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Health-Related Mobile Application Categories and Physical Activity Among Hungarian University Students: A Cross-Sectional Study

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Abstract

Health-related mobile applications are often examined as a single exposure, although different categories are commonly used in combination. This cross-sectional study examined the associations of four application categories—calorie counters, diet planners, physical activity trackers and workout planners—with physical activity among 522 students at two Hungarian universities. Physical activity was assessed with the Hungarian long-form International Physical Activity Questionnaire. Ordinal logistic regression models, adjusted for sex, age group and university, were fitted separately and jointly. In the separate models, users of calorie counters (odds ratio [OR] = 2.25, 95% confidence interval [CI] 1.48–3.40), diet planners (OR = 2.23, 95% CI 1.20–4.15) and physical activity trackers (OR = 2.82, 95% CI 1.87–4.26) had higher odds of higher physical activity. After mutual adjustment, the associations remained for physical activity trackers (OR = 2.42, 95% CI 1.58–3.70) and calorie counters (OR = 1.76, 95% CI 1.14–2.72), whereas diet planner and workout planner use were not significantly associated. The results were consistent in sensitivity analyses, except for workout planners, whose associations differed between the universities. Health-related applications should not be treated as a homogeneous exposure, and overlapping categories should be modelled jointly.

Keywords: physical activity; mobile applications; mHealth; digital health; university students; International Physical Activity Questionnaire; ordinal logistic regression

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1. Introduction

1.1. Physical Activity as a Global Public Health Priority

Regular physical activity is among the most robustly supported determinants of population health. The World Health Organization recommends that adults accumulate 150–300 min of moderate-intensity or 75–150 min of vigorous-intensity aerobic activity per week, together with muscle-strengthening activity on at least two days [1]. Adherence is poor and deteriorating: pooled analyses of 507 population-based surveys covering 5.7 million participants indicate that 31.3% of adults worldwide did not meet these recommendations in 2022, compared with 27.5% in 2016 [2,3], although surveillance of such trends remains methodologically demanding [4]. Physical inactivity is a leading contributor to the global burden of non-communicable disease [5,6] and, if its prevalence remains unchanged, is projected to generate 499.2 million preventable cases and approximately

520 billion international dollars (INT$) in direct health-care costs by 2030 [7]. University students warrant particular attention: inactivity is widespread across markedly different national contexts [8], is shaped by well-characterised individual, social and environmental determinants [9–13], and low activity levels have been repeatedly documented in this population [14–17].

1.2. Physical Activity, Health App Use and the Student Context in Hungary

Hungary illustrates why total physical activity and leisure-time exercise should be distinguished. In the 2022 Special Eurobarometer, 59% of Hungarian respondents reported never exercising or playing sport, compared with 45% across the EU27, an increase of six percentage points since 2017 [18]. Yet in a nationally representative survey using the long-form IPAQ, about 63% of Hungarian adults were classified as highly active, mainly through work and household activities rather than leisure-time sport, and activity categories did not differ significantly between age groups [19]. Evidence for Hungarian university students is limited and depends strongly on the instrument: students from four Visegrád-country universities, including one in Hungary, reported higher total IPAQ activity than Ukrainian students but similar leisure-time activity [20]; 71.5% of business students in Budapest were classified as low active by the IPAQ short form [21]; and students at the University of Debrecen reached 10,000 steps on only 17% of monitored days [22].

Digital self-monitoring is nevertheless common. In a nationally representative survey conducted in 2021, 18.5% of Hungarian adults had already used a health application and 30.6% a sensor such as a smartwatch [23]. Among young adults, health application use appears widespread but unstable: in a non-representative sample from the Debrecen area, most respondents had used a health application, most often for step counting, running or cycling tracking and diet management, and motivation and social influence were the strongest correlates of intention to use [24], whereas Hungarian students who did not use or had abandoned lifestyle applications cited perceived superfluity, lack of interest, loss of motivation and boredom [25]. Students' engagement in sport is also shaped by the institutional context, including their embeddedness in university sport and their peer networks [26]. These features—low leisure-time sport, high activity accumulated outside leisure time, and frequent but often discontinued application use—make Hungarian university students a relevant setting in which to examine whether different application categories are associated with physical activity.

1.3. Digital Health and Mobile Health Applications

Digital health—"the field of knowledge and practice associated with the development and use of digital technologies to improve health" [27]—has become a central instrument of health promotion. Health-related mobile applications reach a substantial share of the population, with reported use ranging from roughly one fifth to one half of smartphone owners depending on setting and survey year [28–32]. Uptake is socially patterned, users are consistently younger, better educated, more eHealth-literate and of higher socioeconomic position than non-users [31–34], a gradient interpreted as a source of new digital inequalities [31] and consistent with unified models of technology acceptance [35]. Among university students, application ownership is common and oriented predominantly towards physical activity monitoring [36–39].

1.4. Categories of Health-Related Mobile Applications

Health-related applications do not form a homogeneous class [40]. Representative population data show that distinct categories attract systematically different user profiles [31], and exploratory structural equation modelling indicates that categories cluster

into interpretable dimensions rather than a single construct [32]. The behaviour change technique (BCT) taxonomy offers a framework for describing how these categories may differ [41]. Calorie counters and physical activity trackers are typically designed around self-monitoring of behaviour and feedback—the technique explaining the largest share of heterogeneity in the effectiveness of diet and activity interventions, with interventions combining self-monitoring with further control-theory techniques outperforming others (effect size 0.42 versus 0.26) [42]. Diet planners and workout planners, by contrast, are typically designed around action planning, goal setting and graded tasks, mechanisms grounded in the theory of planned behaviour and in social cognitive theory [43,44]. This distinction may also matter in practice: content analyses show that publicly available activity applications implement on average only five of 23 possible behaviour change techniques and vary widely in quality [45,46]; reviews of calorie-counting and diet-related applications document heterogeneous functionality and effectiveness [47–49]; self-determination theory predicts that externally imposed monitoring may undermine autonomous motivation rather than support it [50]; and category-level differentiation has been shown to matter for movement behaviour even among non-health applications [51].

1.5. Current Scientific Evidence

Experimental evidence for application-based interventions is more modest than is often assumed. A meta-analysis of randomised trials found no significant effect of smartphone applications on daily step count (mean difference 476.75 steps/day; 95% CI −229.57 to 1183.07; $p = 0.19$) [52], and subsequent syntheses report small and frequently short-lived effects [53–55]. Wearable activity trackers, by contrast, show more consistent benefit, corresponding to approximately 40 additional minutes of walking per day [56]. In student populations, digital interventions increase activity, though not universally [15,57–62]. Observational evidence is more uniformly positive: application users are more likely than non-users to meet activity recommendations (56.2% versus 47.8%) [63], users of applications or trackers have almost twice the odds of meeting aerobic guidelines (OR 1.91; 95% CI 1.07–3.46) [64], and comparable associations have been reported in recreational runners, commercial-application users and general adult samples [65–67]. This evidence is nevertheless directionally ambiguous, since physical activity itself strongly predicts application adoption [34,68,69]. Higher activity among application users is moreover not unequivocally beneficial: self-monitoring application use is associated with compulsive exercise and disordered eating behaviours [70,71], and application categories co-occur to a degree that complicates their separate interpretation [72].

1.6. Research Gap

Recent work has begun to differentiate within the broad category of health applications, but along two incompatible lines. Oba et al. [73] modelled ten application functions simultaneously in a multinomial logistic regression predicting IPAQ-based activity categories; Konishi et al. [74] and Takano et al. [75] extended this design prospectively over six months, the latter examining usage styles in the same cohort. None of these models, however, adjusted for sociodemographic characteristics, and all were restricted to physical activity applications and to application users. Hahn et al. [76] instead distinguished application categories—physical-activity-focused and dietary-focused self-monitoring applications—in a population-based sample of emerging adults, reporting higher total and moderate-to-vigorous activity among users of each type after sociodemographic adjustment. Wang et al. [77] combined diet and physical activity applications into a single four-level user-type variable with proxy behavioural outcomes.

Two limitations persist. First, the categories examined remain coarse: we found no observational study which has separated calorie counting from diet planning, or activity tracking from workout planning, although these sub-categories may draw on different behaviour change techniques [41,42]. Second, and more consequentially, where multiple categories have been examined they have been modelled in separate regressions. Hahn et al. [76] explicitly note that their application categories were not mutually exclusive, so that users of one category are contained within the reference group of the other; the association of each category with physical activity after adjustment for the others (its mutually adjusted association) therefore cannot be estimated from such models.

1.7. Study Aim

We address both limitations in a cross-sectional study of university students. Physical activity was assessed with the International Physical Activity Questionnaire, an instrument validated internationally [78] and in the Hungarian context [79], and participants were classified into IPAQ activity categories according to the official scoring protocol [80]. We model four categories of health-related mobile application—calorie counters, diet planners, physical activity trackers, and workout planners—first in separate ordinal logistic regression models and then simultaneously in a mutually adjusted joint model, controlling throughout for sex, age group, and university. Comparing the estimates from the separate and joint models makes it possible to examine the extent to which the association between each app category and physical activity persists after taking the other app categories into account simultaneously. Because only the use of application categories was recorded, and not the specific functions or behaviour change techniques that participants engaged with, the study describes associations at the level of application categories and does not test the mechanisms through which applications might affect physical activity. Given the cross-sectional design, these associations cannot be interpreted causally.

2. Materials and Methods

2.1. Study Design

This cross-sectional questionnaire-based study examined the association between health-related mobile application use and physical activity among university students in Hungary. Data were collected at two higher education institutions with different disciplinary profiles: the Faculty of Health Sciences of the University of Debrecen and the University of Nyíregyháza. The Faculty of Health Sciences offers exclusively health-related degree programmes, whereas the University of Nyíregyháza covers a broader range of academic disciplines. Thus, the institutional comparison reflects differences in both institutional setting and disciplinary profile, although both institutions are located in the same city. Data collection took place during the second semester of the 2024/2025 academic year at the University of Debrecen and during the first semester of the 2025/2026 academic year at the University of Nyíregyháza. The datasets were subsequently harmonised and merged into a single database for statistical analysis.

2.2. Participants and Data Collection

Participants were recruited through an open invitation at the Faculty of Health Sciences of the University of Debrecen and the University of Nyíregyháza, resulting in a convenience sample. Eligible participants were active undergraduate (BSc) or graduate (MSc) students aged 18 years or older and enrolled in Hungarian-language degree programmes. Doctoral (PhD) students were excluded. Participation was voluntary and anonymous. All questionnaires, online and paper-based alike, began with written information on the aim of the study, the voluntary and anonymous nature of participation, the handling of the data, the

estimated completion time and the requirement to be at least 18 years old. Completing and submitting the questionnaire was considered consent to participate; to preserve anonymity, no individual verbal or signed consent was requested.

Data were collected using anonymous, self-administered questionnaires. At the University of Debrecen, the survey was administered exclusively online, whereas both online and paper-based questionnaires were used at the University of Nyíregyháza. In total, 688 questionnaires were obtained: 354 from the Faculty of Health Sciences, University of Debrecen, and 334 from the University of Nyíregyháza. After applying the eligibility criteria described in Section 2.3, 522 participants remained in the analytical sample used for the regression analyses; the sample derivation is presented in Figure 1.

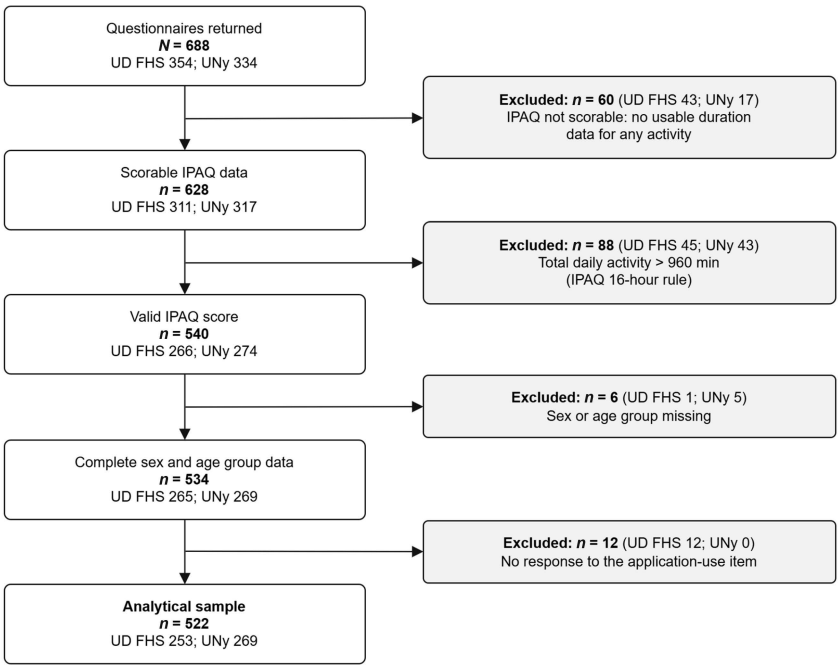


Figure 1. Flow of participants from returned questionnaires to the analytical sample. IPAQ: International Physical Activity Questionnaire; UD FHS: University of Debrecen, Faculty of Health Sciences; UNy: University of Nyíregyháza.

The study was conducted in accordance with the Declaration of Helsinki and was approved by the Regional and Institutional Research Ethics Committee, Clinical Center, University of Debrecen (RKEB 7145-2025).

2.3. Data Preparation

Before the statistical analysis, the datasets from the two institutions were processed separately. Data preparation involved systematic cleaning, quality and logical consistency checks, harmonisation of variable formats and coding schemes, and standardisation of variables in the two datasets. The two datasets were subsequently merged into a single database. For the present analysis, the IPAQ data of both institutions were reprocessed from the original survey exports and rescored using the official IPAQ scoring protocol [80]; the scoring rules are described in Section 2.4.3.

Of the 688 returned questionnaires (354 from the University of Debrecen, Faculty of Health Sciences [UD FHS] and 334 from the University of Nyíregyháza [UNy]), IPAQ data could not be scored in 60 cases (8.7%) because no duration data were available for any activity (UD FHS: 43, 12.1%; UNy: 17, 5.1%); in 19 of these cases, the entire IPAQ section had been left blank. A further 88 participants (UD FHS: 45; UNy: 43) were excluded because

their reported total daily physical activity exceeded 960 min, in accordance with the 16-h rule of the IPAQ protocol [80], leaving 540 participants with valid IPAQ scores. After the exclusion of 6 participants with missing data on sex or age group and 12 participants (all at UD FHS) who did not respond to the application-use item, the analytical sample comprised 522 participants: 253 (48.5%) from UD FHS and 269 (51.5%) from UNy (Figure 1). These figures correspond to 71.5% of the questionnaires returned at UD FHS and 80.5% of those returned at UNy. The reasons for exclusion are presented separately for each university in Table S2, and excluded and included participants are compared within each university in Table S3.

Physical activity variables were processed and categorised as described in Section 2.4.3. The resulting harmonised dataset was then used for descriptive and inferential statistical analyses.

2.4. Measures

The questionnaire comprised three sections covering sociodemographic characteristics, health-related mobile application use, and physical activity.

2.4.1. Sociodemographic Characteristics

Sociodemographic information included sex, age, university affiliation and study mode (full-time or part-time). Age was recorded in predefined categories rather than as a continuous variable; for the regression analyses, it was grouped into three categories (18–25, 26–40 and ≥41 years), and descriptive statistics are reported by category. Data on the specific degree programme and on the level of study (BSc or MSc) were not available. Self-rated financial situation, chronic illness and paid employment were also recorded and were used as additional covariates in a sensitivity analysis (Section 2.6).

2.4.2. Health-Related Mobile Application Use

Health-related mobile application use was assessed with a single multiple-choice item: "Which healthy-lifestyle applications do you use regularly? (Multiple answers are possible.)" (Hungarian original: "Milyen egészséges életmóddal kapcsolatos alkalmazásokat használ rendszeresen? (Több választ is megjelölhet.)"). The response options were calorie counter; diet planner and recipe applications; physical activity tracker (e.g., Adidas Running, Nike Run Club); workout plan applications (e.g., Abs Workout); "I do not use any"; and "other", with a free-text field. The term "regularly" was not defined in the questionnaire; the classification therefore reflects participants' own interpretation of regular use. No guidance was given on how to classify applications with multiple functions: participants assigned the applications they used to the categories themselves and could select several categories. Each of the four categories was coded as a separate dichotomous variable (user vs. non-user), and the four variables were analysed both separately and jointly in the regression models. Participants who selected none of the options were treated as having missing data on application use (Section 2.3), and responses in the "other" category were not analysed. No information was collected on the frequency, duration or intensity of use. A separate item asked which application functions (e.g., goal setting, progress display, reminders) participants used, but not in relation to specific application categories; the behaviour change techniques used within each category could therefore not be determined. The item and its English translation are provided in Table S11.

2.4.3. Physical Activity Assessment

The validated Hungarian version of the long-form International Physical Activity Questionnaire (IPAQ-LF) [78,79] was used to measure participants' physical activity. The

questionnaire covers physical activity during the previous seven days across four domains: work, transport, domestic and garden activities, and leisure time.

Responses were scored using the official IPAQ scoring protocol [80]. Activity intervals of less than 10 min were recoded as zero, and weekly frequencies were recorded on a scale from 0 to 7 days for each activity item. Durations were calculated from the hour and minute fields; when only one of the two fields was completed, the other was taken as zero. Activity items with missing frequency or duration were treated as no reported activity for that item, and participants who reported zero days for all activity items were assigned 0 MET-minutes/week (low category). In accordance with the long-form scoring protocol, total daily durations for walking, moderate-intensity activity, and vigorous-intensity activity were then summed across the domains, and each of these three totals was truncated at 180 min. Where truncation was required, the constituent items were proportionally scaled to preserve their relative contribution to the respective total. Cycling for transport and vigorous garden or yard work were classified as moderate-intensity activities, as described in the protocol. The metabolic equivalent of task (MET) values defined by the protocol were applied to the appropriate activity items. Participants whose summed daily duration across all relevant activity items exceeded 960 min (16 h) before truncation were excluded in accordance with the protocol; time spent in motorised transport was not included in this total. Because this criterion is evaluated on the untruncated durations, it is unaffected by the truncation described above, and the same participants are excluded regardless of the order in which the two steps are applied. Participants for whom a total MET-minutes/week score could not be calculated were treated as missing rather than assigned to the low activity category. Based on the resulting scores, participants were classified into three physical activity categories—low, moderate, and high—which served as the outcome variable in all analyses.

2.5. Statistical Analysis

All statistical analyses were conducted in IBM SPSS Statistics version 22.0 (IBM Corp., Armonk, NY, USA). Categorical variables are reported as frequencies and percentages, and total physical activity as the median and interquartile range. The distribution of the IPAQ physical activity categories among users and non-users of each application category was examined with Pearson's χ^2 tests (Table S1). Associations among the four application categories were assessed with Pearson's χ^2 tests without continuity correction, with the φ coefficient as the effect size; the p-values of the six pairwise comparisons were adjusted with the Benjamini–Hochberg false discovery rate procedure [81].

Because the outcome, the IPAQ physical activity category (low < moderate < high), is ordered and the low activity group was small ($n = 45$), ordinal logistic regression with a logit link (proportional odds model) [82] was used as the primary analysis. This model estimates a single odds ratio (OR) for each predictor, which applies to both cut-points of the outcome (low vs. moderate or high, and low or moderate vs. high); an OR > 1 indicates higher odds of being in a higher physical activity category for users than for non-users. The proportional odds assumption was assessed with the test of parallel lines and, for each application category, by comparing the ORs of two cumulative binary logistic regressions corresponding to the two cut-points (Table S5).

For each application category, a separate model was fitted first, estimating the association of that category with physical activity irrespective of the use of other categories. A joint model including all four categories was then fitted to estimate mutually adjusted associations, that is, the association of each category with physical activity after adjustment for the use of the other three. Because many participants used more than one category (Section 3.2), comparing the separate and joint estimates shows to what extent the association of a given

category reflects overlapping use of other categories. All models were adjusted for sex, age group and university; the reference categories were non-use of the application category, female sex, age ≥ 41 years and UNy. The contribution of each application category was tested with a likelihood-ratio (LR) test comparing the model with and without the given category. Multicollinearity in the joint model was checked with variance inflation factors. Model fit was assessed with the LR test of the full model and Nagelkerke's R^2; Pearson and deviance goodness-of-fit statistics are not reported because of sparse covariate patterns.

Results are reported as ORs with 95% confidence intervals (CIs), and interpretation focuses on the magnitude and precision of the estimates rather than on statistical significance alone. The four application categories were treated as one family of hypotheses in the separate models and as another in the joint model, and the LR p-values were adjusted within each family with the Holm procedure [83]. The sensitivity analyses (Section 2.6) address the same hypotheses with alternative model specifications and are interpreted in terms of the consistency of the direction and magnitude of the estimates; the analyses of leisure-time physical activity were exploratory and were not corrected for multiple testing. Statistical significance was set at $p < 0.05$.

Regression analyses were based on complete cases. All models were fitted in the same analytical sample ($n = 522$), except for the extended covariate models ($n = 513$; Section 2.6).

2.6. Selection, Sensitivity and Exploratory Analyses

To assess possible selection, participants excluded from and included in the analytical sample were compared separately within each university with respect to sex, age group, study mode, questionnaire mode, regular sport participation and use of the four application categories, using Pearson's χ^2 tests (Table S3). These comparisons are descriptive.

Three sensitivity analyses were performed. First, the separate and joint models were refitted as multinomial logistic regression models with low physical activity as the reference category, which do not assume proportional odds (Table S4). Second, to assess whether the results depended on the university, the ordinal models were fitted separately at each university, and application × university interaction terms were tested with LR tests in the full sample (Table S6). Third, the models were refitted with additional adjustment for self-rated financial situation, chronic illness and paid employment in the participants with complete covariate data ($n = 513$), with the basic and extended models fitted in the same participants (Table S7). Regular sport participation was not included as a covariate, because it is part of the outcome and may lie on the pathway between application use and physical activity (over-adjustment).

In an exploratory analysis, leisure-time physical activity (MET-minutes/week in the leisure-time domain, including walking) was compared between users and non-users of each application category with Mann–Whitney U tests, and the proportion of participants reaching 600 MET-minutes/week in the leisure-time domain was compared with Pearson's χ^2 tests (Tables S8 and S9). The effect size was calculated as $r = |Z|/\sqrt{N}$ [84], with 0.1 and 0.3 indicating small and medium effects, respectively [85]. The contribution of the four IPAQ domains to total physical activity was described as the share of the summed MET-minutes/week (Table S10).

3. Results

3.1. Sample Characteristics

Of the 688 returned questionnaires, 522 were included in the analytical sample (Section 2.3, Figure 1): 253 (48.5%) from UD FHS and 269 (51.5%) from UNy. Three quarters of the participants were women (76.6%), and half were older than 25 years (26–40 years: 25.7%; ≥41 years: 24.1%). Most participants were part-time students (58.2%), and 57.7%

were in paid employment. Age was closely related to study mode: 80.8% of participants aged 18–25 years studied full-time, whereas 97.3% of those older than 25 years were part-time students. Median total physical activity was 3486 MET-minutes/week (interquartile range 1782–5554; mean 4010, SD 2871; range 0–17,898). The characteristics of the analytical sample are presented in Table 1.

Table 1. Sociodemographic characteristics, physical activity level, and health-related mobile application use in the analytical sample ($n = 522$).

Characteristic	Category	*n*	%
Sex	Male	122	23.4
	Female	400	76.6
Age group (years)	18–25	262	50.2
	26–40	134	25.7
	≥41	126	24.1
University	UD FHS	253	48.5
	University of Nyíregyháza	269	51.5
Study mode [1]	Full-time	218	41.8
	Part-time	303	58.2
Self-rated financial situation [1]	Below average	115	22.3
	Average	268	52.0
	Above average	132	25.6
Chronic illness [1]	Yes	108	20.8
	No	412	79.2
Paid employment	Yes	301	57.7
	No	221	42.3
IPAQ physical activity category	Low	45	8.6
	Moderate	175	33.5
	High	302	57.9
Health-related mobile application use	User of at least one of the four categories	265	50.8
Number of application categories used	0	257	49.2
	1	155	29.7
	2	75	14.4
	3	29	5.6
	4	6	1.1
Type of application used [2]	Physical activity tracker	159	30.5
	Calorie counter	144	27.6
	Workout planner	57	10.9
	Diet planning and recipe application	56	10.7

Percentages are column percentages of the analytical sample; percentages may not sum to 100.0 because of rounding. [1] Valid percentages; missing: study mode 1, financial situation 7, chronic illness 2. [2] Multiple responses were possible. IPAQ: International Physical Activity Questionnaire; UD FHS: University of Debrecen, Faculty of Health Sciences.

The proportion of questionnaires with scorable IPAQ data was lower at UD FHS than at UNy (87.9% vs. 94.9%; $\chi^2(1) = 10.752$, $p = 0.001$), as was inclusion in the analytical sample (71.5% vs. 80.5%; $\chi^2(1) = 7.723$, $p = 0.005$; Table S2). At UD FHS, excluded and included participants did not differ significantly in sex, age group, study mode, regular sport participation or the use of any application category (all $p \geq 0.123$). At UNy, excluded participants were more often men (41.5% vs. 26.8%, $p = 0.019$), online respondents (83.1% vs. 66.5%, $p = 0.009$) and workout planner users (24.6% vs. 11.5%, $p = 0.006$; Table S3). At UNy, exclusion under the 960-min rule was more frequent among online than among paper respondents (18.6% vs. 2.1%) and among men than among women (21.7% vs. 10.2%), whereas non-scorable IPAQ data did not differ by questionnaire mode (5.6% vs. 4.0%, $p = 0.536$).

3.2. Associations Among Health-Related Mobile Application Categories

All six pairs of application categories were significantly associated (Table 2). The associations were weak to moderate ($\varphi = 0.086$–0.257); the strongest were between calorie counter and diet planner use ($\varphi = 0.257$) and between calorie counter and physical activity tracker use ($\varphi = 0.234$). All associations remained significant after Benjamini–Hochberg correction; the weakest, between calorie counter and workout planner use, was at the margin of significance ($\varphi = 0.086$, adjusted $p = 0.049$). Of the 265 users of at least one category, 110 used two or more (Table 1). These tests describe the co-occurrence of application categories, not differences in physical activity.

Table 2. Associations among the use of different types of health-related mobile applications ($n = 522$).

Application Pair	Used Both, *n*	χ^2	df	*p*-Value	BH-Adjusted *p*	φ
Calorie counter × diet planner	34	34.463	1	<0.001	<0.001	0.257
Calorie counter × physical activity tracker	69	28.610	1	<0.001	<0.001	0.234
Diet planner × physical activity tracker	30	15.819	1	<0.001	<0.001	0.174
Physical activity tracker × workout planner	30	14.850	1	<0.001	<0.001	0.169
Diet planner × workout planner	13	9.748	1	0.002	0.002	0.137
Calorie counter × workout planner	22	3.883	1	0.049	0.049	0.086

Pearson's χ^2 tests (without continuity correction) with the φ coefficient as effect size; all variables coded as user vs. non-user. Rows are ordered by decreasing effect size. BH: Benjamini–Hochberg false discovery rate correction across the six pairs.

3.3. Separate Ordinal Logistic Regression Models

In the separate models, adjusted for sex, age group and university, users of calorie counters (OR = 2.25, 95% CI 1.48–3.40), diet planners (OR = 2.23, 95% CI 1.20–4.15) and physical activity trackers (OR = 2.82, 95% CI 1.87–4.26) had higher odds of being in a higher physical activity category than non-users (Table 3). These associations remained significant after Holm correction (adjusted $p \leq 0.015$). For workout planners, the estimate was also above 1 but imprecise, and the confidence interval included 1 (OR = 1.50, 95% CI 0.84–2.67; LR $p = 0.155$). The test of parallel lines did not indicate a violation of the proportional odds assumption in any model ($p \geq 0.300$), and the estimates for the two cut-points had the same direction for every application category (Table S5).

Table 3. Separate ordinal logistic regression models predicting IPAQ physical activity category, one model per application category ($n = 522$ in each model).

Application Category	OR (95% CI)	*p*-Value	LR χ^2 (df = 1)	LR *p*-Value	Holm-Adjusted *p*	Test of Parallel Lines χ^2 (df = 5), *p*	Nagelkerke R^2
Calorie counter	2.25 (1.48–3.40)	<0.001	15.338	<0.001	<0.001	3.531, 0.619	0.053
Diet planner	2.23 (1.20–4.15)	0.011	7.114	0.008	0.015	2.943, 0.709	0.035
Physical activity tracker	2.82 (1.87–4.26)	<0.001	26.791	<0.001	<0.001	4.772, 0.444	0.078
Workout planner	1.50 (0.84–2.67)	0.170	2.026	0.155	0.155	6.064, 0.300	0.023

Each model included one application category together with sex, age group and university; the outcome was the IPAQ physical activity category (low < moderate < high). OR > 1 indicates higher odds of being in a higher physical activity category for users compared with non-users (reference: non-user), assumed equal across both cut-points (proportional odds). *p*-value: Wald test; LR: likelihood-ratio test of the application variable (difference in model χ^2 compared with the covariate-only model, $\chi^2 = 8.121$, df = 4); Holm: Holm correction across the four application categories. Pearson and deviance goodness-of-fit statistics are not reported because of sparse covariate patterns. OR: odds ratio; CI: confidence interval.

3.4. Joint Ordinal Logistic Regression Model

In the joint model, which included all four application categories together with the covariates (model $\chi^2(8) = 45.235$, $p < 0.001$; Nagelkerke $R^2 = 0.100$), physical activity

tracker use (OR = 2.42, 95% CI 1.58–3.70) and calorie counter use (OR = 1.76, 95% CI 1.14–2.72) remained associated with higher odds of being in a higher physical activity category after mutual adjustment, also after Holm correction (adjusted $p < 0.001$ and $p = 0.031$, respectively; Table 4). For diet planners, the OR decreased from 2.23 in the separate model to 1.50 (95% CI 0.78–2.88), and for workout planners from 1.50 to 1.14 (95% CI 0.62–2.09); neither was statistically significant. The attenuation for diet planners is consistent with their overlap with calorie counter use, the most strongly associated pair of categories (Table 2). Variance inflation factors ranged from 1.02 to 1.58, and the proportional odds assumption was not rejected (test of parallel lines $\chi^2(8) = 9.592$, $p = 0.295$). Of the covariates, only university was associated with physical activity category (UD FHS vs. UNy: OR = 1.48, 95% CI 1.04–2.13).

Table 4. Joint ordinal logistic regression model predicting IPAQ physical activity category, including all four application categories ($n = 522$).

Predictor	OR (95% CI)	*p*-Value	LR χ^2 (df = 1)	LR *p*-Value	Holm-Adjusted *p*
Application use (user vs. non-user)					
Calorie counter	1.76 (1.14–2.72)	0.011	6.574	0.010	0.031
Diet planner	1.50 (0.78–2.88)	0.225	1.521	0.217	0.435
Physical activity tracker	2.42 (1.58–3.70)	<0.001	17.769	<0.001	<0.001
Workout planner	1.14 (0.62–2.09)	0.670	0.192	0.661	0.661
Covariates					
Male (vs. female)	1.43 (0.93–2.19)	0.105			
Age 18–25 years (vs. ≥41)	0.72 (0.47–1.12)	0.147			
Age 26–40 years (vs. ≥41)	0.81 (0.49–1.34)	0.414			
UD FHS (vs. University of Nyíregyháza)	1.48 (1.04–2.13)	0.032			

Model $\chi^2 = 45.235$, df = 8, $p < 0.001$; Nagelkerke $R^2 = 0.100$; test of parallel lines $\chi^2 = 9.592$, df = 8, $p = 0.295$. Associations are mutually adjusted for the other application categories and the covariates. OR > 1 indicates higher odds of being in a higher physical activity category (reference: non-user, female, ≥41 years, University of Nyíregyháza). LR: likelihood-ratio test comparing the joint model with the model omitting the given application category; Holm: Holm correction across the four application categories. OR: odds ratio; CI: confidence interval; UD FHS: University of Debrecen, Faculty of Health Sciences.

3.5. Sensitivity and Exploratory Analyses

The multinomial models showed the same pattern (Table S4). In the separate models, the LR tests were significant for calorie counters, diet planners and physical activity trackers, but not for workout planners ($p = 0.065$); in the joint model, they were significant for physical activity trackers ($p < 0.001$) and calorie counters ($p = 0.021$). For calorie counters, diet planners and physical activity trackers, the estimates were larger for the high-versus-low than for the moderate-versus-low contrast; only one workout planner user was in the low activity category, which resulted in very wide confidence intervals for this category.

The associations of calorie counter, diet planner and physical activity tracker use were similar in direction and magnitude at the two universities, with no significant application × university interaction ($p \geq 0.135$; Table S6). For workout planners, the estimates were in opposite directions (UD FHS: OR = 0.57, 95% CI 0.26–1.28; UNy: OR = 4.31, 95% CI 1.69–11.00; interaction $p < 0.001$), so that the near-null estimate in the full sample combined two opposing institution-specific associations. Because this difference was not hypothesised in advance, it is regarded as exploratory.

With additional adjustment for self-rated financial situation, chronic illness and paid employment ($n = 513$), the ORs changed only slightly, and the pattern of statistical significance was unchanged in both the separate and the joint models (Table S7).

In the exploratory analysis, leisure-time physical activity was higher among users than among non-users of calorie counters (median 607.8 vs. 352.5 MET-minutes/week, $p = 0.004$),

physical activity trackers (840.0 vs. 264.0, $p < 0.001$) and workout planners (990.0 vs. 396.0, $p = 0.001$), but not significantly for diet planners (663.0 vs. 396.0, $p = 0.071$); all effect sizes were small ($r = 0.079$–0.237; Table S8). For workout planners, leisure-time activity was higher among users at both universities, although the difference was significant only at UNy (Table S9). Leisure-time activity accounted for 22.5% of the total MET-minutes/week, and 37.1% of the participants in the high activity category did not reach 600 MET-minutes/week in the leisure-time domain (Table S10).

4. Discussion

4.1. Principal Findings

This study examined the associations between four categories of health-related mobile applications and physical activity among university students, using ordinal logistic regression adjusted for sex, age group and university. In the separate models, users of calorie counters, diet planners and physical activity trackers had higher odds of being in a higher physical activity category than non-users (ORs 2.23–2.82), whereas the estimate for workout planners was smaller and imprecise. After mutual adjustment for the other application categories, the associations of physical activity tracker and calorie counter use remained, whereas those of diet planner and workout planner use were attenuated and were no longer statistically significant.

This pattern was consistent across the sensitivity analyses: the multinomial models, the extended covariate adjustment and the university-specific models yielded estimates of similar direction and magnitude for calorie counters, diet planners and physical activity trackers. The exception was workout planner use, which showed opposite associations at the two universities. Because this heterogeneity was not anticipated and the number of workout planner users was small, the findings for workout planners are regarded as exploratory.

4.2. Interpretation of the Findings

The comparison of the separate and joint models helps to interpret these associations. Because the application categories were often used together (Table 2), the separate estimates partly reflect the concurrent use of other categories. This was most evident for diet planners: their OR decreased from 2.23 to 1.50 after mutual adjustment, and diet planner use overlapped most strongly with calorie counter use ($\varphi = 0.257$). The association of diet planners with physical activity may therefore partly reflect concurrent calorie counting. By contrast, the ORs of physical activity trackers (from 2.82 to 2.42) and calorie counters (from 2.25 to 1.76) decreased only moderately, indicating mutually adjusted associations that were not fully explained by the use of the other categories.

These differences should not be overinterpreted. A statistically significant association for one category and a non-significant association for another does not imply that the two associations differ significantly from each other: in the joint model, the confidence intervals of the four categories overlapped considerably (Table 4). The results therefore show which associations were estimated with sufficient precision in the present sample rather than a clear-cut distinction between application types.

The two categories that retained their associations, physical activity trackers and calorie counters, typically include self-monitoring functions, whereas diet planners and workout planners are typically designed around action planning [41,42]. Because the functions that participants actually used were not measured for each category, this study cannot determine whether self-monitoring underlies the observed associations, and behaviour change techniques are discussed here only as a possible framework. The association of calorie counter use is notable because these applications are not designed to increase physical activity. It may reflect a broader health- or weight-oriented lifestyle in which dietary self-

monitoring and physical activity co-occur, or reverse causation, with physically active students being more inclined to monitor their diet; neither explanation could be tested with the present data.

The findings for workout planners illustrate a limitation of using total physical activity as the outcome. Workout planner users reported more leisure-time physical activity than non-users at both universities, although the difference was significant only at UNy, whereas their association with the total physical activity category had opposite directions at the two universities. Because the IPAQ total score also includes work, transport and domestic activities, which accounted for about three quarters of the total MET-minutes/week in this sample, applications aimed at structured exercise may be more closely related to leisure-time activity than to total activity. This interpretation is hypothesis-generating and should be tested with domain-specific or device-based measures.

Physical activity category was higher at UD FHS than at UNy after adjustment (OR = 1.48, 95% CI 1.04–2.13). Because university, the season of data collection and the composition of the two student populations cannot be separated in this design, this difference is not interpreted substantively, and university was included in the models only as a covariate.

4.3. Comparison with Previous Literature

The findings are broadly consistent with previous observational studies that have reported positive associations between health-related mobile application use and physical activity. Population-based studies have found that health-related mobile application users were more likely to meet physical activity recommendations than non-users [63], while users of mobile health applications or wearable activity trackers showed higher odds of achieving recommended levels of aerobic physical activity [64]. Comparable associations have been reported among recreational runners [65], commercial fitness application users [66], and adults in the general population [67]. Interpretation of these associations is complicated by evidence that higher physical activity may itself be associated with the use of health-related applications [32,34,68], raising the possibility of reverse causation. Most of these studies, however, treated health-related mobile applications as a single exposure or compared users with non-users without distinguishing between application categories. They therefore provided limited insight into whether the observed associations varied according to the type of application used.

More recent studies have begun to address this heterogeneity by examining individual application functions [73–75] or broader application categories [76,77]. Although this represents an important shift away from treating health applications as a homogeneous construct, application categories have generally been examined in separate regression models, even when concurrent use of multiple application types was recognised [76]. In the present study, four conceptually distinct application categories were examined simultaneously while adjusting for relevant sociodemographic characteristics. All four associations were attenuated after mutual adjustment, most markedly for diet planners, suggesting that associations observed in separate models may partly reflect the concurrent use of other application categories (Section 4.2). The present results illustrate the practical consequence of this design issue: three of the four categories were significantly associated with physical activity when modelled separately, whereas two remained so under mutual adjustment. Because the categories are not mutually exclusive, separate models cannot estimate the mutually adjusted association of any single category, and the two modelling approaches can therefore support different conclusions from the same data [31,41,76].

4.4. Scientific and Practical Implications

For research, the findings indicate that health-related mobile applications should not be treated as a single exposure. Because application categories are frequently used together, studies should record the categories used and model them jointly, so that mutually adjusted associations can be estimated; comparing separate and joint estimates also shows to what extent the association of a category depends on overlapping use. Future studies should also measure which functions are used within each category and how often, as the present data could not establish whether self-monitoring or other behaviour change techniques underlie the observed associations.

The practical implications are limited by the cross-sectional design. Physical activity tracking was the application category most consistently associated with physical activity, in both the separate and the joint models and in all sensitivity analyses; whether promoting such applications would increase physical activity, however, can only be established by intervention studies. In the Hungarian context, where leisure-time sport participation is low [18] and application use is common but often discontinued [24,25], university health promotion could build on the applications that students already use rather than introducing new ones. The association of calorie counter use does not imply that nutrition-oriented applications should be recommended to increase physical activity; it more plausibly reflects a broader health- or weight-oriented lifestyle. For developers, it remains to be tested which behaviour change techniques are most relevant, such as self-monitoring and feedback in tracking applications or action planning and goal setting in planning applications [41–44].

4.5. Strengths and Limitations

This study has several strengths. A key strength is the simultaneous examination of four categories of health-related mobile applications in both separate and mutually adjusted models, allowing their associations with physical activity to be evaluated while accounting for concurrent application use. Further strengths include the inclusion of students from two institutions with different disciplinary profiles and the use of the validated Hungarian version of the IPAQ Long Form [79]. An additional strength is the scoring of physical activity according to the IPAQ guidelines, including the ten-minute bout rule, truncation of daily durations and weekly frequencies, and exclusion of implausibly high reported activity under the 16-h rule. The robustness of the findings was supported by several sensitivity analyses, including multinomial models, university-specific models and extended covariate adjustment.

Several limitations should be considered. First, the cross-sectional design does not allow conclusions about the direction or causality of the observed associations. For example, higher physical activity may itself be associated with subsequent adoption of activity-tracking applications, and this possibility cannot be excluded. In addition, although the models were adjusted for sociodemographic characteristics and, in a sensitivity analysis, for financial situation, chronic illness and paid employment, residual confounding by unmeasured factors such as health motivation or body mass index cannot be ruled out. Second, all variables were self-reported and may therefore be subject to recall and social desirability bias, and incomplete responses to individual IPAQ items may have led to some misclassification of physical activity. Third, application use was assessed with a single item: the term “regularly” was not defined, participants classified multifunctional applications themselves, and no information was collected on the frequency, duration or intensity of use or on the functions used within each category. Fourth, the sample was a convenience sample from two institutions; the findings therefore cannot be generalised to Hungarian university students as a whole or to other populations and cultural settings.

Statistical precision was also limited. The low activity category included 45 participants, and the number of users was relatively small for diet planners ($n = 56$) and workout planners ($n = 57$); only two diet planner users and one workout planner user were in the low activity category (Table S1). This contributed to wide confidence intervals, particularly in the multinomial sensitivity analysis, and warrants caution in interpreting the estimates for these categories. The analytical sample comprised 75.9% of the returned questionnaires, and inclusion was lower at UD FHS than at UNy (71.5% vs. 80.5%). Within each university, excluded and included participants were similar in most measured characteristics, but at UNy excluded participants were more often men, online respondents and workout planner users (Table S3); selection related to these or to unmeasured characteristics therefore cannot be excluded. University was associated with physical activity category in the joint model, but because university, the season of data collection and the composition of the two student populations cannot be separated, this association is not interpreted as an institutional effect.

The proportion of participants classified as highly active was high (57.9%), largely because of activity in the work, transport and domestic domains: leisure time accounted for only 22.5% of the total MET-minutes/week, and 37.1% of the highly active participants did not reach 600 MET-minutes/week in leisure time (Table S10). This may partly reflect the recognised tendency of self-administered long-form instruments to overestimate physical activity, as well as broader methodological challenges in physical activity surveillance [4,78,79]. Application users may also report their physical activity differently because they monitor it more closely. The age distribution also differed from that of the emerging-adult samples examined in comparable studies [76], with 49.8% of participants aged over 25 years and 24.1% aged 41 years or older, almost all of them part-time students, which limits direct comparability. Finally, women accounted for 76.6% of the analytical sample, indicating a further limitation in the representativeness of the sample.

5. Conclusions

The findings suggest that the associations between health-related mobile application use and physical activity vary by application category. Calorie counter, diet planner and physical activity tracker use were associated with higher odds of being in a higher physical activity category when examined separately, whereas only physical activity tracker and calorie counter use remained associated after mutual adjustment for the other categories. The findings for workout planners differed between the two universities and should be regarded as exploratory. These results underscore the importance of distinguishing between health-related mobile application categories and accounting for their concurrent use rather than treating them as a homogeneous exposure in observational research [31,32,76].

Because the study was cross-sectional and based on a convenience sample of students from two Hungarian universities, the findings cannot be generalised to all Hungarian university students, and causal conclusions cannot be drawn. Future studies should investigate these associations using longitudinal designs, larger and more representative samples, and more detailed measures of application use, including the functions used within each category. Such approaches may help determine whether the pattern observed here reflects meaningful differences between application categories or is partly attributable to the limited statistical precision of the present sample.

Supplementary Materials: The following supporting information can be downloaded at https://www.mdpi.com/article/10.3390/app162211410/s1. Table S1: Distribution of IPAQ physical activity categories among users and non-users of each application category ($n = 522$); Table S2: Reasons for non-scorable IPAQ data and sample selection by university; Table S3: Comparison of excluded participants and the analytical sample, separately by university; Table S4: Sensitivity analysis: separate and joint multinomial logistic regression models (reference outcome: low physical activity; $n = 522$);

Table S5: Proportional odds check for each application category: two cumulative binary logistic regressions compared with the ordinal estimate (separate models, $n = 522$); Table S6: Sensitivity analysis by university: ordinal logistic regression models fitted separately at each university, and application × university interaction in the full sample; Table S7: Sensitivity analysis with extended covariate adjustment: ordinal logistic regression models in participants with complete covariate data ($n = 513$); Table S8: Exploratory analysis: leisure-time physical activity among users and non-users of each application category ($n = 522$); Table S9: Leisure-time physical activity (MET-min/week, including walking) by application use, separately by university (exploratory); Table S10: Contribution of the IPAQ domains to total physical activity (share of the summed MET-min/week, %), overall and by IPAQ category; Table S11: Questionnaire item on health-related mobile application use: Hungarian original and English translation.

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Abbreviations

The following abbreviations are used in this manuscript:

BCT	Behaviour change technique
CI	Confidence interval
IPAQ	International Physical Activity Questionnaire
IPAQ-LF	International Physical Activity Questionnaire, long form
LR	Likelihood ratio
MET	Metabolic equivalent of task
OR	Odds ratio
UD FHS	University of Debrecen, Faculty of Health Sciences
UNy	University of Nyíregyháza

References

1. Bull, F.C.; Al-Ansari, S.S.; Biddle, S.; Borodulin, K.; Buman, M.P.; Cardon, G.; Carty, C.; Chaput, J.; Chastin, S.; Chou, R.; et al. World Health Organization 2020 Guidelines on Physical Activity and Sedentary Behaviour. *Br. J. Sports Med.* **2020**, *54*, 1451–1462. [CrossRef]
2. Strain, T.; Flaxman, S.; Guthold, R.; Semenova, E.; Cowan, M.; Riley, L.M.; Bull, F.C.; Stevens, G.A. National, Regional, and Global Trends in Insufficient Physical Activity among Adults from 2000 to 2022. *Lancet Glob. Health* **2024**, *12*, e1232–e1243. [CrossRef]
3. Guthold, R.; Stevens, G.A.; Riley, L.M.; Bull, F.C. Worldwide Trends in Insufficient Physical Activity from 2001 to 2016. *Lancet Glob. Health* **2018**, *6*, e1077–e1086. [CrossRef]

4. Hallal, P.C.; Andersen, L.B.; Bull, F.C.; Guthold, R.; Haskell, W.; Ekelund, U. Global Physical Activity Levels: Surveillance Progress, Pitfalls, and Prospects. *Lancet* **2012**, *380*, 247–257. [CrossRef]
5. Lee, I.-M.; Shiroma, E.J.; Lobelo, F.; Puska, P.; Blair, S.N.; Katzmarzyk, P.T. Effect of Physical Inactivity on Major Non-Communicable Diseases Worldwide. *Lancet* **2012**, *380*, 219–229. [CrossRef]
6. Ding, D.; Lawson, K.D.; Kolbe-Alexander, T.L.; Finkelstein, E.A.; Katzmarzyk, P.T.; van Mechelen, W.; Pratt, M. The Economic Burden of Physical Inactivity. *Lancet* **2016**, *388*, 1311–1324. [CrossRef]
7. Santos, A.C.; Willumsen, J.; Meheus, F.; Ilbawi, A.; Bull, F.C. The Cost of Inaction on Physical Inactivity to Public Health-Care Systems. *Lancet Glob. Health* **2023**, *11*, e32–e39. [CrossRef]
8. Pengpid, S.; Peltzer, K.; Kassean, H.K.; Tsala Tsala, J.P.; Sychareun, V.; Müller-Riemenschneider, F. Physical Inactivity and Associated Factors among University Students in 23 Low-, Middle- and High-Income Countries. *Int. J. Public Health* **2015**, *60*, 539–549. [CrossRef]
9. Deliens, T.; Deforche, B.; De Bourdeaudhuij, I.; Clarys, P. Determinants of Physical Activity and Sedentary Behaviour in University Students: A Qualitative Study Using Focus Group Discussions. *BMC Public Health* **2015**, *15*, 201. [CrossRef]
10. Ferreira Silva, R.M.; Mendonça, C.R.; Azevedo, V.D.; Raoof Memon, A.; Noll, P.R.E.S.; Noll, M. Barriers to High School and University Students' Physical Activity: A Systematic Review. *PLoS ONE* **2022**, *17*, e0265913. [CrossRef]
11. Tafireyi, R.; Grace, J.M. The Physical Activity and Health Promotion Activities of Global University Students: A Review of Reviews. *Glob. Health Promot.* **2022**, *29*, 63–73. [CrossRef]
12. Kosztin, N.; Balatoni, I. Magyarországi Egyetemek Hallgatóinak Sportolási Szokásai. Áttekintő Irodalmi Elemzés [Sporting Habits of Students at Hungarian Universities: A Review of the Literature]. *Acta Med. Sociol.* **2021**, *12*, 92–102. (In Hungarian) [CrossRef]
13. Balatoni, I.; Szépné Varga, H.; Müller, A.; Kovács, S.; Kosztin, N.; Csernoch, L. Sporting Habits of University Students in Hungary. *Balt. J. Health Phys. Act.* **2019**, *11*, 27–37. [CrossRef]
14. Leśniak, P.; Chrzanowska, S.; Stanios, M.; Krzyżanowski, T.; Nowak, J.; Cichy, I.; Popowczak, M. Physical Activity Levels of University Students Based on the International Physical Activity Questionnaire. *Appl. Sci.* **2026**, *16*, 5472. [CrossRef]
15. Yuan, F.; Peng, S.; Khairani, A.Z.; Liang, J. A Systematic Review and Meta-Analysis of the Efficacy of Physical Activity Interventions among University Students. *Sustainability* **2024**, *16*, 1369. [CrossRef]
16. Aly, M.; AlMarzooqi, M.; Mohamed, S.; Alzahrani, T.M.; Abdelkarim, O. Daily Step Counts before, during, and after COVID-19 Pandemic: A Smartphone-Tracking Study of University Students in Egypt and Saudi Arabia. *BMC Public Health* **2023**, *23*, 1365. [CrossRef]
17. Konda, S.; Ogasawara, I.; Fujita, K.; Aoyama, C.; Yokoyama, T.; Magome, T.; Yulong, C.; Hashizume, K.; Matsuo, T.; Nakata, K. Variability in Physical Inactivity Responses of University Students during COVID-19 Pandemic. *Int. J. Environ. Res. Public Health* **2022**, *19*, 1958. [CrossRef]
18. European Commission. *Special Eurobarometer 525: Sport and Physical Activity*; Publications Office of the European Union: Luxembourg, 2022. [CrossRef]
19. Bácsné Bába, É.; Ráthonyi, G.; Müller, A.; Ráthonyi-Odor, K.; Balogh, P.; Ádány, R.; Bács, Z. Physical Activity of the Population of the Most Obese Country in Europe, Hungary. *Front. Public Health* **2020**, *8*, 203. [CrossRef]
20. Bergier, J.; Tsos, A.; Popovych, D.; Bergier, B.; Niźnikowska, E.; Ács, P.; Junger, J.; Salonna, F. Level of and Factors Determining Physical Activity in Students in Ukraine and the Visegrad Countries. *Int. J. Environ. Res. Public Health* **2018**, *15*, 1738. [CrossRef]
21. Barka, N.; Wang, F.; Jarai, R.; Boros, S. Examining the Relationship between Physical Activity and Sleep among University Students. *Front. Sports Act. Living* **2025**, *7*, 1640770. [CrossRef]
22. Ráthonyi, G.; Takács, V.; Szilágyi, R.; Bácsné Bába, É.; Müller, A.; Bács, Z.; Harangi-Rákos, M.; Balogh, L.; Ráthonyi-Odor, K. Your Physical Activity Is in Your Hand—Objective Activity Tracking among University Students in Hungary, One of the Most Obese Countries in Europe. *Front. Public Health* **2021**, *9*, 661471. [CrossRef]
23. Girasek, E.; Boros, J.; Döbrössy, B.; Susánszky, A.; Győrffy, Z. E-páciensek Magyarországon: Digitális egészséggel kapcsolatos ismeretek, szokások egy országos reprezentatív felmérés tükrében [E-Patients in Hungary: Digital Health Knowledge and Habits in the Light of a Nationwide Representative Survey]. *Orv. Hetil.* **2022**, *163*, 1159–1165. (In Hungarian) [CrossRef]
24. Kovács, T.; Várallyai, L. Egészségügyi mobilapplikációkra történő használati szándék mérése UTAUT-modellben: Tanulmány egy online felmérés eredményei alapján [Measuring the Intention to Use Health Mobile Applications in the UTAUT Model: A Study Based on an Online Survey]. *Inf. Társad.* **2021**, *21*, 166–187. (In Hungarian) [CrossRef]
25. Kovácsné Tóth, Á.; Ercsey, I.; Keller, V. Az életmód applikációk használatának akadályai egy feltáró kutatás tapasztalatai alapján [Barriers to Using Lifestyle Applications: Lessons from an Exploratory Study]. *Egészségfejlesztés* **2023**, *64*, 17–29. (In Hungarian) [CrossRef]
26. Kovács, K.E.; Kovács, K.; Szabó, F.; Dan, B.A.; Szakál, Z.; Moravecz, M.; Szabó, D.; Olajos, T.; Csukonyi, C.; Papp, D.; et al. Sport Motivation from the Perspective of Health, Institutional Embeddedness and Academic Persistence among Higher Educational Students. *Int. J. Environ. Res. Public Health* **2022**, *19*, 7423. [CrossRef]

27. World Health Organization. *Global Strategy on Digital Health 2020–2025*; World Health Organization: Geneva, Switzerland, 2021.
28. Krebs, P.; Duncan, D.T. Health App Use among US Mobile Phone Owners: A National Survey. *JMIR mHealth uHealth* **2015**, *3*, e101. [CrossRef]
29. Ernsting, C.; Dombrowski, S.U.; Oedekoven, M.; O'Sullivan, J.L.; Kanzler, M.; Kuhlmey, A.; Gellert, P. Using Smartphones and Health Apps to Change and Manage Health Behaviors: A Population-Based Survey. *J. Med. Internet Res.* **2017**, *19*, e101. [CrossRef]
30. Shen, C.; Wang, M.P.; Chu, J.T.; Wan, A.; Viswanath, K.; Chan, S.S.C.; Lam, T.H. Health App Possession among Smartphone or Tablet Owners in Hong Kong: Population-Based Survey. *JMIR mHealth uHealth* **2017**, *5*, e77. [CrossRef]
31. Bol, N.; Helberger, N.; van Weert, J.C.M. Differences in Mobile Health App Use: A Source of New Digital Inequalities? *Inf. Soc.* **2018**, *34*, 183–193. [CrossRef]
32. Gulec, H.; Smahel, D.; Huang, Y. Patterns and Characteristics of Mobile App Use to Promote Wellness and Manage Illness: Cross-Sectional Study. *J. Med. Internet Res.* **2026**, *28*, e71363. [CrossRef]
33. Stühmann, L.M.; Paprott, R.; Heidemann, C.; Baumert, J.; Hansen, S.; Zahn, D.; Scheidt-Nave, C.; Gellert, P. Health App Use and Its Correlates among Individuals with and without Type 2 Diabetes. *JMIR Diabetes* **2020**, *5*, e14396. [CrossRef]
34. Robbins, R.; Krebs, P.; Jagannathan, R.; Jean-Louis, G.; Duncan, D.T. Health App Use among US Mobile Phone Users: Analysis of Trends by Chronic Disease Status. *JMIR mHealth uHealth* **2017**, *5*, e197. [CrossRef]
35. Venkatesh, V.; Morris, M.G.; Davis, G.B.; Davis, F.D. User Acceptance of Information Technology: Toward a Unified View. *MIS Q.* **2003**, *27*, 425–478. [CrossRef]
36. Montagni, I.; Cariou, T.; Feuillet, T.; Langlois, E.; Tzourio, C. Exploring Digital Health Use and Opinions of University Students: Field Survey Study. *JMIR mHealth uHealth* **2018**, *6*, e65. [CrossRef]
37. Alqahtani, N.; Bashatah, A.; Alharbi, M.K.; Syed, W. Exploring Usage and Perceived Effectiveness of Fitness Trackers and Mobile Health Applications among University Students in Saudi Arabia. *Sci. Rep.* **2025**, *15*, 37531. [CrossRef]
38. Dute, D.J.; Bemelmans, W.J.E.; Breda, J. Using Mobile Apps to Promote a Healthy Lifestyle among Adolescents and Students: A Review of the Theoretical Basis and Lessons Learned. *JMIR mHealth uHealth* **2016**, *4*, e39. [CrossRef]
39. Mahmood, A.; Kedia, S.; Wyant, D.K.; Ahn, S.; Bhuyan, S.S. Use of Mobile Health Applications for Health-Promoting Behavior among Individuals with Chronic Medical Conditions. *Digit. Health* **2019**, *5*, 1–17. [CrossRef]
40. Tóth, K.; Takács, P.; Balatoni, I. Users' Expectations of Smart Devices during Physical Activity—A Literature Review. *Appl. Sci.* **2024**, *14*, 3518. [CrossRef]
41. Michie, S.; Richardson, M.; Johnston, M.; Abraham, C.; Francis, J.; Hardeman, W.; Eccles, M.P.; Cane, J.; Wood, C.E. The Behavior Change Technique Taxonomy (v1) of 93 Hierarchically Clustered Techniques. *Ann. Behav. Med.* **2013**, *46*, 81–95. [CrossRef]
42. Michie, S.; Abraham, C.; Whittington, C.; McAteer, J.; Gupta, S. Effective Techniques in Healthy Eating and Physical Activity Interventions: A Meta-Regression. *Health Psychol.* **2009**, *28*, 690–701. [CrossRef]
43. Ajzen, I. The Theory of Planned Behavior. *Organ. Behav. Hum. Decis. Process.* **1991**, *50*, 179–211. [CrossRef]
44. Bandura, A. Health Promotion from the Perspective of Social Cognitive Theory. *Psychol. Health* **1998**, *13*, 623–649. [CrossRef]
45. Middelweerd, A.; Mollee, J.S.; van der Wal, C.N.; Brug, J.; te Velde, S.J. Apps to Promote Physical Activity among Adults: A Review and Content Analysis. *Int. J. Behav. Nutr. Phys. Act.* **2014**, *11*, 97. [CrossRef]
46. Bondaronek, P.; Alkhaldi, G.; Slee, A.; Hamilton, F.L.; Murray, E. Quality of Publicly Available Physical Activity Apps: Review and Content Analysis. *JMIR mHealth uHealth* **2018**, *6*, e53. [CrossRef]
47. Dugas, K.; Giroux, M.-A.; Guerroudj, A.; Leger, J.; Rouhafzay, A.; Rouhafzay, G.; Jbilou, J. Calorie-Counting Apps for Monitoring and Managing Calorie Intake in Adults Living with Weight-Related Chronic Diseases: Decade-Long Scoping Review (2013–2024). *JMIR mHealth uHealth* **2026**, *14*, e64139. [CrossRef]
48. Curtin, E.; Green, R.; Brown, K.A.; Nájera Espinosa, S.; Chandrasekar, A.; Hopkins, L.; Turner, G.; Alae-Carew, C.; Ullian, K.; Scheelbeek, P. The Effectiveness of Mobile App-Based Interventions in Facilitating Behaviour Change towards Healthier and More Sustainable Diets. *Int. J. Behav. Nutr. Phys. Act.* **2025**, *22*, 122. [CrossRef]
49. Fewings, A.; Vandelanotte, C.; Irwin, C.; Ting, C.; Williams, E.; Khalesi, S. The Use and Acceptability of Diet-Related Apps and Websites in Australia: Cross-Sectional Study. *Digit. Health* **2022**, *8*, 1–20. [CrossRef]
50. Teixeira, P.J.; Carraça, E.V.; Markland, D.; Silva, M.N.; Ryan, R.M. Exercise, Physical Activity, and Self-Determination Theory: A Systematic Review. *Int. J. Behav. Nutr. Phys. Act.* **2012**, *9*, 78. [CrossRef]
51. Shi, M.; Zhao, Z.; Fan, X. Associations of Accelerometer-Measured Physical Activity, Sedentary Behaviour and Different Types of Smartphone Apps Usage among University Students: A 7-Day Tracking Study. *BMC Public Health* **2025**, *25*, 4336. [CrossRef]
52. Romeo, A.; Edney, S.; Plotnikoff, R.; Curtis, R.; Ryan, J.; Sanders, I.; Crozier, A.; Maher, C. Can Smartphone Apps Increase Physical Activity? Systematic Review and Meta-Analysis. *J. Med. Internet Res.* **2019**, *21*, e12053. [CrossRef]
53. Laranjo, L.; Ding, D.; Heleno, B.; Kocaballi, B.; Quiroz, J.C.; Tong, H.L.; Chahwan, B.; Neves, A.L.; Gabarron, E.; Dao, K.P.; et al. Do Smartphone Applications and Activity Trackers Increase Physical Activity in Adults? Systematic Review, Meta-Analysis and Metaregression. *Br. J. Sports Med.* **2021**, *55*, 422–432. [CrossRef]

54. Schoeppe, S.; Alley, S.; Van Lippevelde, W.; Bray, N.A.; Williams, S.L.; Duncan, M.J.; Vandelanotte, C. Efficacy of Interventions That Use Apps to Improve Diet, Physical Activity and Sedentary Behaviour: A Systematic Review. *Int. J. Behav. Nutr. Phys. Act.* **2016**, *13*, 127. [CrossRef]
55. Mönninghoff, A.; Kramer, J.N.; Hess, A.J.; Ismailova, K.; Teepe, G.W.; Tudor Car, L.; Müller-Riemenschneider, F.; Kowatsch, T. Long-Term Effectiveness of mHealth Physical Activity Interventions: Systematic Review and Meta-Analysis of Randomized Controlled Trials. *J. Med. Internet Res.* **2021**, *23*, e26699. [CrossRef]
56. Ferguson, T.; Olds, T.; Curtis, R.; Blake, H.; Crozier, A.J.; Dankiw, K.; Dumuid, D.; Kasai, D.; O'Connor, E.; Virgara, R.; et al. Effectiveness of Wearable Activity Trackers to Increase Physical Activity and Improve Health: A Systematic Review of Systematic Reviews and Meta-Analyses. *Lancet Digit. Health* **2022**, *4*, e615–e626. [CrossRef]
57. Bi, S.; Yuan, J.; Wang, Y.; Zhang, W.; Zhang, L.; Zhang, Y.; Zhu, R.; Luo, L. Effectiveness of Digital Health Interventions in Promoting Physical Activity among College Students: Systematic Review and Meta-Analysis. *J. Med. Internet Res.* **2024**, *26*, e51714. [CrossRef]
58. Plotnikoff, R.C.; Costigan, S.A.; Williams, R.L.; Hutchesson, M.J.; Kennedy, S.G.; Robards, S.L.; Allen, J.; Collins, C.E.; Callister, R.; Germov, J. Effectiveness of Interventions Targeting Physical Activity, Nutrition and Healthy Weight for University and College Students: A Systematic Review and Meta-Analysis. *Int. J. Behav. Nutr. Phys. Act.* **2015**, *12*, 45. [CrossRef]
59. Peng, S.; Yuan, F.; Othman, A.T.; Zhou, X.; Shen, G.; Liang, J. The Effectiveness of E-Health Interventions Promoting Physical Activity and Reducing Sedentary Behavior in College Students: A Systematic Review and Meta-Analysis of Randomized Controlled Trials. *Int. J. Environ. Res. Public Health* **2022**, *20*, 318. [CrossRef]
60. Maselli, M.; Ward, P.B.; Gobbi, E.; Carraro, A. Promoting Physical Activity among University Students: A Systematic Review of Controlled Trials. *Am. J. Health Promot.* **2018**, *32*, 1602–1612. [CrossRef]
61. Kim, H.-N.; Seo, K. Smartphone-Based Health Program for Improving Physical Activity and Tackling Obesity for Young Adults: A Systematic Review and Meta-Analysis. *Int. J. Environ. Res. Public Health* **2020**, *17*, 15. [CrossRef]
62. Whatnall, M.C.; Sharkey, T.; Hutchesson, M.J.; Haslam, R.L.; Bezzina, A.; Collins, C.E.; Ashton, L.M. Effectiveness of Interventions and Behaviour Change Techniques for Improving Physical Activity in Young Adults: A Systematic Review and Meta-Analysis. *J. Sports Sci.* **2021**, *39*, 1754–1771. [CrossRef]
63. Carroll, J.K.; Moorhead, A.; Bond, R.; LeBlanc, W.G.; Petrella, R.J.; Fiscella, K. Who Uses Mobile Phone Health Apps and Does Use Matter? A Secondary Data Analytics Approach. *J. Med. Internet Res.* **2017**, *19*, e125. [CrossRef]
64. Tong, H.L.; Maher, C.; Parker, K.; Pham, T.D.; Neves, A.L.; Riordan, B.; Chow, C.K.; Laranjo, L.; Quiroz, J.C. The Use of Mobile Apps and Fitness Trackers to Promote Healthy Behaviors during COVID-19: A Cross-Sectional Survey. *PLoS Digit. Health* **2022**, *1*, e0000087. [CrossRef]
65. Dallinga, J.M.; Mennes, M.; Alpay, L.; Bijwaard, H.; Baart de la Faille-Deutekom, M. App Use, Physical Activity and Healthy Lifestyle: A Cross Sectional Study. *BMC Public Health* **2015**, *15*, 833. [CrossRef]
66. Petersen, J.M.; Kemps, E.; Lewis, L.K.; Prichard, I. Associations between Commercial App Use and Physical Activity: Cross-Sectional Study. *J. Med. Internet Res.* **2020**, *22*, e17152. [CrossRef]
67. Alshahrani, N.Z. Predictors of Physical Activity and Public Safety Perception Regarding Technology Adoption for Promoting Physical Activity in Jeddah, Saudi Arabia. *Prev. Med. Rep.* **2024**, *43*, 102753. [CrossRef]
68. Ozaki, I.; Nishijima, M.; Shibata, E.; Zako, Y.; Chiang, C. Factors Related to mHealth App Use among Japanese Workers: Cross-Sectional Survey. *JMIR Hum. Factors* **2024**, *11*, e54673. [CrossRef]
69. Ernsting, C.; Stühmann, L.M.; Dombrowski, S.U.; Voigt-Antons, J.N.; Kuhlmey, A.; Gellert, P. Associations of Health App Use and Perceived Effectiveness in People with Cardiovascular Diseases and Diabetes: Population-Based Survey. *JMIR mHealth uHealth* **2019**, *7*, e12179. [CrossRef]
70. Hahn, S.L.; Hazzard, V.M.; Loth, K.A.; Larson, N.; Klein, L.; Neumark-Sztainer, D. Using Apps to Self-Monitor Diet and Physical Activity Is Linked to Greater Use of Disordered Eating Behaviors among Emerging Adults. *Prev. Med.* **2022**, *155*, 106967. [CrossRef]
71. Moody, S.; Ross, L.; Opitz, M.-C.; Hemmings, A.; İnce, B.; Bryson, C.; Kuehne, C.; Douglas, D.; Phillips, M.; Langhorne, V.; et al. Associations between the Use of Fitness and Diet Tracking Technology and Disordered Eating Behaviour: A Systematic Review. *Eur. Eat. Disord. Rev.* **2025**, *33*, 1288–1313. [CrossRef]
72. Gazibara, T.; Cakic, M.; Cakic, J.; Grgurevic, A.; Pekemezovic, T. Sociodemographic Characteristics and Digital Behaviors Associated with the Use of Fitness and Diet Apps among Adolescents. *J. Res. Health Sci.* **2024**, *24*, e00619. [CrossRef]
73. Oba, T.; Takano, K.; Katahira, K.; Kimura, K. Use Patterns of Smartphone Apps and Wearable Devices Supporting Physical Activity and Exercise: Large-Scale Cross-Sectional Survey. *JMIR mHealth uHealth* **2023**, *11*, e49148. [CrossRef]
74. Konishi, N.; Oba, T.; Takano, K.; Katahira, K.; Kimura, K. Functions of Smartphone Apps and Wearable Devices Promoting Physical Activity: Six-Month Longitudinal Study on Japanese-Speaking Adults. *JMIR mHealth uHealth* **2024**, *12*, e59708. [CrossRef]
75. Takano, K.; Oba, T.; Katahira, K.; Kimura, K. Usage Styles of Physical Activity Apps Are Associated with Long-Term Activity Levels: A 6-Month Prospective Analysis. *INQUIRY* **2026**, *63*, 1–12. [CrossRef]

76. Hahn, S.L.; Kramer-Kostecka, E.N.; Hazzard, V.M.; Barr-Anderson, D.J.; Larson, N.; Neumark-Sztainer, D. Weight-Related Self-Monitoring App Use among Emerging Adults Is Cross-Sectionally Associated with Amount and Type of Physical Activity and Screen Time. *INQUIRY* **2023**, *60*, 1–10. [CrossRef]
77. Wang, Q.; Egelandsdal, B.; Amdam, G.V.; Almli, V.L.; Oostindjer, M. Diet and Physical Activity Apps: Perceived Effectiveness by App Users. *JMIR mHealth uHealth* **2016**, *4*, e33. [CrossRef]
78. Craig, C.L.; Marshall, A.L.; Sjöström, M.; Bauman, A.E.; Booth, M.L.; Ainsworth, B.E.; Pratt, M.; Ekelund, U.; Yngve, A.; Sallis, J.F.; et al. International Physical Activity Questionnaire: 12-Country Reliability and Validity. *Med. Sci. Sports Exerc.* **2003**, *35*, 1381–1395. [CrossRef]
79. Ács, P.; Betlehem, J.; Oláh, A.; Bergier, J.; Melczer, C.; Prémusz, V.; Makai, A. Measurement of Public Health Benefits of Physical Activity: Validity and Reliability Study of the International Physical Activity Questionnaire in Hungary. *BMC Public Health* **2020**, *20*, 1198. [CrossRef]
80. IPAQ Research Committee. Guidelines for Data Processing and Analysis of the International Physical Activity Questionnaire (IPAQ)—Short and Long Forms, Revised November 2005. Available online: https://biobank.ndph.ox.ac.uk/ukb/ukb/docs/ipaq_analysis.pdf (accessed on 13 August 2026).
81. Benjamini, Y.; Hochberg, Y. Controlling the False Discovery Rate: A Practical and Powerful Approach to Multiple Testing. *J. R. Stat. Soc. Ser. B* **1995**, *57*, 289–300. [CrossRef]
82. McCullagh, P. Regression Models for Ordinal Data. *J. R. Stat. Soc. Ser. B* **1980**, *42*, 109–142. [CrossRef]
83. Holm, S. A Simple Sequentially Rejective Multiple Test Procedure. *Scand. J. Stat.* **1979**, *6*, 65–70.
84. Fritz, C.O.; Morris, P.E.; Richler, J.J. Effect Size Estimates: Current Use, Calculations, and Interpretation. *J. Exp. Psychol. Gen.* **2012**, *141*, 2–18. [CrossRef]
85. Cohen, J. A Power Primer. *Psychol. Bull.* **1992**, *112*, 155–159. [CrossRef]

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