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Healthier But Not Happier? The Lifestyle Habits of Health Influencer Followers

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Abstract

How young adults access health information has changed rapidly with the rise of social media and the new wave of Instagram health influencers. Therefore, it is important to investigate whether following health influencers on Instagram is strictly beneficial to the physical and mental health of their followers. In this cross-sectional study, 1,022 young adults (aged 18–25) across New Zealand, the United States, and the United Kingdom, completed a survey in 2021 of their lifestyle habits including measures of social media usage, dietary and exercise habits, and mental health. Results showed that health influencer followers (HIFs) reported more vigorous exercise ($p < .001$), higher fruit and vegetable intake ($p < .001$), and better well-being ($p < .001$) but also greater distress (a factor comprised of depression, anxiety and negative mood; $p = .006$) compared to non-followers, controlling for age, gender, ethnicity, education level, socioeconomic status, and body mass index. Higher distress was especially pronounced among those who followed food or diet-related health influencers ($p < .001$). Moreover, following health influencers disrupted the typical protective relationship between health behaviours and distress. Among health influencer followers, more vigorous physical activity was associated with higher distress levels. This was in sharp contrast to the lack of a relationship for non-followers, and the typical protective relationship in non-users of Instagram. These findings suggest that following health influencers may disrupt the positive relationship between health behaviours and mental health. Follow-up research exploring prospective patterns could reveal the exact impact of following health influencers on mental health.

Keywords: Instagram; health; influencer; flourishing; mental health; exercise; diet

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Introduction

Instagram is an image or video sharing app launched in 2010 (Siegler, 2010), that has now amassed over two billion active users worldwide (Statista, 2018), and is particularly popular amongst young adults (aged 18–24; Pew Research Centre, 2021). Instagram is one of the primary platforms for *influencers*, a term used to describe people who “shape audience attitudes through blogs, tweets and the use of other social media” (Freberg et al., 2011; pp. 90; Han & Balabanis, 2024). Influencers often embody a niche that they are experts in (Harrigan et al., 2021) and post content related to this niche. Given that people tend to learn new patterns of behavior by observing others, particularly if they believe that person is an expert regarding the behavior (Bandura, 1971), influencers hold immense power to affect the thoughts and actions of those that follow them (Freberg et al., 2011; Han & Balabanis, 2024). Indeed, there is now substantial empirical evidence for the "influencer effect", or the myriad ways in which social media stars change the attitudes and behaviours of their followers (Han & Balabanis, 2024; Hudders et al., 2021). Although the effect of influencers is prominent in relation to marketing and consumer behaviour (Hudders et al., 2021), their influence extends to a much wider range of outcomes related to politics (Soares et al., 2018) and health (Engel et al., 2024; Powell & Pring, 2024).

Health influencers are a particular sub-category of influencers that promote health and fitness as their expertise (Pilgrim & Bohnet-Joschko, 2019). An example of a health influencer is Kayla Itsines, who has amassed 13.4 million followers on Instagram (Itsines, 2021) in September 2021. Kayla Itsines primarily creates posts relating to workout routines, such as her famous "Biking Body Guide", alongside promoting healthy dietary choices like adhering to the Mediterranean diet. Although there are several social media platforms where health influencers post content (e.g., TikTok, YouTube, Facebook), Instagram is one of the most popular platforms among health influencers, as users often turn to them for both inspiration and information (Lim et al., 2022). The rise of Instagram health influencers raises the question of the relative benefit of following them for young adults. Does following health influencers benefit young adults by inspiring them to engage in more healthy lifestyles, with accompanying mental health benefits? Or does following health influencers fail to translate into healthier habits, and even possibly contribute to poorer mental health through upwards comparison and unattainable body ideals (Verduyn et al., 2020; Wang et al., 2017)? In this article, we use the term health influencer followers (HIFs) to describe people who follow health influencer accounts on Instagram.

There are several possible theoretical benefits to following health influencers. Health influencers may prompt positive exercise and dietary habits in their followers, in turn benefitting followers' physical and mental health. Research has shown that positive health behaviours can be promoted by public health messaging, defined as advertising or communication undertaken by organizations or governments with the goal of improving public health and well-being (Merchant et al., 2021). A prominent example was the "QUIT NOW" Australian campaign that ran from 2010 to 2018, which utilized social media platforms such as Facebook and Twitter to accelerate delivery of its anti-smoking message (Bayly et al., 2021). Research has shown that social media public health messaging may facilitate increased interest and engagement with both exercise (Gilbert et al., 2021; Zhang et al., 2015) and healthy dietary habits (Vander Wyst et al., 2019; Vianna & Barbosa, 2020).

Health influencer messaging may be even *more influential* in affecting health behavior engagement than traditional messaging channels because influencers are often perceived as more credible, trustworthy, knowledgeable, authentic and attractive than other message channels (reviewed in Han & Balabanis, 2024). Other mechanisms driving influencer effects include identification with and trust in influencers (compared to celebrities, Schouten et al., 2020), parasocial bonds (followers' identification and attachment with influencers), and homophily (followers' perception of similarity to influencers; Han & Balabanis, 2024).

There is some evidence of positive benefits to following health influencers on health outcomes. A survey of social media users in 2017 found that 32% of the 232 adult participants surveyed reported that social media influencers motivated them to make healthier food choices (Byrne et al., 2017). Other research shows that Instagram use can inspire "benign envy", whereby others serve as inspiration to self-improve, which is linked to greater positive affect (Meier & Schäfer, 2018). The positive benefits of health influencers could reflect changes in followers' intentions to engage in healthy lifestyles. According to the Integrated Behavioral Model (IBM), the most influential factor for behavior performance is intention to perform the behavior (Montaño & Kasprzyk, 2015). Health influencers may increase intention to perform health behaviours by reinforcing norms around healthy behaviours (e.g., through behavioural example such as sharing and anecdotally validating various exercise workouts or nutritional advice like meal prepping). Health influencers may also create positive attitudes towards the behaviours within their audience through observation. This includes using reinforcing language within the video aimed at encouraging their audience (e.g., "it's so easy to prepare this meal, you should give it a try!"). As a result, HIFs may engage in more exercise and eat more healthfully.

However, there are also possible harms to following health influencers. Health influencer content may reinforce the "fit-ideal" (Anne, 2016; Boepple et al., 2016; Carrotte et al., 2017; Pilgrim & Bohnet-Joschko, 2019; Tiggemann & Zaccardo, 2018), which is the concept that an athletic or fit body is thought to be the ideal body type (Homan, 2010). The "fit-ideal" is associated with increased body dissatisfaction and depressive symptoms (Blashill & Wilhelm, 2014; Golian et al., 2014; Sherlock & Wagstaff, 2019; Soares Filho et al., 2020). The "fit ideal" may also drive compulsive levels of exercise and obsessions with healthy or pure diets (orthorexia), which could have negative implications for mental health due to their potential fit-ideal internalisation (Homan, 2010; Lichtenstein et al., 2017). Exercising for health and well-being motivations is associated with a more positive body image, whereas extrinsic or appearance-related motivations to exercise are associated with poorer body image (Panão & Carraça, 2020; Prichard & Tiggemann, 2008). Indeed, a recent systematic review of 12 intervention studies that manipulated exposure to social media influencers sharing health information or idealized Instagram images showed mostly negative effects on outcomes such as unhealthy food intake, mood, and body dissatisfaction (Powell & Pring, 2024). Similar negative patterns were found in a scoping review of 51 studies of social media influencers and adolescent health, which showed that health influencers promote unrealistic body images, unhealthy food, and substance use (Engel et al., 2024). These findings also dovetail with the wider work on harms of viewing Instagram related #fitspiration imagery (Prichard et al., 2020; Tiggemann & Zaccardo, 2015), particularly images of a sexualized nature (Prichard et al., 2023). For all these reasons, including exposure to the "fit ideal" and unrealistic body images, HIFs may show poorer mental health compared to non-followers.

Paradoxically, HIFs might even show these mental health impairments even when engaging in healthy lifestyles, which are normally associated with mental health benefits (Conner et al., 2017; Mandolesi et al., 2018; Scully et al., 1998; Wickham et al., 2020). This could mean that HIFs might not show the typical between-person relationship between levels of engagement health behaviours and mental health and well-being. Compulsive exercise and appearance-related motivations to exercise and eat well could serve to disrupt the typical positive relationship between healthy behaviours and mental health. Said another way, there could be a moderating effect of HIFs on the relationship between health behaviours and mental health. Among followers, greater engagement in health behaviours may not correlate with better mental health, whereas among non-followers, greater engagement in health behaviours may correlate with better mental health, as is normally the case. However, research has not yet tested whether following health influencers acts as a moderator of the relationship between healthy behaviours and mental health.

Lastly, there could be negative consequences from Instagram usage itself, not just following health influencers on Instagram. Social media usage has been correlated with poor adolescent well-being and reduced health behavior engagement (O'Reilly et al., 2018; Wojdan et al., 2021), decrements in body image (Holland & Tiggemann, 2016), as well as poorer mental health (albeit in complex ways, with small to medium effect sizes, often dependent on problematic usage, and evidencing some benefit to mental health depending on use; Huang, 2022; Meier & Reinecke, 2021). Use of visual platforms like Instagram may be particularly harmful to mental health because they focus on appearance, which drives social comparison and negative body image (Engeln et al., 2020; Vandenbosch, et al., 2022). Indeed, a recent study found that greater frequency of Instagram browsing was associated with greater body dissatisfaction, which was mediated via upward comparisons with influencers, among nearly 300 female adolescents and young adults (Pedalino & Camerini, 2022). Additionally, there may be differences between users and non-users of social media in personality traits that affect mental health (Brailovskaia & Margraf, 2016; Twomey & O'Reilly, 2017). However, not all research suggests harm from Instagram usage per se. A systematic review published in 2021 published by Faelens and colleagues found mixed evidence linking greater Instagram use to poorer mental health or well-being, but did find a link between Instagram use and poorer body image, particularly in those who engaged with "fitspiration" content (i.e., content designed to inspire people to be fit, typically through exercise and eating behaviours; Jerónimo & Carraça, 2022; Faelens et al., 2021). Therefore, when investigating HIFs, it is important to distinguish their behavioural patterns from people who use Instagram but do not follow health influencers ("non-followers") and people who do not use Instagram ("non-users").

The Current Study

The goal of this research is to investigate the physical and mental health of young adults aged 18 to 25 who follow health influencers on Instagram (HIFs). This demographic was selected for their disproportional prevalence in social media usage (Pew Research Centre, 2021) with the potential to disrupt mental health with problematic use (Huang, 2022). First, we tested whether young adult HIFs report engaging in more positive health behaviours related to exercise and diet compared to non-followers and non-users. We hypothesized *a priori* that HIFs will report engaging in more exercise and report eating more healthfully (i.e., more fruits and vegetables, less processed food) compared to non-followers and non-users. Second, we tested whether HIFs show differences in their mental health and well-being compared to non-followers and non-users. We did not have an *a priori* hypothesis about the direction of this relationship given prior research suggesting either benefits or harms of health influencer content to the mental state of HIFs. Third, we tested whether the typical positive relationship between health behavior engagement and mental health/well-being would be disrupted within young adult HIFs. We hypothesized *a priori* that following health influencers would moderate the statistical relationship between health behaviours and mental health and well-being; namely, HIFs will display an attenuated or even negative association between health behaviours and mental health/well-being (i.e., due to possible motivations behind the health behaviours or the compulsivity of these behaviours), whereas non-followers and non-users would show the normally positive association between health behaviours and mental health and well-being.

Methods

Design

This was a cross-sectional correlational design utilising survey data.

Participants and Procedure

Participants were 1,022 young adults aged 18–25 who took part in the "Lifestyles of Young Adults Survey", administered in May to November 2021. Young adult participants were recruited from three countries: New Zealand (NZ) university students from the University of Otago, United States of America (US) through Amazon's Mechanical Turk (Mturk), and United Kingdom (UK) through survey provider Prolific. These countries were selected because they are primarily English-speaking countries and show similar social media usage rates (Pew Research Centre, 2021; Statista, 2021a, 2021b). NZ participants were recruited from the Department of Psychology Experimentation Programme and remunerated with course credit, with additional male participants recruited from the wider university and remunerated with $10 NZD. US participants were recruited through the Mturk marketplace and were required to be within the selected age range (18–25) and living in the United States. They were remunerated with $3.50 USD for completing the survey. UK participants were recruited through Prolific, were required to be within the age range (18–25), and living in the United Kingdom. They were remunerated with £4.00 GBP. Payment was based upon the average minimum wage for those aged 18–25 in each country. Both of the online recruitment websites used Captcha codes to confirm that the participant is not a bot, along with two attention checks embedded in the survey, which needed to be passed for inclusion in analysis and payment. Participants who passed the inclusion criteria filled out an online survey that contained questions about demographic characteristics, health behaviours, social media habits, and mental health and well-being, in that order. The survey was followed by debriefing and remuneration. The entire survey was managed online without in-person contact.

Figure A1 shows the flow of participants including reasons for exclusion. Initially, 1,194 participants accessed the survey, 1,166 consented to take the survey, and 1,032 completed the survey. A further 10 participants were excluded for missing key variables needed for the analysis, leaving 1,022 participants for analysis.

Measures

The Lifestyle of Young Adults Survey collected data regarding a variety of lifestyle and psychological measures. Of the wider survey, 59 items were utilised for this study's analysis, as detailed below.

Social Media Usage

Social media usage was measured using a scale modified from Scharkow (2016). Participants were asked *How often do you use the following social networking sites or apps?*. The social media sites listed were Instagram, Facebook, Pinterest, Reddit, Snapchat, TikTok, Tumblr, Twitter, and YouTube, and an "other" section where participants could list sites that may have been omitted. Usage of each site was rated on a scale with six response options: 0 (*Never*), 1 (*Once a month or less*), 2 (*At least monthly*), 3 (*At least weekly*), 4 (*At least daily*), and 5 (*Multiple times daily*)[1]. Then, if participants indicate that they used Instagram to any capacity (answered 1–5), subsequent questions were asked regarding who they follow, with a "Tick all that apply" instruction. This primary focus on Instagram users was due to its substantial user population, particularly amongst young adults in 2021 (Pew Research Centre, 2021). This question was *What types of people or accounts do you follow on Instagram?*. Options that were included in the survey were: *Celebrities (film stars, singers, TV stars)*, *Health Influencers: Exercise or Fitness Focused*, *Health Influencers: Diet or*

Food Focused, *Beauty and Makeup Influencers*, *Fashion Influencers*, *Photography (nature, animals, etc.)*, and *Other* which had an attached text box. This allowed us to differentiate between Instagram users who follow health influencers (HIFs) and those who do not. HIFs were classified as a participant who answered that they use Instagram, *and* checked either the Health Influencers: *Exercise or Fitness Focused*, *Health Influencers: Diet or Food Focused*, or both. A non-follower used Instagram, but did not follow either of these health influencer accounts. Non-users were classed as people who indicated 0 (*Never*) for Instagram usage. Exercise/Fitness and Diet/Food influencers were chosen because these two domains encompass the majority of health influencer content (Pilgrim & Bohnet-Joschko, 2019).

Physical Activity

The level of physical activity was measured through The International Physical Activity Questionnaire—Short Form (IPAQ SF; Craig et al., 2017). The IPAQ-SF consists of 7 items, which measure a person's self-reported moderate and vigorous physical activity, walking time, and sedentary time during the last seven days. Although some studies investigating the validity of the IPAQ-SF show mixed results (Craig et al., 2017; Hagströmer et al., 2006; Lee et al., 2011; Saglam et al., 2010), walking and vigorous exercise measures show higher validity (Lee et al., 2011), therefore for analysis we only used walking and vigorous exercise scores. Walking and vigorous exercise (in minutes/week) were recoded into quintiles for analysis due to skewedness of data.

Dietary Habits

Dietary habits were measured through modified questions stemming from the 2008/09 New Zealand Adult Nutrition Survey (Parnell et al., 2011), and the Short Food Survey (Hendrie et al., 2017). The survey questions were developed to obtain an accurate representation of participants' average consumption of different groups of food. The survey included seven questions about ultra-processed food: soft drinks; fast food; hot chips/French fries; sweets (candies, chocolate); refined baked goods (cakes, cookies, etc.); refined snacks (potato chips, crisps, etc.); and processed meat (bacon, sausages, chicken nuggets). Participants reported often they ate each food group in a "typical week" using six response options (*Never, Less than once per week, 1–2 times per week, 3–4 times per week, 5–6 times per week, or 7 or more times per week*; responses coded 0, .5, 1, 3, 5, and 7 respectively). We summed the scores from these seven items (mean imputing any missing values) to create an ultra-processed food index score, which could range from 0 to 49 weekly incidences of consuming ultra-processed food (for more detail, see Conner et al., 2020). The survey also contained four questions assessing typical fruit and vegetable intake (raw fruit, raw vegetables, cooked fruit, and cooked vegetables; Brookie et al., 2018). Participants reported how many servings of each type of fruit and vegetables they typically ate "per day" using six response options (*Never, Less than one serving per day, 1 serving, 2 servings, 3 servings, 4 or more servings*; responses coded 0, .5, 1, 2, 3, 4, respectively). We summed the scores from these four items (mean imputing any missing values) to create a daily fruit and vegetable index score, which could range from 0 to 14 total daily servings of fruit and vegetables.

Psychological Variables

The mental health, mood, and well-being of the participants was measured through the 8-item PROMIS Emotional Distress—Depression and the 8-item PROMIS Emotional Distress—Anxiety Short Form 8a questionnaires (Pilkonis et al., 2011), positive mood and negative mood through an 18-item measure based on the affective circumplex (Russell & Barrett, 1999), and well-being through the 8-item Flourishing Scale (Diener et al., 2010). The PROMIS items were answered for the standard "past 7-days" timeframe on a scale from 1 (*Never*) to 5 (*Always*) and were summed (α_{dep} = .943, α_{anx} = .933). The PROMIS questionnaires has shown high convergent validity in non-clinical populations (correlations between PROMIS anxiety and depression scales and legacy anxiety and depression scales of between 0.72 and 0.83; Cella et al., 2010). The circumplex mood measure consisted of 9 items to measure negative mood (angry, hostile, stressed, anxious, nervous, tense, hopeless, sad, unhappy) and 9 items to measure positive mood (energetic, enthusiastic, excited, cheerful, happy, pleasant, calm, content, relaxed), reflecting high, medium, and low levels of activation; people were asked how often they "typically" felt each mood on a scale from 0 (*None of the time*) to 4 (*Most of the time*), which were averaged (α_{pos} = .888, α_{neg} = .892). The Flourishing Scale consisted of 8 items enquiring about their general perception of their well-being (e.g., *I am engaged and interested in my daily activities*), answered on a scale from 1 (*Strongly disagree*) to 7 (*Strongly agree*), which was summed (α = .899; mean imputing any missing values); the Flourishing Scale shows high convergent validity with subjective happiness and life satisfaction scales (*r* = .583 and .496 respectively; Silva & Caetano, 2013) suggesting its adequacy in measuring psychological well-being.

Demographic Variables

In addition, the survey included questions related to age, gender (male, female, and gender diverse), ethnicity, socioeconomic status (SES), education level, and height and weight. SES was assessed using a six-item measure from Griskevicius et al. (2011) which included three items about childhood economic background (e.g., *My family usually had enough money for things when I was growing up*.) and three questions about current/future economic situation (e.g., *I have enough money to buy things I want*.), with each item answered from 1 (*Strongly Disagree*) to 7 (*Strongly Agree*). All six items were averaged with higher scores indicating higher SES (α = .792). Education was indicated by selecting their highest level of education from the following options: 1 (*Did not complete high school*), 2 (*Completed high school*), 3 (*Currently attending University, Polytechnic, or other tertiary institution for undergraduate degree*), 4 (*Completed undergraduate degree at University, Polytechnic or other tertiary institution*), 5 (*Currently attending University, Polytechnic, or other tertiary institution for higher degree*), and 6 (*Completed higher degree at University, Polytechnic or other tertiary institution*). Self-reported height and weight was used to compute Body Mass Index (BMI), calculated by dividing each participant's weight in kilograms by height in metres squared.

Data Preparation and Analysis

All statistical analyses were carried out using IBM's SPSS Statistics v26 Software (IBM, 2016). Prior to analysis, participants were categorized into three groups based on their social media usage patterns: (1) participants who did not use Instagram ("non-users"); (2) participants who used Instagram but did not follow health influencers ("non-followers"); and (3) participants who used Instagram and who followed health influencers ("followers", HIFs).

Next, descriptive statistics were calculated for demographic, health, and psychological variables. Tests were run to determine whether there were significant differences between non-users, non-followers, and followers in the categorical variables of age, gender, and ethnicity (Chi-Squared tests), and in the continuous variables of age, SES, BMI, walking quintiles, vigorous exercise quintiles, ultra-processed food intake, fruit and vegetable intake, depressive symptoms, anxiety, negative mood, positive mood, and flourishing (all using a one-way ANOVA, with Tukey post-hoc tests to compare differences between groups). Factor analysis was further used to reduce the number of mental health, mood, and well-being variables from five to a smaller number of factors given the overlap in variables (Baglin, 2014; Yong & Pearce, 2013). Factor analysis yielded a two-factor solution with a distress factor (depression, anxiety, and negative mood) and a well-being factor (positive mood and flourishing).

After the univariate analyses, multiple regression models were run to determine the association between health influencer following status on the four health behaviours (walking, vigorous physical activity, ultra-processed food intake, fruit and vegetable intake), and two mental health factor scores (distress and well-being), when controlling for covariates of age, gender, ethnicity, SES, and education. We used a Helmert coding procedure (Sundström, 2010), in which non-users were compared to non-followers and HIFs, then non-followers were compared to HIFs. In the first comparison, non-users were coded as −.667, and non-followers and HIFs were coded as .333. In the second comparison, non-users were coded as 0, non-followers were coded as −.5, and HIFs were coded as .5. Lastly, we conducted moderator analyses using PROCESS (Hayes, 2012) to determine whether the relationships between health behaviours and distress and well-being were moderated by health influencer following status.

For interpretation, we adjusted the *p* value downward in all analyses from $p < .05$ to $p < .005$ to limit the number of false positives following recommendations from Benjamin et al. (2018).

Results

Descriptive Statistics

Table 1 shows descriptive statistics for the variables. The average age of this cohort was 22.09 (18.00–25.00, *SD* = 2.41). The sample was 55.4% female, relatively ethnically homogeneous, consisting of individuals who were completing tertiary education at an undergraduate level and who reported average socioeconomic status (SES). There was a relatively high total exercise rate in the sample, with medians of 225 walking minutes a week, and 120 minutes of vigorous physical activity per week. Participants showed a high consumption rate of fruit and vegetables (M = 4.91 servings per day, SD = 2.59) compared to population averages, which is around 3.5 servings per day (Dodd et al., 2010).

Table 1. *Demographic, Health, and Mental Health Variables for the Total Sample and the Three Instagram User Groups.*

				Instagram Users (n = 949)	
Demographic Variables		Total (n = 1,022)	Non-Users (n = 73)	Health Influencer Non-Followers (n = 538)	Health Influencer Followers (HIFs) (n = 411)
Mean (SD) or N (%)[1]					
Gender[1]	Female	566 (55.4%)	13 (17.8%)$_a$	266 (49.4%)$_b$	287 (69.8%)$_c$
	Male	445 (43.5%)	58 (79.5%)$_a$	264 (49.1%)$_b$	123 (29.9%)$_c$
	Gender Diverse	11 (1.1%)	2 (2.7%)$_a$	8 (1.5%)$_{a,b}$	1 (0.2%)$_b$
Age		22.09 (2.41)	22.49 (2.24)$_a$	21.79 (2.34)$_n$	22.39 (2.50)$_a$
Ethnicity[1]	White	770 (75.3%)	48 (65.8%)$_a$	399 (74.2%)$_a$	323 (78.6%)$_a$
	Asian	86 (8.4%)	5 (6.8%)$_a$	59 (11.0%)$_b$	22 (5.4%)$_a$
	Black	33 (3.2%)	4 (5.5%)$_a$	16 (3.0%)$_a$	13 (3.2%)$_a$
	Māori	30 (2.9%)	4 (5.5%)$_a$	14 (2.6%)$_a$	12 (2.9%)$_a$
	Other	103 (10.1%)	12 (16.4%)$_a$	50 (9.3%)$_a$	41 (10.0%)$_a$
SES		4.58 (1.16)	3.90 (1.21)$_a$	4.47 (1.18)$_b$	4.84 (1.16)$_c$
Education		3.65 (1.23)	3.15 (1.151)$_a$	3.54 (1.197)$_a$	3.90 (1.231)$_b$
BMI[2]		23.83 (5.44)	25.59 (6.83)$_a$	23.70 (5.42)$_a$	23.83 (5.44)$_a$
Health Variables					
Walking[3]		225.00 (300)	225.00 (315)$_a$	225.00 (300)$_a$	225.00 (315)$_a$
Walking Quintiles		2.92 (1.38)	2.97 (1.44)$_a$	2.93 (1.40)$_a$	2.90 (1.36)$_a$
Vigorous Exercise[3]		120.00 (270)	120 (180)$_a$	90.00 (240)$_a$	150.00 (300)$_b$
Vigorous Exercise Quintiles		2.76 (1.42)	2.54 (1.35)$_a$	2.54 (1.43)$_a$	3.09 (1.37)$_b$
Ultra-Processed Food Intake (frequency/week)		11.90 (6.43)	10.81 (6.57)$_a$	11.68 (6.12)$_a$	12.38 (6.77)$_a$
Fruit and Vegetable Intake (servings/day)		4.89 (2.55)	3.73 (2.10)$_a$	4.45 (2.43)$_a$	5.68 (2.55)$_b$
Mental Health Raw Variables					
Depressive Symptoms		57.30 (9.23)	55.52 (11.48)a	56.76 (8.99)a	58.33 (9.01)a4
Anxiety		59.08 (9.63)	56.97 (12.14)$_a$	58.89 (9.54)$_a$	59.71 (9.20)$_a$
Negative Mood		1.68 (0.83)	1.58 (0.95)$_a$	1.65 (0.81)$_a$	1.74 (0.83)$_a$
Positive Mood		2.29 (0.75)	2.02 (0.88)$_a$	2.22 (0.76)$_a$	2.43 (0.69)$_b$
Flourishing		41.58 (8.45)	38.50 (15.00)$_a$	43.00 (13.00)$_a$	44.00 (9.00)$_b$
Mental Health Factor Scores					
Distress		0.00 (1.00)	−0.33 (1.12)$_a$	−0.07 (0.95)$_a$	0.15 (1.02)$_b$
Well-being		0.00 (1.00)	−0.50 (1.10)$_a$	−0.11 (1.00)$_b$	0.24 (0.91)$_c$

Note. BMI = body mass index; SD = standard deviation; SES = socioeconomic status. [1] Data reflect Mean (SD) for continuous variables or N (%) for categorical variables except where noted. [2] Six participants did not have BMI data, so BMI n = 1,016 [3] Median (Interquartile range) presented due to variable being positively skewed. [4] Although post-hoc tests showed no significant differences between groups, there was an omnibus effect observed overall. $_{a,b,c}$ Difference in letters denotes statistical significance p < .005.

Table 1 also shows the descriptive statistics for the three Instagram user groups. There was a high rate of Instagram usage within the sample. Out of 1,022 participants, only 73 participants (7.1% of the sample) reported not using Instagram ("Non-Users"). By contrast, 949 participants (92.9% of the sample) indicated they used Instagram. Of these Instagram users, 538 participants (52.6% of the sample) did not follow health influencers ("Health Influencer Non-Followers") and 411 participants (40.2% of the sample) followed health influencers (HIFs). Of the 411 participants who followed health influencers, 332 participants (32.5% of the sample) followed exercise/fitness health influencers, 259 participants (25.3% of the sample) followed diet/food health influencers, and 180 participants (17.7% of the sample) followed both types of health influencers.

Without controlling for potential covariates, there were some key significant differences between non-users, non-followers, and HIFs. Firstly, HIFs were more likely to be female than male or gender diverse. Secondly, HIFs had higher socioeconomic status ($p < .001$), and higher education levels ($p < .001$) than non-followers. Thirdly, HIFs showed a higher level of vigorous exercise ($p < .001$) and fruit and vegetable intake ($p < .001$) than non-followers and non-users of Instagram. Lastly, HIFs showed higher levels of distress ($p < .001$) and well-being than non-users and non-followers ($p < .001$). Similar patterns were found when comparing participants who followed exercise/fitness health influencers versus diet/food health influencers, although average distress was higher among those following diet/food influencers (n = 259; M = .239; SD = .981) than exercise/fitness influencers (n = 332; M = .059, SD = .981), both of which differed from non-users and non-followers, ps < .001. No significant differences were found between groups in age, ethnicity, BMI, minutes spent walking, negative mood, or anxiety.

Regression Results—Main Effects

Table 2 (Top) presents the regression results predicting health variables from demographic covariates and health influencer following status using Helmert codes. Only vigorous physical activity and fruit and vegetable intake were tested as dependent variables, as these were the only two health variables that showed significant differences between groups in unadjusted analyses. When added to the covariate model, health influencer following variables explained 2.6% of the variance in vigorous exercise, $R^2 = .026$, $F(2, 1014) = 16.309$, $p < .001$. Specifically, health influencer following predicted a higher level of exercise compared to non-followers (b = 0.493, SE = 0.088, $p < .001$). Similar results were found for predicting fruit and vegetable intake. When added to the covariate model, health influencer following variables explained 2.3% of the variance in fruit and vegetable intake, $R^2 = .023$, $F(2, 1014) = 14.531$, $p < .001$. Specifically, health influencer following predicted higher levels of fruit and vegetable intake compared to non-followers (b = 0.816, SE = 0.156, $p < .001$).

Table 2 (Bottom) presents the multiple regression results predicting distress and well-being from demographic covariates and health influencer following and Instagram usage patterns. When added to the covariate model, health influencer following variables explained 1.2% of the variance in distress, $R^2 = .012$, $F(2, 2014) = 6.558$, $p = .001$. However, health influencer following did not significantly predict distress below the $p < .005$ cut off level (b = 0.185, SE = 0.067, $p = .006$). When added to the covariate model, health influencer following variables explained 1.4% of the variance in well-being, $R^2 = .014$, $F(2, 2014) = 8.787$, $p < .001$). Here, health influencer following was associated with higher levels of well-being compared to non-followers (b = 0.216, SE = 0.061, $p < .001$). Instagram usage alone was not sufficient to predict distress (b = 0.326, SE = 0.125, $p = .009$) or well-being (b = 0.287, SE = 0.113, $p = .011$) below the $p < .005$ cut off level.

Regression patterns from Table 2 were nearly identical when testing participants who followed exercise/fitness health influencers versus food/diet health influencers. The one exception was that following food/diet health influencers was significantly associated with greater distress below the $p < .005$ cut off level compared to non-followers (b = 0.263, SE = 0.079, $p < .001$), whereas following Exercise/Fitness influencers did not significant predict elevated distress compared to non-followers (b = 0.104, SE = 0.069, $p = .134$).

No statistical assumptions that underlie the regression analyses were violated in any of the tested models. The residuals of the regressions were normal. The models were homoscedastic.

Regression Results—Moderators

There were two significant patterns of moderation for distress. First, there was evidence that health influencer following moderated the relationship between vigorous exercise and distress (see Figure 1; Vigorous exercise x Helmert2 cross-product, b = 0.143, SE = 0.046), $p = .002$). Among HIFs, more vigorous exercise was associated with *greater* distress (simple slope b = 0.140, SE = 0.037, $p < .001$), compared to a null relationship between vigorous exercise and distress in non-followers (simple slope b = −0.002, SE = 0.031, $p = .937$). Among non-users of Instagram, there was the normally protective relationship between vigorous exercise and distress whereby more vigorous exercise was associated with *lower* distress, although this slope did not significantly differ from zero (simple slope b = −0.127, SE = 0.086, $p = .138$). There were no significant differences between users and non-users of Instagram. Patterns were similar when testing participants who followed exercise/fitness health influencers versus food/diet health influencers. Overall, this pattern of moderation indicates a potential disruption to the protective association between vigorous exercise and distress amongst health influencer followers (HIFs).

Table 2. *Multiple Regression Results Showing the Association Between Social Media Use Categories on Vigorous Physical Activity and Fruit and Vegetable Intake (Top) and Distress and Well-being (Bottom), Controlling for Demographic Covariates (N = 1,022).*

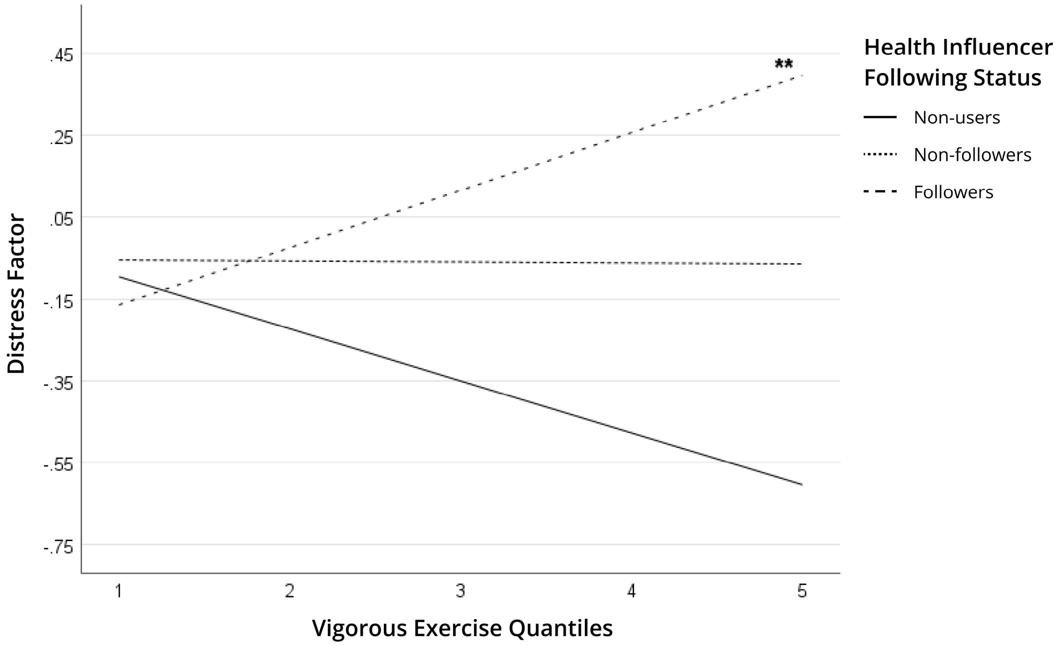
Predictors	Vigorous Physical Activity Quintiles *b* (*SE*), *p*	95% CI Lower-higher	Fruit and Vegetable Intake *b* (*SE*), *p*	95% CI Lower-higher
Intercept	3.188 (0.076), $p < .001$	3.039, 3.338	4.803 (0.136), $p < .001$	4.537, 5.069
Age	0.011 (0.019), $p = .578$	−0.027, 0.048	−0.013 (0.034), $p = .697$	−0.080, 0.053
Male-Female/Other	−0.705 (0.085), $p < .001$	−0.871, −0.539	0.244 (0.151), $p = .106$	−0.052, 0.540
White-Non-White	−0.251 (0.095), $p = .008$	−0.438, −0.065	−0.574 (0.169), $p < .001$	−0.906, −0.241
SES	0.263 (0.037), $p < .001$	0.190, 0.336	0.538 (0.066), $p < .001$	0.408, 0.668
Education	0.197 (0.039), $p < .001$	0.121, 0.273	0.404 (0.069), $p < .001$	0.268, 0.539
Non-user vs. Instagram User[1]	0.247 (0.164), $p = .132$	−0.075, 0.568	0.539 (0.292), $p = .065$	−0.034, 1.111
Non-follower vs. Health Influencer Follower[2]	0.493 (0.088), $p < .001$	0.321, 0.665	0.816 (0.156), $p < .001$	0.509, 1.122
R square covariates only	.161		.174	
R square change Instagram Vars	.026, $F(2, 1014) = 16.309$, $p < .001$		.023 $F(2, 1014) = 14.531$, $p < .001$	
Total *R* square	.187		.198	
Predictors	**Distress *b* (*SE*), *p***	**95% CI Lower-higher**	**Well-being *b* (*SE*), *p***	**95% CI Lower-higher**
Intercept	−0.139 (0.058), $p = .016$	−0.253, −0.026	0.012 (0.053), $p = .821$	−0.091, 0.115
Age	0.021 (0.014), $p = .142$	−0.007, 0.050	−0.012 (0.013), $p = .342$	−0.038, 0.013
Male-Female/Other	0.176 (0.065), $p = .006$	0.050, 0.303	−0.070 (0.058), $p = .232$	−0.185, 0.045
White-Non-White	−0.137 (0.072), $p = .059$	−0.279, 0.005	−0.138 (0.066), $p = .035$	−0.267, −0.010
SES	−0.064 (0.028), $p = .024$	−0.119, −0.008	0.334 (0.026), $p < .001$	0.284, 0.385
Education	0.037 (0.030), $p = .211$	−0.021, 0.095	0.060 (0.027), $p = .025$	0.008, 0.113
Non-user vs. Instagram User[1]	0.326 (0.125), $p = .009$	0.080, 0.571	0.287 (0.113), $p = .011$	0.065, 0.509
Non-follower vs. Health Influencer Follower[2]	0.185 (0.067), $p = .006$	0.054, 0.316	0.216 (0.061), $p < .001$	0.097, 0.335
R square covariates only	.029		.201	
R square change Instagram Vars	.012, F(2, 1014) = 6.588, $p = .001$		.014 $F(2, 1014) = 8.787$, $p < .001$	
Total *R* square	.041		.214	

Note. *b* = unstandardized beta coefficient, CI = confidence interval, *SE* = standard error. [1] Helmert Code 1 compared non-users of Instagram ($n = 73$) versus users of Instagram ($n = 949$). [2] Helmert Code 2 compared within Instagram users: non-followers of health influencers ($n = 538$) versus health influencer followers, HIFs ($n = 411$).

Second, there was evidence that usage of Instagram moderated the relationship between fruit and vegetable intake and distress (see Figure 2; FV x Helmert1 cross-product, $b = 0.165$, $SE = 0.056$, $p = .004$). For Instagram users, a non-significant positive relationship between fruit and vegetable intake and *higher* distress was observed (simple slope $b = 0.046$, $SE = 0.018$, $p = .012$; simple slope $b = 0.048$, $SE = 0.019$, $p = .013$ respectively), compared to the non-significant protective relationship between fruit and vegetable intake and *lower* distress in non-users (simple slope $b = -0.118$, $SE = 0.055$, $p = .033$). This pattern implicates a disruptive impact of Instagram use overall, which was not particularly accentuated for HIFs.

For well-being, there were no significant moderation effects of Instagram usage or HIF status on the relationship of well-being with either vigorous activity (Figure 3) or fruit and vegetable intake (Figure 4). All groups showed beneficial relationships between health behaviours and well-being, although this slope only significantly differed from 0 in the relationship between fruit and vegetable intake and well-being in non-followers (simple slope $b = 0.093$, $SE = 0.016$, $p < .001$).

Figure 1. *Moderation Effects of Health Influencer Following on the Relationship Between Vigorous Exercise and Distress.*



Note. Simple slopes significant at p < .005 are starred **.

Figure 2. *Moderation Effects of Health Influencer Following on the Relationship Between Fruit and Vegetable Intake and Distress.*

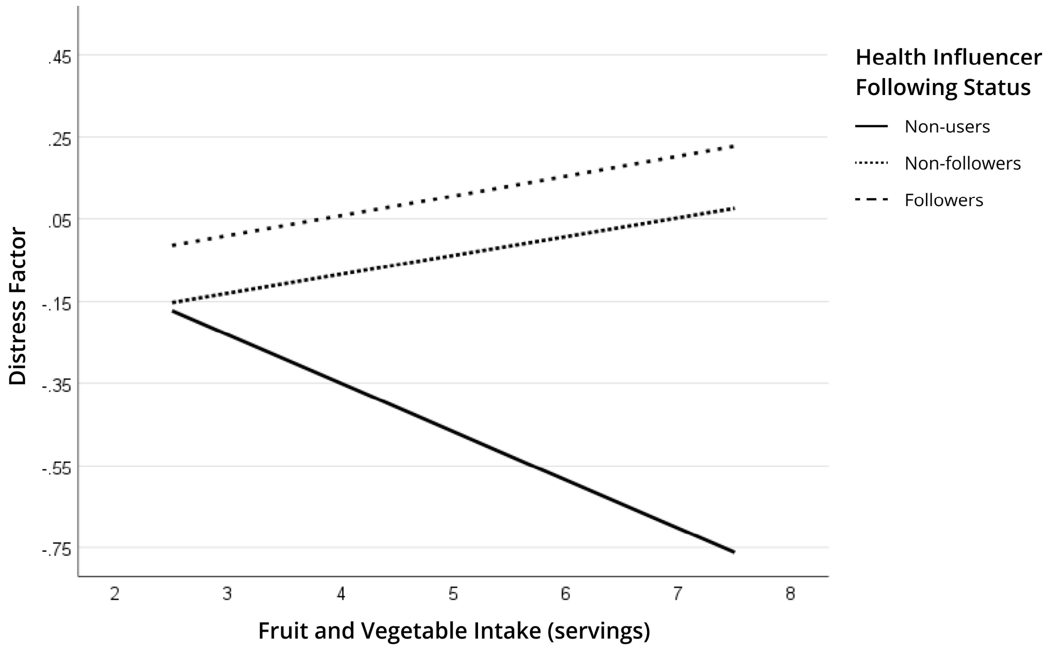


Figure 3. *Moderation Effects of Health Influencer Following on the Relationship Between Vigorous Exercise and Well-Being.*

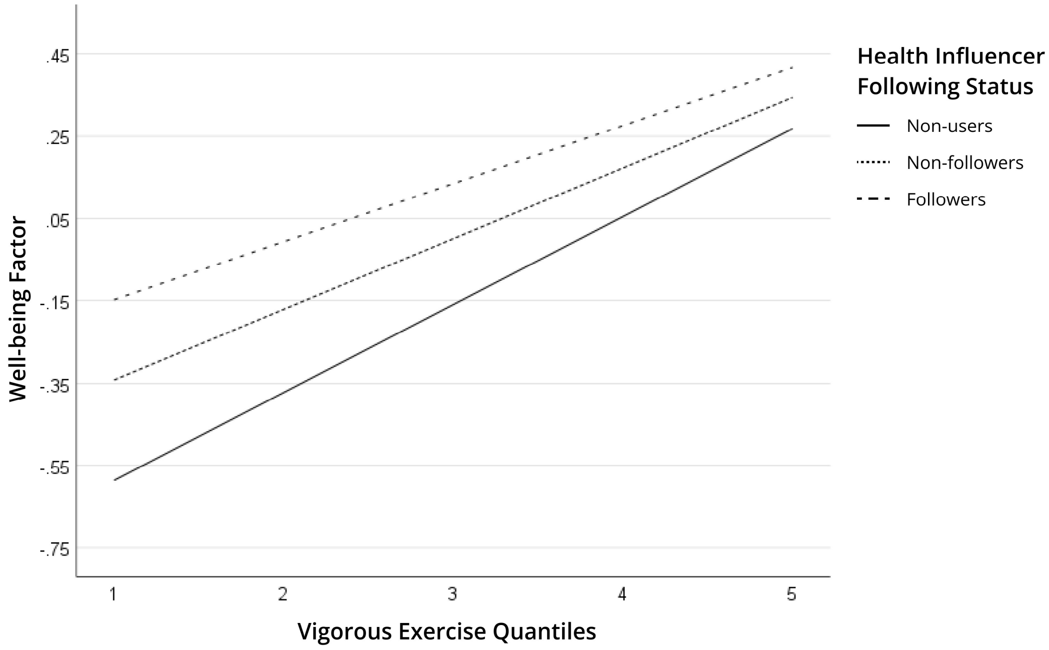
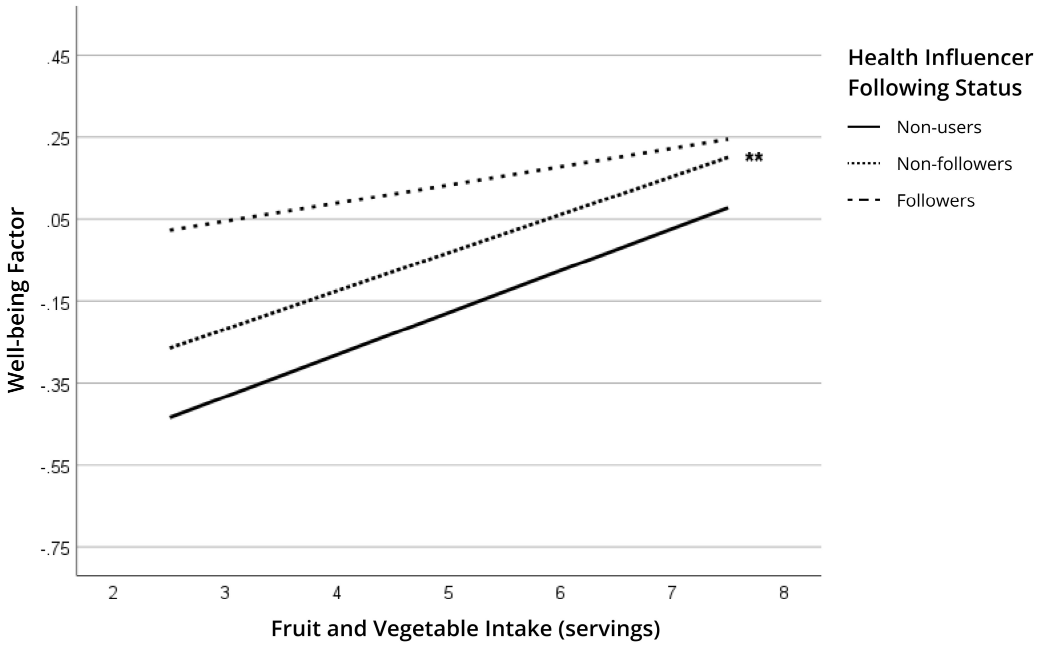


Figure 4. *Moderation Effects of Health Influencer Following on the Relationship Between Fruit and Vegetable Intake and Well-Being.*



Note. Simple slopes significant at p < .005 are starred **.

Discussion

These findings shed light on the lifestyles of young adults who follow health influencers online through Instagram. This study found that young adult HIFs are more likely to report engaging in vigorous exercise and consuming more fruits and vegetables than non-followers, suggesting more healthy lifestyles. In unadjusted models, HIFs also reported higher levels of distress *and* greater well-being than non-followers, but these differences were attenuated in adjusted models and no longer exceeded our conservative threshold of significance ($p < .005$). However, people who followed diet/food health influencers did report greater distress than non-followers in adjusted models at $p < .001$. This finding suggests a greater vulnerability among young adults who follow diet/food related influencers than who follow exercise/fitness influencers. Finally, this study found evidence that HIFs had an unexpected relationship between vigorous exercise and distress in that more vigorous exercise was associated with *greater* distress in people who follow health influencers compared to people who use Instagram but do not follow health influencers. This pattern contrasts with the normally protective relationship between more vigorous exercise and *lower* distress found in non-Instagram users and the wider literature (Barbour et al., 2007; Ensari et al., 2015). The following sections discuss the demographic characteristics of HIFs, the potential causes for the differences in health behaviours between followers and non-followers, and potential mechanisms that may explain the elevated distress as a function of exercise for HIFs.

Who are HIFs?

HIFs were more likely to be female, higher in SES, and higher in education compared to non-followers. Women may be more likely to follow health influencers due to the gendered appeal of the "appearance focused" nature of health influencers (Egli et al., 2011; Molanorouzi et al., 2015). People higher in SES and education have greater access to exercise and dietary resources (Garcia et al., 1995; Murray et al., 2012) and tend to live healthier lifestyles (Adler & Newman, 2002; Pampel et al., 2010) despite the rising costs of doing so (Edmunds, 2022). As such, they may find health influencers to be more relevant to their daily lives and engage with it more than others. Interestingly, there were few demographic differences between non-users and users of Instagram aside from SES, which was lowest in non-users, mid-range for non-followers, and highest in followers.

Health Influencer Followers Are Healthier

HIFs reported higher levels of both vigorous physical exercise and fruit and vegetable intake than non-followers. Specifically, they engaged in 150 minutes of vigorous exercise per week, compared to 90 minutes per week in non-followers and 120 minutes per week in non-users. These are all above the 75 minutes of vigorous exercise per week recommended by the American College of Sports Medicine (Garber et al., 2011). Similarly, HIFs reported eating nearly 6 servings of fruit and vegetables per day, compared to 4 servings in non-followers and non-users. Intake of 6 servings is above the recommended 5+ servings per day for adults, and well above the usually low intake of fruits and vegetables in the young adult population, which is around 3.5 servings per day (Dodd et al., 2010). Importantly, these associations remained significant in the multiple regression models when controlling for the demographic differences. These patterns suggest that HIFs may be healthier than non-followers, at least in their self-reported behaviour.

Whether following health influencers directly causes health behaviours is less clear and cannot be inferred from this correlational data. If an individual follows health influencers, they may already have a pre-existing motivation to exercise or eat healthily, as they must be interested enough in health influencer content to follow them. Therefore, elevations in healthy behaviours in HIFs may be due to pre-existing motivations. However, it is possible that health influencers could help maintain positive health behaviours, as seen in the transtheoretical model (Prochaska & Velicer, 1997). Exercise can be maintained through targeting the exerciser's self-efficacy (Fallon et al., 2005), which health influencers could target through positively-framed feedback (van de Ridder et al., 2015). While HIFs may already want to lead a healthy lifestyle, health influencers could play an important role in maintaining this behaviour. Longitudinal data would be integral in further delineating the factors related to positive health behaviour change over time and the possible bidirectional relationships between social media and behaviour.

Greater Distress and Well-Being

Interestingly, in unadjusted models, HIFs showed higher levels of both distress (a single factor yielded from depression, anxiety and negative mood scores) and well-being than non-followers. Firstly, we would expect the well-being scores of HIFs to be higher, as they are exercising more and eating better, which should lead to greater feelings of physical vitality and flourishing (Głąbska et al., 2020; Mandolesi et al., 2018). The well-being index, more than the distress index, included aspects related to physical vitality (feeling "energetic", "enthusiastic", and the like) which could be disproportionately higher amongst healthy individuals. However, HIFs also reported greater distress. This finding is consistent with previous research on the negative effects of following Instagram health influencers (e.g., Powell & Pring, 2024). This pattern could be due to a number of mechanisms, including upward social comparison. Upwards social comparison refers to an individual comparing themselves to another who they perceive to be better than themselves (Wheeler, 1966). The physical attractiveness of health influencers may prompt the upwards social comparison of their followers, which leads to adverse effects including greater distress (Hu & Liu, 2020; Jan et al., 2017; Sherlock & Wagstaff, 2019; Pedalino & Camerini, 2022; Tsay-Vogel & Krakowiak, 2019; Wang et al., 2017; Yoon et al., 2019). HIFs may struggle to be happy with their lifestyle habits and physique, when they are comparing themselves to the idealized versions of themselves. This effect of upwards social comparison may be especially pronounced among those who follow diet-related influencers which may trigger body image issues (Engel et al., 2024; Holland & Tiggemann, 2016; Powell & Pring, 2024), especially if influencers are promoting restrictive diets to achieve the thin or "fit ideal" body type (Faelens et al., 2021; Jerónimo & Carraça, 2022).

There may also be differences in intentions driving exercise or dietary habits between groups. Autonomous motivations behind performing health behaviours (e.g., exercising for health purposes) are more beneficial for body image and well-being than appearance related motivations (Panão & Carraça, 2020; Prichard & Tiggemann, 2008), which could lead to inverse relationships between well-being and both exercise (Panão & Carraça, 2020) and dietary behaviours (Carrotte et al., 2017). Considering the emphasis of health influencers on the appearance of their bodies through often digitally altered photographs that appeal towards a given aesthetic, it is possible that HIFs may be exercising or dieting for appearance-related purposes, and therefore show greater levels of distress and poorer well-being. Future research should qualitatively examine whether HIFs cite appearance-related motivations as their main drive for increased health behaviour engagement to clarify the patterns seen here. The higher level of distress *and* well-being in HIFs than non-followers suggests that there are multiple different processes happening simultaneously: the positive effects of exercise and fruit and vegetable intake on feelings of physical vitality, and potentially the negative effects of upwards social comparison, or damaging intentions behind exercise, contributing to feelings of depressed mood, anxiety, and negative mood.

Moderation by Health Influencer Following

Hypothesis 3 was partially supported: HIFs status significantly moderated the relationship between vigorous physical activity and distress, but not well-being. HIFs who engaged in more vigorous physical activity reported greater distress, not lower distress, as is usually the norm (Barbour et al., 2007; Ensari et al., 2015). A similar pattern was found for the relationship between fruit and vegetable intake and distress, in that HIFs who ate more fruits and vegetables reported lower well-being (however, this simple slope did not exceed the $p < .005$ cut off and was similar to non-followers). Nevertheless, there appears to be a general trend that among health influencer followers, those who engaged in more intense health behaviours evidenced more distress. This finding has several potential explanations and implications.

The first explanation could be that HIFs use intensive exercise as a protection against pre-existing depressive symptoms. It is possible that those who are aware of the positive benefits of exercise use it intentionally as a way to combat depression. Therefore, they may seek help in maintaining positive health behaviours. Knowledge of the mood-boosting benefits of exercise is commonly known and often highlighted on national mental health advocacy internet resources (Victoria State Goverment, 2023; MHFNZ, 2019; UK Mental Health Foundation, 2022). Those who know that healthy behaviours benefit mental health may use these strategies to mitigate their poor mental health. This may account for the paradoxical relationship among health behaviours and distress in this population. Again, longitudinal data could be used to study these trajectories over time.

It is also possible that those who follow health Influencers show greater levels of compulsive exercise behaviours. Compulsive exercise is a disorder in which an individual is "addicted" to exercise, so much so that it leads to significant impairment or distress (Lichtenstein et al., 2017). Health influencers may increase athletic-ideal internalization of HIFs, which can increase levels of compulsive exercise (Homan, 2010). Therefore, HIFs who exercise the most may be doing so compulsively, and suffering from higher depressive symptoms associated with the disorder (Lichtenstein et al., 2017), despite showing more positive health behaviours. This could be tested through probes of intention behind exercise, as well as surveying HIFs and non-followers regarding their compulsive exercise habits.

In summary, the finding that HIFs have an altered relationship between healthy behaviours and distress may be valuable to the literature. However, more rigorous testing must be done to replicate this relationship. Additionally, follow-up research should aim to examine this relationship longitudinally to determine whether these proposed explanations may account for the patterns observed in the current study.

Limitations

There were several limitations to this study. Firstly, the cross-sectional design limits the ability to infer causal direction among variables. Thus, we cannot determine the degree of influence that health influencers have over health behaviours. This is integral in determining whether the increased health behaviours are a direct result of health influencer following. Additionally, the survey did not measure exercise intention or explore the reasons behind health influencer following that would valuable in testing for underlying mechanisms. Future research should aim to measure intentions behind exercise and diet, and reasons why people initially follow health influencers (e.g., to motivate exercise, to improve appearance, etc.). Thirdly, we only investigated following two types of health influencers (exercise/fitness and diet/food). Although we believe this captures a majority of health influencer content, and there was a high degree of overlap in following (54.2% of HIFs followed both), there may be other health influencer content or broader wellness influencers that we could have surveyed (e.g., related to sleep, relaxation, breathing, or mindfulness). Future studies should consider examining whether specific health influencer content matters in terms of the physical and mental health of its followers. Although similar patterns were found when analysing people who followed exercise/fitness influencers or diet/food influencers, higher distress was observed in people who followed diet/food influencers. It will be important for future research to replicate and explain this finding, ideally in pre-registered research with hypotheses designated before data collection. The present study was not pre-registered.

Other limitations of the study included the relatively homogenous nature of the sample's ethnicity; a more diverse population may reveal that health influencers impact ethnicities differently. Additionally, this study focused on Instagram as the influencing platform and did not survey health influencer following on other platforms such as TikTok, Snapchat, or YouTube. Nor did we assess the intensity of platform use. We focused on Instagram because it was the primary platform for influencers at the time we designed our study. Future research should broaden the types of platforms assessed, and consider measuring intensity of use, keeping in mind that technology evolves quickly. Finally, the data reported in this study could be impacted by social desirability bias, whereby people respond in ways they believe are more socially desirable (Grimm, 2010). HIFs are likely very knowledgeable about what they "should" be doing in regards to health behaviours, and may overinflate their responses in self-report assessments. Although our survey was anonymised and social media questions were imbedded in a much longer survey (thereby obscuring knowledge of hypotheses which can increase social desirability), there may still be bias in self-reports of health behaviours. Future studies may consider supplemental objective data of behaviour via wearable technology to support stronger inferences.

Conclusions

Is following health influencers a good or bad thing for young adults? It may be both. This study found evidence that health influencer followers (HIFs) had healthier behaviours than non-followers, but also higher distress and well-being. The typical protective relationship between health behaviours like vigorous exercise and lower distress also appeared disrupted in HIFs. Instead, among HIFs, those who exercised most vigorously appeared the most distressed. In summary, although HIFs are healthier physically, they may not be happier. This invites caution and further research before recommending health influencers as a healthy way of changing behaviours. Future research is needed to replicate these patterns and measure these findings longitudinally to discover mechanistic and causal pathways between health influencer following and health outcomes.

Footnotes

[1] Whereas Scharkow (2016) had only four response options (1 = *at least weekly*, 2 = *at least monthly*, 3 = *once a month or less* and 4 = *never*), the current survey contained two more response categories (at least daily, and multiple times daily) to better capture behaviour in a young adult sample and reversed the numbers on the scale so that higher numbers indicate more usage. The result is a six-point scale from 0 to 5.

Conflict of Interest

The authors have no conflicts of interest to declare.

Authors' Contribution

Jack R. H. Cooper: Writing—original draft. **Quinn Campbell:** Conceptualization, data curation, formal analysis, investigation, validation, visualization, writing—original draft. **Tamlin S. Conner:** Conceptualization, formal analysis, methodology, project administration, resources, software, supervision, validation, writing—original draft.

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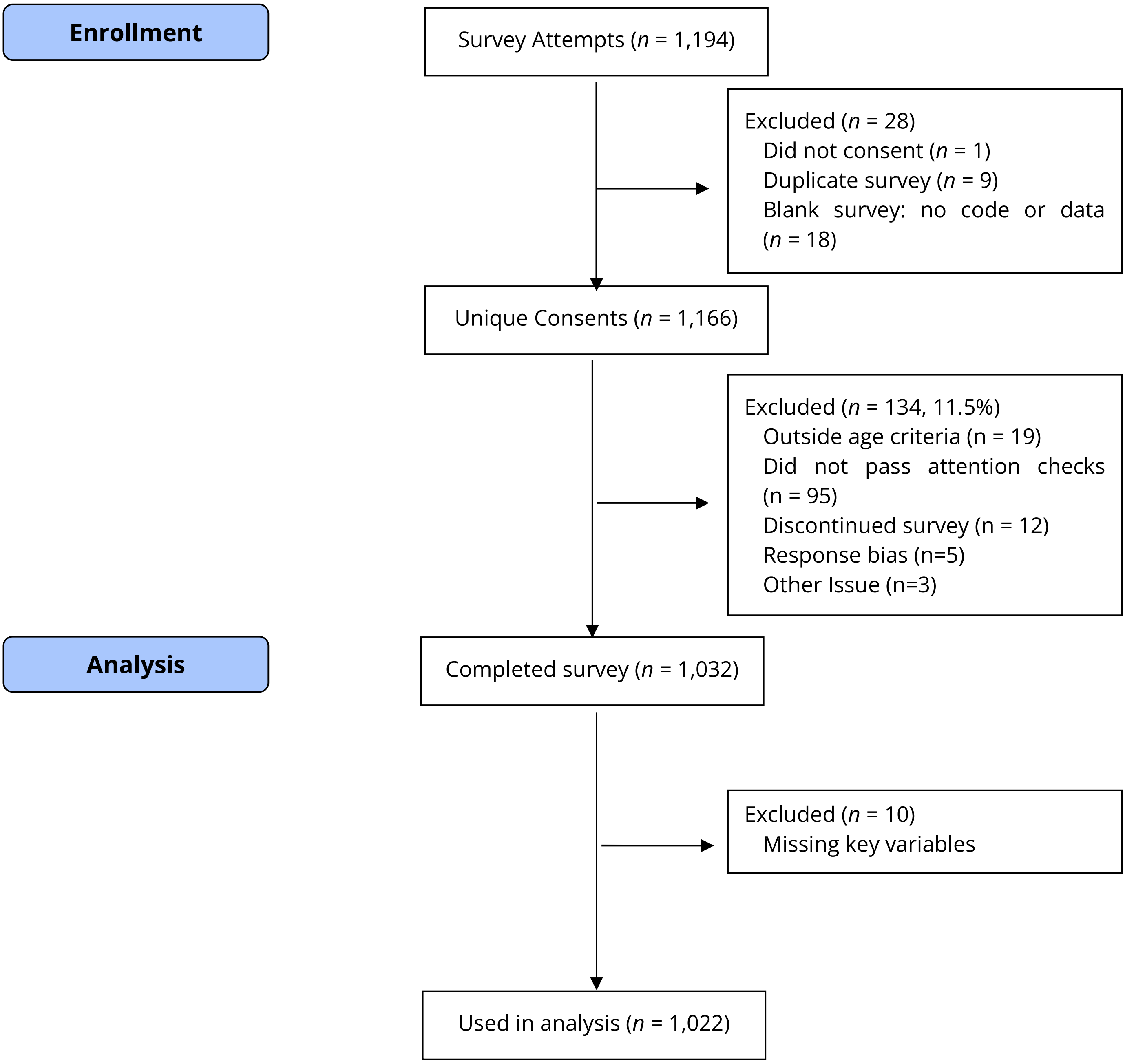
Appendix

Figure A1. *Consort Flow Diagram of Participants for 2021 Lifestyle of Young Adults Survey.*



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