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Digital Technology Use and Muscle-Building Behaviors in Young Adults

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Abstract

Objective: Digital technology use and muscle-building behaviors reflect a wide range of behaviors with associated health risks. However, links between these behaviors remain unknown and was a gap this study aimed to address.

Method: Data were collected from a diverse sample of 1,483 young adults (mean age 22.2±2.0 years) participating in the population-based EAT 2018 (Eating and Activity over Time) study. Gender-stratified modified Poisson regression models were used to determine cross-sectional associations between three types of digital technology use (screen time, social media, weight-related self-monitoring apps) and five types of muscle-building behaviors (changing eating, exercise, protein powders/shakes, pre-workout drinks, steroids/growth hormone/creatine/amino acids) in young adulthood, adjusted for sociodemographic characteristics and body mass index.

Results: Screen time and social media were either not found to be associated with muscle-building behaviors, or in a few instances, associated with less use of these behaviors (e.g., screen time and pre-workout drinks in men). In contrast, use of weight-related self-monitoring apps

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was positively associated with all muscle-building behaviors, including steroids/growth hormone/creatine/amino acids in men (prevalence ratio [PR]=1.83; 95% confidence interval [CI]: 1.13–2.97) and women (PR=4.43; 95% CI: 1.68–11.68).

Discussion: While most recreational screen time may represent sedentary behaviors not related to muscle-building behaviors, weight-related self-monitoring apps are highly associated with more muscle-building behaviors and could be a future target for interventions to discourage the use of steroids and other harmful muscle-building substances.

Keywords

social media; screen time; apps; muscle-enhancing behavior; anabolic-androgenic steroids; protein; performance-enhancing substances

Introduction

Muscle-building behaviors include changing eating patterns, exercising, consuming protein powders or shakes, pre-workout drinks, and using steroids, creatine, or amino acids for the purpose of increasing muscle mass and decreasing body adiposity (Murray et al. 2016, 2017; Nagata, Ganson, and Murray 2020; Nagata, Brown, et al. 2019). While some muscle-building behaviors in moderation (e.g. exercising, eating patterns) can be healthful, others (e.g. steroids) can have harmful effects (Pope et al., 2014) and may be linked to eating disorders (Murray, Accurso, Griffiths, & Nagata, 2018) and muscle dysmorphia (Murray et al., 2017; Nagata, Peebles, Hill, et al., 2020). Sports team participation, self-perception of being underweight, and body dissatisfaction are known predictors of engagement in muscle-building behaviors (Eisenberg et al. 2012; Nagata, Ganson, Griffiths, et al. 2020; Nagata, Murray, et al. 2019). However, an unexplored potential predictor of muscle-building behaviors includes use of digital technologies, such as screen time, social media, and smartphone applications (apps).

Digital technology use is ubiquitous and represents diverse modalities with a wide range of health risks and benefits (Lissak 2018; Nagata, Abdel Magid, and Gabriel 2020). For example, recreational screen time, such as watching television and movies, playing video games, and engaging with social media, are often sedentary (LeBlanc et al., 2017; Shimoga, Erlyana, & Rebello, 2019) and may displace active muscle-building behaviors. However, social media use has been linked with body dissatisfaction and disordered eating behaviors (Lonergan, Mitchison, Bussey, & Fardouly, 2021; Sidani, Shensa, Hoffman, Hanmer, & Primack, 2016), which aligns with theoretical models of body dissatisfaction and disordered eating and muscle-building behaviors. For example, the Tripartite Influence Model posits that parents, peers, and media (including social media) contribute to the development of body dissatisfaction and muscle dissatisfaction, which could lead to engagement in muscle-building behaviors (Tylka, 2021; Van Den Berg, Thompson, Obremski-Brandon, & Coovert, 2002). The bodies often portrayed on popular social media forums (e.g., fitspiration type content) overrepresent bodies that are overtly muscular and lean, which may elicit body dissatisfaction and increase a drive for muscularity and leanness (Lonergan et al., 2021).

Weight-related self-monitoring devices and related smartphone apps, such as Fitbit and MyFitnessPal, are another form of digital technology that are common among young adults. (Papalia, Wilson, Bopp, & Duffey, 2018) Weight-related self-monitoring apps are technologies that help users track their weight and/or behaviors that affect their weight, such as diet and physical activity. Individuals could use weight-related self-monitoring apps to achieve muscle building-related goals (e.g. tracking macronutrient intake or workouts). Weight-related self-monitoring apps have been associated with both recommended health promotion behaviors (e.g. meeting recommended physical activity guideline levels) (U.S. Department of Health and Human Services, 2018) and disordered weight and shape control behaviors, including excessive or compulsive exercise and supplement use (Hahn, Sonneville, Kaciroti, Eisenberg, & Bauer, 2021; Simpson & Mazzeo, 2017). However, different purposes for using weight-related self-monitoring apps (e.g., healthy eating, being physically active, managing weight) may be associated with differential risk of engaging in various types of muscle-building behaviors. To our knowledge, this has never been studied.

The objective of this study was to determine the association between three types of digital technology use (screen time, social media, and weight-related self-monitoring apps) and five types of muscle-building behaviors (changing eating, exercise, protein powders/shakes, pre-workout drinks, steroids/growth hormone/creatine/amino acids) in young adults. We hypothesized that, while recreational screen time is mostly sedentary and would be inversely related to muscle-building behaviors, social media and weight-related self-monitoring apps would be positively associated with muscle-building behaviors, particularly steroids/growth hormone/creatine/amino acids.

Methods

Study Design and Sample

Data were collected as part of EAT 2010–2018 (Eating and Activity over Time), a population-based cohort of youth recruited in Minnesota who have been followed from adolescence to young adulthood (Eisenberg et al. 2012; Hazzard et al. 2020; Neumark-Sztainer et al. 2012). This analysis used cross-sectional data from young adults in EAT 2018, when specific questions about digital technology use were included as a new area of research, based on feedback from focus groups. The overall goal of EAT 2010–2018 is to study weight status, dietary intake, weight control behaviors, physical activity, and related factors among adolescents who transitioned to young adulthood. The racially/ethnically and socioeconomically diverse baseline (2009–2010) sample was recruited as adolescents from 20 public middle schools and high schools in the Minneapolis/St. Paul metropolitan area of Minnesota. Surveys and anthropometric measures were completed by 2793 adolescents at baseline. At follow-up, contact information was not available for 410 original participants; 1568 completed follow-up as young adults (2017–2018), 65.8% of those who could be contacted. The EAT 2018 survey was distributed via web and mail.

After excluding 85 participants who did not provide sufficient data on exposure or outcome variables, the present study included 1,483 participants. The University of Minnesota’s Institutional Review Board Human Subjects Committee approved all study procedures.

Survey and Measures

The EAT 2018 survey included self-reported items assessing a range of factors of potential relevance to weight status and weight-related behaviors, including digital technology use and muscle-building behaviors. The EAT 2018 survey was pretested with focus groups consisting of 29 young adults, and test-retest reliability of the measures was assessed in a subgroup of 112 young adult survey participants.

Exposures: Digital technology use

Screen time: Participants were asked "how many hours of recreational screen time (for example, television, computer, social media, video games, smartphone or tablet) do you have a day? Do not include activities you do for work or school." The question was asked separately for weekdays and weekends, and a weighted average was calculated with hours per day as a continuous variable (test-retest $r = 0.76$) (Sirard et al., 2013).

Social media: Participants were asked "in the past week, on average, how many total minutes per day have you spent using social media (for example, Facebook, Twitter, Instagram, Reddit, Pinterest or Snapchat)?" Responses were converted to hours per day as a continuous variable (test-retest $r = 0.69$).

Weight-related self-monitoring apps: Participants were asked, "in the past year, did you use a mobile app, tracker device (such as Fitbit), or web-based programs to help you …" (a) make healthy eating choices, (b) be physically active, (c) manage your weight, with yes/no response options for each item (test-retest agreement range: 83.6% – 89.2%). Each purpose was examined separately and combined into an overall any use variable if they marked "yes" to any of the three options. We elected to have both separate and an overall measure because the use purposes were not mutually exclusive and many participants selected more than one purpose.

Outcomes: Muscle-building behaviors: Using an item adapted from previous studies (Eisenberg et al., 2012; Field et al., 2005; McCabe & Ricciardelli, 2001; Smolak, Murnen, & Thompson, 2005), muscle-building behaviors were assessed by asking participants whether they had done any of "the following things in order to increase your muscle size or tone during the past year?": (a) "Changed my eating," (b) "Exercised more," (c) "Used protein powder or shakes," (d) "Used a pre-workout drink (such as Jack3D, Cellucor C4, JYM, etc.), (e) "Used steroids," and (f) "Used another muscle-building substance (such as creatine, amino acids, hydroxyl methylbutyrate [HMB], DHEA, or growth hormone)" with options of yes/no for each type (test-retest agreement range: 80.4% – 88.3%). We examined each muscle-building behavior separately, except for combining use of (e) steroids and (f) another muscle-building substance, as done previously (Nagata, Peebles, Hill, et al. 2020), due to few participants reporting steroid use and the more harmful health effects of some of these substances.

Covariates: Age, gender (male, female, or different identity), and race/ethnicity were based on self-report. Socioeconomic status in adolescence was based on an algorithm using parental education level (highest level of educational attainment of either parent), family eligibility for public assistance, eligibility for free or reduced-cost school meals, and employment status of the mother or father, and categorized into low, medium, or high (Eisenberg et al. 2012; Neumark-Sztainer et al. 2002, 2003). Body mass index (BMI) was calculated using self-reported height and weight, which were found to highly correlate with objectively measured height and weight in young adults (Himes, Hannan, Wall, & Neumark-Sztainer, 2005).

Statistical Analysis: Descriptive statistics for indices of digital technology use and muscle-building behaviors were calculated by gender, and differences by gender were examined using one-way analysis of variance (ANOVA) tests for continuous variables and chi-square tests for dichotomous variables. As most outcomes examined were relatively common (>10% prevalence), modified Poisson regression models (i.e., using robust standard errors) (Zou, 2004) were conducted to calculate prevalence ratios representing associations between digital technology use and muscle-building behaviors in young adulthood. Modified Poisson regression is preferred over logistic regression when outcomes are common, as odds ratios produced by logistic regression tend to be overestimates in such instances (Zou, 2004). Separate regression models were conducted for each type of digital technology use and each type of muscle-building behavior. Primary regression models were stratified by gender given different prevalence of digital technology use and muscle-building behaviors in men and women (Eisenberg et al., 2012; Hahn, Bauer, et al., 2021; Hahn, Sonneville, et al., 2021; Nagata, Ganson, Griffiths, et al., 2020; Nagata, Ganson, et al., 2021). Furthermore, we found significant interactions by gender for screen time ($p = .03$) and social media use ($p = .04$) predicting steroids/growth hormone/creatine/amino acids use. While there were too few gender-diverse participants ($N = 10$) to permit gender-stratified analyses in this group, these participants were included in analyses conducted in the full sample; these results are reported in Supplemental Table 1 (available online). Age, race/ethnicity, socioeconomic background, and BMI were included as covariates in all regression models, given that they could be confounders for the association between digital technology use and muscle-building behaviors. Digital technology use (Nagata, Iyer, et al., 2021; Nagata, Ganson, et al., 2021) and muscle building-behavior use (Eisenberg et al. 2012; Nagata, Ganson, Griffiths, et al. 2020; Nagata, Murray, et al. 2019) have been shown to differ by age, race/ethnicity, socioeconomic background, and BMI. Attrition from EAT 2010 to EAT 2018 did not occur entirely at random, such that non-responders were more likely to be male, non-white, and have parents with low educational attainment. To account for differential loss to follow-up, and allow for extrapolation back to the original EAT 2010 school-based sample, inverse probability weighting was used in all analyses (Little, 1986; Seaman & White, 2013). All analyses were conducted using Stata 16.1.

Results

Our analytic sample included 606 men, 867 women, and 10 gender-diverse participants in young adulthood, with a mean age of 22.2 (SD = 2.0) years. The weighted sample was diverse (19.7% white, 28.9% Black/African American, 19.7% Asian/Asian American, 16.9% Hispanic/Latino/a, and 14.9% mixed or other race), and 39.6% were in the lowest category of socio-economic status. Mean recreational screen time use was 3.5, 3.7, and

4.4 hours per day, while mean social media use was 1.5, 1.9, and 1.8 hours per day, for men, women, and gender-diverse participants, respectively (Table 1). Overall, 36.9% of men, 48.4% of women, and 49.1% of gender-diverse participants reported using any weight-related self-monitoring app, with the most common purpose cited as being physically active (28.3%, 39.7%, and 40.5%, respectively). The most commonly reported type of muscle-building behavior across gender identities was exercising more, reported by 72.5% of men, 58.3% of women, and 80.3% of gender-diverse participants (Table 1). Significant differences by gender were observed for most indices of digital technology use and muscle-building behaviors, with post-hoc analyses indicating greater use of social media and each type of mobile app/tracker device among women than men and greater prevalence of each type of muscle-building behavior except steroids among men than women (Table 1).

Recreational screen time was inversely associated with changing eating to build muscles, protein powders/shakes, and pre-workout drinks but not exercising more or using steroids/growth hormone/creatine/amino acids in men (Table 2). Recreational screen time was not associated with muscle-building behaviors in women, except for an inverse association with steroids/other muscle-building behaviors (Table 3). Social media use per day was not associated with muscle-building behaviors in men or women, except for an inverse association with steroids/growth hormone/creatine/amino acids in women.

Use of weight-related self-monitoring apps was associated with greater use of all muscle-building behaviors in men and women (Tables 2 and 3, respectively). In particular, any use of weight-related self-monitoring apps was associated with steroids/growth hormone/creatine/amino acids in men (prevalence ratio [PR] = 1.83; 95% confidence interval [CI]: 1.13, 2.97), including those using weight-related self-monitoring apps for making healthy eating choices (PR = 2.11; 95% CI: 1.28, 3.49) and for being physically active (PR = 1.69; 95% CI: 1.03, 2.79). In women, any use of weight-related self-monitoring apps was associated with greater use of steroids/growth hormone/creatine/amino acids as well (PR = 4.43; 95% CI: 1.68, 11.68). In both men and women, use of weight-related self-monitoring apps for any reason (i.e., for making healthy eating choices, for being physically active, and for managing weight) was associated with greater use of all other muscle-building behaviors (changing eating, exercising more, protein powder/shakes, and pre-workout drinks).

Discussion

In this population-based cross-sectional study of emerging adults, we found that recreational screen time and social media use were either not associated, or associated with less use of muscle-building behaviors. In contrast, use of weight-related self-monitoring apps was associated with greater use of muscle-building behaviors, notably, the use of steroids, growth hormone, creatine, and amino acids. These differences in associations reflect the wide range of types and uses of digital technology, with different purposes and implications for health. Understanding how weight-related self-monitoring apps used for various purposes may be linked to steroid use is important given serious physical and mental health consequences of steroids and other substances.

The inverse association between recreational screen time and muscle-building behaviors may be explained by the sedentary nature of these technologies. For the most part, people are sedentary when watching television and videos, and playing computer games (LeBlanc et al., 2017). Screen viewing may displace time for physical activity and muscle-building behaviors. Similarly, young adults may be mostly sedentary when browsing social media, which aligns with prior research showing that, among sedentary adolescents, frequent social media use was associated with lower levels of exercise (Shimoga et al., 2019). Although social media has previously been linked to body dissatisfaction and disordered eating (Lonergan et al., 2021), we do not see evidence of linkage to muscle-building behaviors such as protein powders/shakes, pre-workout drinks, or steroids. In some cases, social media and muscle-building behaviors are inversely associated, which may represent the sedentary behavior pathway. These findings are also contrary to theoretical models of muscle dissatisfaction, whereby greater time on social media would increase social pressures to adhere to a specific muscular and toned body ideal, thus leading to muscle-building behaviors (Tylka, 2021; Van Den Berg et al., 2002). These associations, or lack of associations, may be due to unmeasured confounding where similar people choose to be sedentary and are not concerned about their muscle size. It is also possible that our measure of social media usage, which is a general measure of time on social media, was not nuanced enough to detect a link with muscle-building activities. For instance, it may be that only certain types of social media are associated with body image variables (e.g., viewing of image-centric platforms such as Instagram where social comparisons are likely to occur, as opposed to text-based platforms such as Twitter or Reddit). Further research delving into these details is recommended.

Interestingly, weight-related self-monitoring apps, irrespective of the purpose, were associated with higher prevalence of all muscle-building behaviors. Building lean muscle can be a challenging task, often involving the counting of macronutrients, which can be aided by weight-related self-monitoring apps. Prior work has shown that weight-related self-monitoring apps are linked to supplement and substance use (such as protein powder, steroids, and pre-workout) (Hahn, Sonneville, et al., 2021). Our findings further suggest that use of weight-related self-monitoring apps for several purposes (including for making healthy eating choices, for being physically active, and for managing weight) was associated with higher prevalence of using unhealthy muscle-building behaviors.

It has been suggested that weight-related self-monitoring promotes the idea of "healthism" and striving for health as a moral obligation or personal responsibility, which teaches users to not trust their body and use any means necessary to achieve "health." This idea may explain why weight-related self-monitoring app users have higher prevalence of using recommended or conventional behaviors (e.g. healthier eating) irrespective of why they used the app as well as unhealthy muscle-building behaviors such as steroids (Berry, Rodgers, & Campagna, 2020). Given the higher use of muscle-building behaviors among weight-related self-monitoring app users, targeted education aimed at weight-related self-monitoring app users should also include information on the potential harms of unhealthy muscle-building behaviors. Digital technology companies that manage the distribution of weight-related self-monitoring apps, such as Apple via the App Store and Google through Google Play, should consider how these apps are correlated with adverse health behaviors, and consider providing education about potential risks associated with muscle-building behaviors within the apps. Policymakers may also consider regulations that restrict the distribution of these apps to young people, as well as inform users of the potential harms associated with weight-related self-monitoring app use.

Strengths and Limitations

Strengths include a large and diverse sample originally drawn from public schools. Contemporary measures of three types of digital technology use and five measures of muscle-building behaviors were assessed to provide a comprehensive picture of the range of less hazardous and more hazardous muscle-building behaviors, and to our knowledge, this is the first study to examine these associations.

Several limitations of the study should also be noted. Data for the current study come from a single state and may not be representative of the entire US or other countries. Given the cross-sectional nature of the study, we are unable to draw conclusions with regard to the temporality of associations found. For instance, people with a preoccupation with muscularity may turn to weight-related self-monitoring apps to assist with their body change endeavors. The Tripartite Influence Model posits temporal relationships between sociocultural pressures (e.g., from media) and body dissatisfaction (Tylka, 2021; Van Den Berg et al., 2002); therefore, future research could examine these relationships experimentally or longitudinally. The item used to assess gender did not distinguish between cisgender and transgender participants (so for example, transgender women may have marked “female” rather than “different identity”). This feature of the measure, combined with the small number of participants not identifying as male or female, precluded meaningful stratified analyses of transgender and gender diverse participants. Analyses did not adjust for sexual orientation, as sexual orientation has not been assessed in the EAT 2010–2018 cohort. Information on the content of recreational screen time and social media were not collected. Social media is a component of recreational screen time and reported usage may overlap; therefore, these two measures were not included in the same model. Additionally, there may have been underreporting of illegal substance use such as steroids due to social desirability bias. Steroids and other muscle-building dietary supplements and substances (e.g., creatine, amino acids, HMB, DHEA, growth hormone) were grouped into a single item and represent different dietary supplements and substances that are intended for a variety of purposes and have different impacts on health. Further, data were not collected on duration, frequency, dosage of usage, which is an area for future research.

Conclusion

We find that digital technology use and muscle-building behaviors are common in young adulthood, with nuanced relationships depending on the specific type of digital technology or muscle-building behavior. We find that most recreational screen time is unrelated or inversely related to muscle-building behaviors, possibly because sedentary time may displace physical activity. In contrast, use of weight-related self-monitoring apps is highly associated with muscle-building behaviors, particularly use of steroids, growth hormone, creatine, and amino acids. Clinicians should assess for digital technology use and muscle-building behaviors, and counsel about the use of harmful muscle-building dietary supplements and substances. There is rising interest in and usage of weight-related self-monitoring apps. Although some apps may be useful for certain people, they could also lead to harmful and extreme behaviors for others. Investigation into the specific risks and benefits of these apps for particular populations, and how to best leverage them for health promotion while mitigating potential harms, could be an important area of future research.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Acknowledgements and Conflicts of Interests:

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Table 1.

Descriptive characteristics by gender

	Men (*N*=606)	Women (*N*=867)	Gender Diverse (*N*=10)	*p*	Effect Size
Digital technology use					
Recreational screen time (hrs/day), *M* (*SD*)	3.5 (1.7)	3.7 (1.7)	4.4 (1.7)	.15	Partial η^2 = .003
Social media use (hrs/day), *M* (*SD*)	1.5 (1.3)^{a}	1.9 (1.3)^{b}	1.8 (1.4) ^{a,b}	< .001	Partial η^2 = .02
Any mobile app/tracker device use, % (*n*)	36.9 (216)^{a}	48.4 (415)^{b}	49.1 (5)^{a,b}	< .001	Cramer's V = .12
For making healthy eating choices	21.1 (120)^{a}	30.2 (260)^{b}	31.9 (3)^{a,b}	< .001	Cramer's V = .10
For being physically active	28.3 (168)^{a}	39.7 (342)^{b}	40.5 (4)^{a,b}	< .001	Cramer's V = .12
For managing weight	21.7 (124)^{a}	31.6 (268)^{b}	23.4 (2)^{a,b}	< .001	Cramer's V = .11
Muscle-building behaviors					
Changing eating, % (*n*)	55.8 (329)^{a}	44.6 (381)^{b}	32.3 (3)^{a,b}	< .001	Cramer's V = .11
Exercising more, % (*n*)	72.5 (432)^{a}	58.3 (504)^{b}	80.3 (8)^{a,b}	< .001	Cramer's V = .15
Protein powder/shakes, % (*n*)	37.7 (224)^{a}	19.6 (167)^{b}	14.1 (1)^{a,b}	< .001	Cramer's V = .20
Pre-workout drinks, % (*n*)	20.9 (116)^{a}	9.5 (81)^{b}	0.0 (0)^{a,b}	< .001	Cramer's V = .16
Steroids, creatine, amino acids, HMB, DHEA, or growth hormone, % (*n*)	10.8 (59)^{a}	3.1 (24)^{b}	9.7 (1)^{a,b}	< .001	Cramer's V = .16
Steroids	1.6 (9)	1.5 (11)	0.0 (0)	.92	Cramer's V = .01
Other substances	10.6 (58)^{a}	2.4 (19)^{b}	9.7 (1)^{a,b}	< .001	Cramer's V = .17

Note. *M* = mean; *SD* = standard deviation; HMB = hydroxyl methylbutyrate; DHEA = dehydroepiandrosterone. Within rows, different superscript letters indicate statistically significant post-hoc differences by gender ($p < .05$). *n*'s represent observed counts, while all other statistics are weighted to account for attrition over time and allow for extrapolation to the original population-based sample.

Table 2.

Cross-sectional associations between digital technology use and muscle-building behaviors among men at EAT 2018

	Changing Eating	Exercising More	Protein Powder/Shakes	Pre-Workout Drinks	Steroids, creatine, amino acids, HMB, DHEA, or growth hormone
	PR (95% CI)				
Recreational screen time (hrs/day)	0.93 (0.89, 0.98)**	0.97 (0.94, 1.00)	0.93 (0.87, 0.99)*	0.86 (0.78, 0.95)**	0.96 (0.82, 1.12)
Social media use (hrs/day)	0.94 (0.88, 1.00)	0.97 (0.93, 1.02)	1.04 (0.95, 1.13)	1.04 (0.91, 1.18)	1.05 (0.86, 1.30)
Any mobile app/tracker device use	1.38 (1.19, 1.60)***	1.18 (1.07, 1.31)**	1.43 (1.16, 1.77)**	2.01 (1.44, 2.80)***	1.83 (1.13, 2.97)*
For making healthy eating choices	1.49 (1.29, 1.73)***	1.23 (1.11, 1.37)***	1.53 (1.22, 1.92)***	1.92 (1.36, 2.69)***	2.11 (1.28, 3.49)**
For being physically active	1.45 (1.25, 1.67)***	1.20 (1.08, 1.32)***	1.52 (1.23, 1.89)***	1.66 (1.18, 2.33)**	1.69 (1.03, 2.79)*
For managing weight	1.30 (1.11, 1.53)**	1.18 (1.06, 1.32)**	1.36 (1.07, 1.73)*	1.60 (1.11, 2.29)*	1.29 (0.73, 2.28)

Note. HMB = hydroxyl methylbutyrate; DHEA = dehydroepiandrosterone; PR = prevalence ratio; CI = confidence interval. The table represents the abbreviated outputs from a series of 30 modified Poisson regression models, with digital technology use type (row header) as the independent variable and muscle-building behavior (column header) as the dependent variable. Models adjusted for age, race/ethnicity, socioeconomic background, and body mass index.

* $p < .05$

** $p < .01$

*** $p < .001$.

Table 3.

Cross-sectional associations between digital technology use and muscle-building behaviors among women at EAT 2018

	Changing Eating	Exercising More	Protein Powder/Shakes	Pre-Workout Drinks	Steroids, creatine, amino acids, HMB, DHEA, or growth hormone
	PR (95% CI)				
Recreational screen time (hrs/day)	0.99 (0.95, 1.04)	1.00 (0.97, 1.04)	0.96 (0.88, 1.04)	0.93 (0.82, 1.05)	0.68 (0.54, 0.86)**
Social media use (hrs/day)	0.98 (0.93, 1.04)	0.98 (0.94, 1.03)	0.96 (0.85, 1.07)	0.89 (0.74, 1.06)	0.65 (0.45, 0.94)*
Any mobile app/tracker device use	1.61 (1.38, 1.89)***	1.43 (1.27, 1.61)***	2.67 (1.94, 3.68)***	3.28 (1.96, 5.48)***	4.43 (1.68, 11.68)**
For making healthy eating choices	1.65 (1.43, 1.91)***	1.43 (1.28, 1.60)****	2.47 (1.87, 3.26)***	3.56 (2.29, 5.53)***	2.28 (0.99, 5.27)
For being physically active	1.57 (1.35, 1.82)***	1.48 (1.32, 1.66)***	2.41 (1.79, 3.23)***	2.40 (1.54, 3.76)***	1.83 (0.83, 4.04)
For managing weight	1.71 (1.48, 1.98)***	1.35 (1.20, 1.51)***	2.09 (1.57, 2.78)***	2.75 (1.75, 4.32)***	2.10 (0.86, 5.10)

Note. HMB = hydroxyl methylbutyrate; DHEA = dehydroepiandrosterone; PR = prevalence ratio; CI = confidence interval. The table represents the abbreviated outputs from a series of 30 modified Poisson regression models, with digital technology use type (row header) as the independent variable and muscle-building behavior (column header) as the dependent variable. Models adjusted for age, race/ethnicity, socioeconomic background, and body mass index.

* $p < .05$

** $p < .01$

*** $p < .001$.