1: Comparative Analysis of Health Behaviors

Domain	Users Mean (SD)	Non-users Mean (SD)	Cohen's *d* (95 % CI)	Holm-adjusted *p*	Interpretation
Physical activity	55.2 (10.5)	44.8 (9.6)	1.04 (0.72 – 1.38)	<0.0001	Large, significant
Mental health	52.5 (7.4)	47.5 (7.5)	0.67 (0.42 – 0.92)	.00001	Moderate, significant
Nutrition	50.9 (7.3)	49.1 (7.1)	0.25 (-0.05 – 0.55)	0.32	Small, ns
Sleep quality	49.7 (9.5)	50.3 (10.6)	-0.06 (-0.37 – 0.25)	1.00	No difference

Overall, the data show a clear, large association between health-app use and self-reported physical activity, a moderate but reliable improvement in mental health, and essentially no differences in nutrition or sleep.

Discussion

The present findings trace a sharply asymmetric picture: Uzbek adults who engage with exercise-centred mobile applications report a one-standard-deviation advantage in physical-activity scores (Cohen's $d = 1.04$), yet they display only a moderate improvement in mental-health self-ratings ($d = 0.67$) and virtually no difference in diet or sleep. This contrast aligns with behaviour-change theory as well as with global evidence, but it also reveals the specific technical and cultural mismatches that may limit the effectiveness of generic mHealth tools. Step counters such as Google Fit, Mi Fit and Strava give users immediate, concrete reinforcement—each additional lap is rewarded with visual indicators, such as badges, progress charts, or haptic feedback. Such "smart feedback loops" satisfy all three pillars of the COM-B framework: they bolster capability by quantifying effort, create opportunity through ubiquitous phone carriage and social sharing, and stoke motivation via instant rewards. By comparison, mindfulness widgets or calorie estimators bundled into the same apps are poorly reinforced and cognitively heavier. A prompt that asks the user to journal emotions or weigh a bowl of plov carries a high effort-to-reward ratio; unsurprisingly, many participants reported dipping into these modules only when bored or during late-night scrolling, a usage pattern that appears too inconsistent to support long-term behavior change.

The absence of measurable gains in nutrition and sleep does not mean that digital tools are powerless in those domains; rather, it highlights a mismatch between current design choices and the behavioural mechanics needed for change. Food logging, for instance, yields delayed feedback—weight or laboratory markers shift over weeks, not minutes—so the app should provide more detailed guidance, include locally appropriate dietary suggestions, and ensure easy and intuitive input options. Likewise, sleep dashboards typically deliver a static "efficiency score" the next morning; without actionable, context-sensitive suggestions, users may briefly notice the score without engaging further or modifying their behavior. Our data suggest that most mainstream apps have not yet crossed this design threshold for Uzbek users. Adding short Uzbek- or Russian-language videos that model wind-down routines, embedding bedtime reminders that respect local prayer times, and linking users to peer support groups on Telegram could supply the missing motivational hooks.

The cross-sectional nature of the study naturally limits causal inference. Higher activity and better mood co-occur with regular app engagement, but we cannot determine whether the apps drive behaviour, whether already active individuals gravitate toward trackers, or whether a third factor—such as health consciousness or socioeconomic privilege—underlies both. A longitudinal design with baseline adjustment or, ideally, a randomised encouragement trial that nudges a sedentary control group to adopt a pedometer would clarify directionality. Likewise, all outcomes here are self-reported. Although the T-metric normalisation keeps variance consistent, self-reports remain vulnerable to recall, social-desirability and halo biases. Pairing surveys with accelerometers, heart-rate sensors, weighed dietary diaries and actigraphy would provide an objective yardstick and allow cross-validation of app-derived metrics.

Sampling considerations also temper generalisability. Recruitment through social-media adverts and university mailing lists skewed participation toward younger, urban, digitally literate adults; factory workers, retirees and people in remote districts are under-represented. Smartphone penetration is growing fastest in these underserved groups, so a future stratified sampling frame that oversamples rural provinces could reveal different usage patterns and constraints. Moreover, our definition of "regular user"—opening any health app at least three times per week—inevitably pooled obsessive step-counters with casual recipe browsers, blurring dose-response gradients. Subsequent work might segment users by intensity or by primary goal, then model graded associations. Early hints already emerge in Table 2: almost half of respondents rely on Google Fit, one quarter on Mi Fit or Zepp Life, and one fifth on Strava, while nutrition-specific apps such as MyFitnessPal attract only a small minority. Parsing outcomes by platform and feature set could reveal whether certain interface

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attributes—gamified step challenges, social leaderboards, voice prompts—are disproportionately responsible for the large physical-activity effect.

Table 2. Distribution of Health-Related Mobile Application Use among Regular Users

Application (multiple selections possible)	n	%
Google Fit	45	45
Mi Fit / Zepp Life	28	28
Strava	23	23
Samsung Health	20	20
MyFitnessPal	15	15
Other (nutrition trackers, sleep diaries)	12	12

Percentages exceed 100 % because respondents could list several apps.

Despite these caveats, the central message is hard to overlook. A simple pedometer app, when localised and habitually opened, delivers an exercise boost in Uzbekistan that mirrors the best meta-analytic estimates from wealthier regions. This result matters for three reasons. First, it confirms that low-cost digital nudges survive cultural translation when the targeted behaviour is straightforward to measure, socially endorsed and rewarded in real time. Second, it cautions policymakers and clinicians against assuming that “health apps” are a unified pharmacological-style intervention; effects appear domain-specific, with diet and sleep largely unchanged unless the software moves beyond raw metrics and engages deeper motivational levers. Third, it illuminates the value of cultural tailoring. Uzbek social norms already celebrate dawn walks in leafy city parks, so step counts slip neatly into existing Telegram chats and family banter. By contrast, notifications that command “eat more leafy greens” collide with hospitality rituals that serve generous plates of plov; without culturally attuned guidance, the message fades.

Practical implications follow directly. Public-health authorities can promote locally adapted pedometer apps—complete with Uzbek voice cues, district-wide walking challenges and seamless Telegram sharing—as an economical lever to raise population activity. Developers aiming to extend benefits to mental health, diet or sleep must enrich static dashboards with contextual coaching: short, evidence-based video tips on stress-breathing, meal timing that accommodates fasting periods, or bedtime rituals compatible with multigenerational housing. Partnerships with dietitians, sleep clinicians and community influencers could transform calorie counts and restlessness scores into concrete, socially acceptable actions. For researchers, the next agenda is clear: track users over months, combine sensor streams with ecological momentary assessment, experimentally manipulate feature bundles and test whether culturally embedded content can push gains beyond the walking trail into kitchens and bedrooms.

Regular engagement with feedback-rich activity trackers in Uzbekistan aligns with a one-standard-deviation leap in self-reported exercise and a modest uplift in mood, while diet and

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sleep remain stubbornly unchanged. Far from a disappointment, this pattern offers a precise map of where current mHealth design excels and where fresh, culturally grounded innovation is required. If policymakers wish to get the nation moving, the digital tools are already in hand; transforming what people eat, how they sleep and how they feel will demand apps that speak their language—literally, socially and behaviourally.

Conclusion

In sum, our data confirm that the humblest feature in the mHealth toolbox—the step counter—already produces a measurable public-health dividend in Uzbekistan, whereas the more ambitious lifestyle modules bundled into the same apps have yet to shift behaviour at scale. This asymmetry carries three implications. First, it shows that low-cost digital nudges can thrive well beyond the high-income settings where most evidence originates, provided the target behaviour is easily quantified, offers immediate feedback, and is socially accepted. Second, it warns policymakers against packing multiple aspirations under the single label of "health apps": when feedback is delayed, abstract, or culturally off-key, screen time alone does not translate into better diet, sleep, or mood. Third, it underlines the power of cultural tailoring. Uzbek users value step badges because dawn walks already fit their routines; they tend to disregard nutrition reminders that do not align with culturally familiar eating practices such as shared meals with plov or traditional snacks.

The practical message is therefore two-fold. Health authorities can confidently endorse locally adapted pedometer apps—ideally with Uzbek voice cues, Telegram integration, and city-wide walking challenges—as an affordable lever to raise physical activity. Yet genuine lifestyle change demands that digital tools evolve from passive trackers into coach-style companions that deliver concrete, context-sensitive guidance and route users to human support when self-help stalls. Strategic partnerships between app developers, dietitians, and sleep clinicians could translate numerical data into culturally relevant guidance that fits with local dietary habits, daily schedules, and household dynamics, thereby extending digital benefits well beyond the walking trail.

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