Every (Insta)gram counts? Applying cultivation theory to explore the effects of Instagram on young users’ body image

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Abstract

Recent research suggests that social networks have replaced traditional media as the main channel by which beauty ideals are conveyed—often resulting in body dissatisfaction and reduced self-esteem among users. While social comparison theory provides an empirically sound approach to these effects, we argue that additional insight may be offered by cultivation theory and its structured exploration of cognitive, attitudinal, and behavioral outcome variables. Thus, the present study scrutinizes the social network Instagram as a potential cultivation system for young adults’ body image. Recruiting 228 participants aged 18 to 34 years, we systematically explore three orders of cultivation, i.e., changes in weight-related knowledge, attitudes, and self-reported dietary restraint. As we differentiate between Instagram use quantity and quality, we observe that mere usage time cannot predict the assumed outcomes; instead, only participants’ tendency to browse Instagram’s public content emerges as a relevant predictor, connecting to biased views on the physical appearance of strangers, as well as more disordered eating behavior. Considering the fact that Instagram use relates more to other-focused than to self-focused perceptions in our study, we argue that cultivation theory can indeed complement social comparison theory in the current understanding of media-transmitted body images. (195 words)

Significance statement: This paper lends both a theoretical foundation as well as empirical support to the argument that highly-visual social media constitute a meaningful cultivation system for body-related attitudes and behaviors among young adults. Our research illustrates how the frequent exposure to the virtual self-presentation of others may affect the way people look at strangers’ bodies or indulge in disordered eating—even if their own body esteem remains intact.

Keywords: social media, cultivation theory, body image, body dissatisfaction, disordered eating
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People’s concept of beautiful appearances does not result from isolated contemplation, but gets shaped—quite literally—by social interactions and the consumption of media. In regard to the latter, a large body of 20th century media research has explored the role of television shows, movies, and printed advertisements as breeding grounds for a problematic body image among mass audiences (Grabe, Ward, & Hyde, 2008). Since the turn of the millennium, however, a notable shift of focus has occurred; acknowledging the evolved media use of the “digital generation,” more and more studies now address the impact of social networking sites (SNS) on people’s perception and evaluation of physical appearances (e.g., Choukas-Bradley et al., 2018; Holland & Tiggemann, 2016; Tiggemann et al., 2018).

Initially, most scientific interest in the relationship between social media and people’s body image revolved around Facebook, the first SNS to achieve global mass-adoptation. Following the platform’s swift rise to success, media psychological studies soon noted that Facebook’s numerous means of self-presentation exerted a rather problematic influence on the bodily perceptions of its users (e.g., Fardouly, & Vartanian, 2015; Stronge et al., 2015; Tiggemann & Slater, 2013)—especially among those who frequently used the website’s photo-related features (Kim & Chock, 2015; Meier & Gray, 2014). In recent years, however, several new SNS have appeared on the global stage, and compared to Facebook, many of them put an even stronger emphasis on the sharing of visual content. In consequence, contemporary body image researchers have redirected their attention yet again, setting out to explore how platforms such as Pinterest (Lewallen & Behm-Morawitz, 2016) or Snapchat (Marengo et al., 2018) influence young people’s concept of the “ideal” body. Most of all, the research field has taken a strong interest in Instagram, a subsidiary of Facebook, which currently ranks as the most popular social network.
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among young adults (Anderson & Jiang, 2018). Apart from a basic commenting function, Instagram disregards any text-based features in order to strictly emphasize the sharing of pictures and videos. In its resulting role as the Internet’s leading “highly-visual social media” (Marengo et al., 2018), the platform has also emerged as a cornerstone to young people’s conceptualization of physical beauty, not least due to its strong focus on fitness, make-up, fashion, and dietary topics (Carrotte, Vella, & Lim, 2015; Hu, Manikonda, & Kambhampati, 2014; Pinkerton et al., 2017).

Along these lines, recent content analyses indicate that Instagram has turned into the main hub for so-called fitpiration and thinspiration content—portmanteaus from the words “fit/thin” and “inspiration”—which glorifies an athletic and healthy, but sometimes also alarmingly skinny appearance (Ghaznavi & Taylor, 2015; Ging & Garvey, 2017; Tiggemann & Zaccardo, 2016). While the creators of the respective uploads usually stress their benevolent intentions, recent studies have demonstrated that fit- and (especially) thinspiration posts tend to have quite negative effects on young audiences, nudging them towards unattainable beauty standards and disordered eating behaviors (Lewallen & Behm-Morawitz, 2016; Tiggemann & Zaccardo, 2016). From a media psychological perspective, this suggests that certain aspects of social media might invoke cultivation processes similar to the ones that have been observed in the context of traditional mass media. However, we note that previous studies have not yet pursued this theoretical angle, as scholars usually prefer to conceptualize SNS effects as short-term, social psychological phenomena. Without wanting to refute the value of this kind of work, the current paper will present readers with arguments—both theoretical and empirical in nature—as to why the research field might benefit from interpreting social media use as a multi-faceted cultivation process.

The Current Understanding of Social Media Effects on Users’ Body Image

When discussing the potential mechanisms behind the negative impact of social media on their users’ body image, scientific literature has mainly resorted to social comparison theory...
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(SCT; Festinger, 1954) as the decisive explanatory framework. This theory suggests that people possess an innate tendency to evaluate their identity, appearance, and beliefs by comparing themselves to others around them, leading to various, often-problematic outcomes. Specifically, research suggests that social comparisons seem to be a bidirectional process; whereas downward comparisons—focusing on people of lower status—serve as a defensive mechanism to reinforce self-esteem (Wills, 1981), upward comparisons that target more successful or supposedly better-natured individuals usually result in negative effects, such as a loss of self-worth or reduced psychological well-being (e.g., Suls & Wheeler, 2000; Tesser, Millar, & Moore, 1989).

With only a few exceptions, social media users tend to manage their virtual self-presentation rather elaborately (Krämer & Winter, 2008; Zhao, Grasmuck, & Martin, 2008), for instance by excluding negative experiences from their profiles or actively manipulating new uploads via filters and enhancement software (Kleemans et al., 2018). In turn, the high prevalence of curated and edited content on SNS has been shown to create an environment of constant upward comparison, prompting dysfunctional self-perceptions among other users (Liu et al., 2017; Vogel et al., 2014; Yang, 2016). As such, Cohen and Blaszczynski (2015) argue that the social nature of platforms such as Facebook and Instagram turns them into a virulent cause for body dissatisfaction, which might even surpass conventional media in terms of influential power. After all, television audiences may consider the displayed perfection as a unique feature of celebrity life; social networking, on the other hand, suggests that beautiful appearances are omnipresent, reaching from one’s closest friends to countless “normal” people all over the world. Moreover, as social media typically suggest that beauty equals likability—kept salient by ubiquitous like and heart buttons—users are conditioned to adopt the conveyed beauty ideals if they look for approval from the virtual community. As a result, a vicious circle of upward social comparisons may ensue.
Finding Additional Value in Cultivation Theory

While SCT certainly offers a relevant approach to body-related social media effects, we believe that the theory is somewhat limited by its chief focus on *self-related* attitudes. In other words, by only addressing how using SNS shapes people’s opinion about their own bodies, the theory fails to acknowledge many other potential consequences of this media practice, such as the formation of wrong assumptions about society or the adoption of new beliefs about others. Furthermore, we argue that SCT-based research is often inhibited by its narrow view on affective outcome variables (e.g., anxiety, reduced self-esteem), whereas it rarely mentions, let alone explains, cognitive or behavioral effects.

To fill in the identified research gaps, the current paper proposes adding another theoretical framework to the scientific investigation of social media effects—one that has received a lot of attention in the context of traditional media, yet become more of a side-note in the exploration of SNS: Cultivation theory (CT). Proposed by Gerbner and Gross (1976), CT assumes that the repeated and extensive use of mass media will entice audiences to absorb the broadcast information into their worldview, successively homogenizing viewers into a singular mainstream. Once this process has advanced for a notable amount of time, a number of problematic consequences may ensue, including the loss of political diversity or a desensitization towards violence (e.g., Fox & Potocki, 2015). Moreover, according to the work of body image scholars, CT not only offers an explanation as to why users of traditional media experience body dissatisfaction (Botta, 1999; Grabe, Ward, & Hyde, 2008; Holmstrom, 2010), but also accounts for subsequent behavioral effects such as the development of eating disorders (Hammermeister et al., 2005; Shanahan & Morgan, 1999). As certain beauty ideals and fitness behaviors are promoted repeatedly by the media of choice, recipients are led to believe that these depictions constitute the societal norm, thus assimilating them into their own attitudinal repertoire (thin-
ideal internalisation). Following this process, even small dissimilarities between one’s own appearance and the cultivated ideal may evoke strong behavioral efforts to conform to the media-transmitted beauty norms.

In the current understanding of CT, each of the described changes corresponds to a different level or so-called order of cultivation. Constituting the ignition spark of the cultivation process, first-order effects describe changes in people’s estimates of real-life frequencies, events, and distributions as they arise from mass media consumption (Hawkins & Pingree, 1982). Proceeding from there, second-order effects encompass transformations of the audience’s attitudes and value systems, which build on top of these changed factual assumptions. Lastly, in a more recent modification of CT, Nabi and Sullivan (2001) added a third order of cultivation, capturing changes in media users’ observable behavior that result from the first two orders of the process. Thus, in summary, contemporary CT describes a hierarchical phenomenon following the prolonged exposure to similar media contents—reaching from cognitive changes to observable conative effects.

Unlike its acclaim in 20th century media psychological literature, however, CT has been featured rather sparsely in the exploration of social media effects. For instance, regarding the popular platform Instagram, only a handful of studies—most of them with extremely limited sample sizes (e.g., Goldstraw & Keegan, 2016; O’Brien, 2015)—even mentions CT. In our interpretation, two reasons might account for this recline in academic interest. Firstly, experimental studies indicate that social media effects often occur quite quickly, sometimes even after a single, brief exposure (e.g., Fardouly et al., 2015; Haferkramp & Kramer, 2011; Kleemans et al., 2018), which arguably undercuts the need for CT’s overarching approach. Secondly, and maybe more importantly, it might be argued that cultivation processes require invariable, standardized stimuli (such as a predetermined television schedule) in order to come into effect; a
requirement that modern SNS and their dynamically adjusted content feeds do not seem to meet. However, we believe that this logic is flawed. In fact, the consumption of conventional media does not necessarily constitute an equalized stimulus either—quite the opposite, media such as television or newspapers typically offer a vast range of content as well, with hundreds of channels or magazines available to customers. Yet, despite this range of potential sources, previous cultivation research has still managed to uncover notable effects, which suggests that people ultimately tend to choose similar media offerings, thus prompting media producers to create more of the same (Bourdieu, 2001; Waisbord, 2004).

In a similar vein, literature suggests that social media experiences may be much more homogenous than their often-claimed customizability suggests. On most SNS, the divide between producers and consumers has blurred, and most new uploads are created by layperson users (user-generated content). According to recent analyses, this has only fostered the homogenization of popular platforms, as many people try to align their posts with “trending” topics or the aesthetics they attribute to a specific site (Ong, 2018; Shamsian, 2018; Yau & Reich, 2019). Moreover, studies show that social media users typically show very high agreement on the gratifications they expect from different SNS (Lee et al., 2015; Phua et al., 2016), further invoking the homogenization of the respective platforms. Following these arguments, we believe that it actually makes a lot of sense to explore highly-visual social media as cultivation nexuses that influence many users in a similar way.

**Hypotheses**

The social network Instagram provides a popular backdrop for fitness, fashion, and other body-related media content (Ehrhardt, 2018). Thus, it comes as little surprise that extensive use of the service has been identified as an antecedent of body dissatisfaction and reduced self-esteem (e.g., Liu et al., 2017; Vogel et al., 2014). However, other potential consequences of
Instagram’s homogenized, often visually enhanced content remain somewhat neglected in the scientific discourse. To overcome this research gap, the current study set out to systematically scrutinize the platform Instagram as a cultivation system for weight-related cognitions, attitudes, and behavior—ranging from changed assumptions about society to the adoption of concrete dietary rules.

During the preparation of our hypotheses, we pondered different ways as to how participants’ Instagram use might affect them. Previous literature suggested to us that the mere duration of social media use might not suffice to explain hypothesized outcomes in a meaningful way (e.g., Frison & Eggermont, 2017; Yang, 2016). This also seemed to apply to our specific research focus: People might spend a lot of time on SNS, but engage only with their own profiles or the content of friends, which would shield them from the proposed cultivation effects. At the same time, we did not want to disregard the factor time altogether, keeping in mind that the whole idea of cultivation revolves around repeated and lengthy media exposure. Moreover, we believed that a longer net time spent on the platform was likely to increase users’ exposure to Instagram’s fitness and dieting content, even if they could not explicitly recall it in a qualitative self-report measure. As such, we decided to include both (a) the weekly time people spent on Instagram, as well as (b) their specific interest in browsing the platforms’ public contents as two separate predictors in our research propositions.

Starting with the first order of cultivation, our first hypothesis assumed changes in participants’ factual assumptions about the general population, as we asked them to estimate the prevalence of both overweight and body satisfaction in their native country. Considering that the highly selective uploads on Instagram convey a distorted impression of real-life (Kleemans et al., 2018), we supposed that active users of the SNS would tend to underestimate the prevalence of overweight, yet overestimate the number of people satisfied with their own body.
H1: Young adults’ (a) Instagram use duration and (b) Instagram browsing activity *negatively* predict their estimation of the overweight prevalence in the general population.

H2: Young adults’ (a) Instagram use duration and (b) Instagram browsing activity *positively* predict their estimation of the body satisfaction prevalence in the general population.

Proceeding to second-order cultivation effects—i.e., the formation of attitudes and norms via media exposure—we explicitly differentiated between views on one’s own body and views on the bodies of strangers. In terms of self-assessment, we expected active Instagram users to hold a less favorable view on their own body, as the repeated exposure to flattering and manipulated imagery should equip them with unrealistic beauty ideals. Arguably, this specific hypothesis marked the one instance where our CT-guided assumptions blended rather well with SCT, mirroring previous findings from social comparison studies (e.g., Liu et al., 2017; Vogel et al., 2014).

H3: Young adults’ (a) Instagram use duration and (b) Instagram browsing activity *negatively* predict their own body esteem.

To explore other-related attitudes, we asked participants to rate various full-body photographs in terms of the weight of the depicted people (ranging from “clearly underweight” to “clearly overweight”). According to CT, we assumed that longer Instagram use, as well as a stronger engagement with the platforms’ public content would lead to stricter weight norms—manifested as a systematic shift towards higher weight ratings in the provided task.

H4: Young adults’ (a) Instagram use duration and (b) Instagram browsing activity *positively* predict the weight level they ascribe to the bodies of strangers.
Addressing the third order of cultivation, we presumed that spending a lot of time on—and actively browsing through—Instagram with its numerous “fitspiring” and nutrition-related posts would affect users’ behavioral intentions regarding meals and diets.

**H5:** Young adults’ (a) Instagram use duration and (b) Instagram browsing activity *positively* predict their dietary restraint.

Despite the on-going alleviation of societal norms, research shows that young women are still subjected to much stricter beauty ideals than men (Carlson Jones, 2004; Hargreaves & Tiggemann, 2004)—a fact that has also been used to explain the skewed gender distribution of clinical eating disorders (e.g., Udo & Grillo, 2018). At the same time, scientific evidence cautions against trivializing male beauty standards, as a growing number of studies indicates that young boys are also severely affected by medially transmitted body ideals (e.g., Agliata & Tantleff-Dunn, 2004; Blashill & Wilhelm, 2014). In consequence, we decided to include both female and male participants in our study, which allowed us to explore whether the assumed cultivation effects would be moderated by participants’ gender. Based on the reviewed evidence on negative outcomes for both men and women, an open-ended research question was formulated instead of a directional hypothesis:

**RQ1:** Are the proposed negative outcomes of Instagram use moderated by participants’ gender?

**Method**

**Participants**

Following a recruitment process via university mailing lists and social media groups, the study’s initial sample consisted of *N* = 234 participants (age *M* = 22.8 years, *SD* = 4.13; 176 women, 57 men, 1 unspecified). In order to be included in the study, participants had to indicate
German as their main language and fall into the age range between 18 and 34 years, since we were specifically interested in body image issues among young adults. However, six obtained datasets exceeded the specified age bracket, so that we only used the data of \( n = 228 \) participants in our final analyses (age \( M = 22.5 \) years, SD = 3.04; 171 women, 56 men, 1 unspecified).

Immediately after accessing the prepared online questionnaire, participants received comprehensive information about the anonymity and protection of their data, as well as the goal of the current research project. Only after they gave their informed consent, participants were allowed to proceed to the actual questionnaire. As a reward for their contribution, every person taking part in this study received a ticket for a €25 gift card raffle; students from the local university could alternatively choose partial course credits.

**Stimulus Materials**

For the exploration of participants’ attitudes towards the bodies of strangers—one aspect of the proposed second-order cultivation effect—we prepared visual stimuli by assembling our own set of 36 full-body photographs (taken from public Instagram profiles). Expecting a systematic distortion in Instagram users’ view on physical appearances, we decided to depict a wide spectrum of the human physique, collecting photos of many different body types (e.g., muscular, slender, chubby, obese). Doing so, we also made sure to portray a perfectly balanced female-to-male ratio, and to include different ethnicities in our collection. To avoid confounding effects that might have arisen from the recognition of celebrities, we further decided to focus on unknown pictures with little social media visibility—even though research suggests that the uploads of laypersons may actually exert quite similar effects on users’ body image than the photos of famous celebrities (Brown & Tiggemann, 2016).

To confirm if our final set of pictures (depicting 18 women and 18 men) indeed resembled the intended broad spectrum of body shapes, we conducted a pretest with \( N = 15 \) independent
student raters (including both Instagram users and non-users), requesting them to sort the selected pictures into five ascending categories (“clearly underweight,” “slightly underweight,” “average,” “slightly overweight,” and “clearly overweight”). By calculating the mean score from the obtained 15 ratings, we found that our 36 pictures were indeed scattered rather equally across the five weight categories, indicating the appropriateness of our materials as a depiction of very different body shapes.

Measures

**Instagram use.** Previous research has cautioned against using only the duration of social media use to explain different outcomes (e.g., Yang, 2016). Therefore, we decided to differentiate between quantitative and qualitative aspects of participants’ Instagram use, adding both as distinct predictors to our exploration of cultivation effects.

To measure the *quantity* of participants’ Instagram use, we simply asked them for the average number of hours they spent on the platform in a normal week—which had to be entered as a numerical value into a text field. Concerning their use *quality*, on the other hand, participants were requested to express how much they typically browsed through the public content of the Instagram community. For this purpose, we adapted four items from a previously published list of SNS activities (Meier & Grey, 2014; Hendrickse et al., 2017), namely “I look at the profiles of other users,” “I read the comments on photos and videos of other users,” “I comment on photos and videos of other users,” and “I use the like function on photos and videos of other users”. All items were presented as 5-point Likert scales (1 = *never*, 5 = *very often*). To further emphasize our focus on the content of strangers, we juxtaposed the described items with two irrelevant questions about the content of friends (e.g., “On Instagram, I look at the photos and videos of friends.”). The resulting *Instagram browsing* index showed very good internal reliability, Cronbach’s $\alpha = .86$. Although it could be argued that two of our chosen items referred more to
the passive exploration of content while the other two addressed active interactions, an
exploratory factor analysis clearly demonstrated the measure’s unidimensionality, with a single
factor explaining 72.2% of the total observed variance.

**Weight-related estimations.** To assess potential changes in participants’ assumptions
about real-life frequencies, we asked them to estimate the percentage of overweight people—i.e.,
those with a body mass index (BMI) above 25 kg/m²—in the total population of Germany.¹

As a second, potentially skewed factual assumption, we explored participants’ estimations
of the country-wide body satisfaction (“What percentage of the German population do you
believe to be happy with their own body?”).²

**Body image attitudes.** Participants’ view on their own body was measured using the
*Body Esteem Scale for Adolescents and Adults* (BESAA; Mendelson, Mendelson, & White,
2001), which contains the three sub-scales appearance satisfaction (10 items, e.g., “I like what I
look like in pictures”), weight satisfaction (8 items, e.g., “I’m proud of my body”), and external
attribution (5 items, e.g., “Other people consider me good-looking”). However, since we were not
interested in factors such as clothing or external validation, we focused our analysis on the
second sub-scale, which strictly addresses attitudes regarding the own body shape and weight. All
items had to be rated on a 5-point Likert scale (1 = *not at all*, 5 = *completely*), with internal
consistency of the weight satisfaction scale turning out excellent, Cronbach’s α = .93.

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¹ The actual value provided by the Robert Koch institute, a subordinate of the German Federal Ministry of Health, is
54% (Schienkiewitz et al., 2017). Accordingly, any number below this value indicated a participant’s
underestimation of the national obesity prevalence, whereas higher percentages indicated an overestimation.

² Using the empirical value provided by a large-scale survey of 1058 Germans (myMarktforschung, 2016), any
answer below 51% indicated an underestimation of the body satisfaction in the broader public, whereas higher values
expressed an overestimation.
For the exploration of participants’ other-related body image, they were required to rate the collected 36 full-body portraits on 5-point scales, ranging from clearly underweight (1) to clearly overweight (5). By averaging all 36 evaluations, we acquired a composite weight rating score spanning the full spectrum of presented body types.

**Dietary behaviors.** The *Eating Attitudes Test* (EAT-26; Garner & Garfinkel, 1979) ranks among the most well-established instruments for a reliable assessment of diet-related motivations and activities. Although the questionnaire has been originally developed for the diagnosis of clinical eating disorders (and still retains its popularity in this field), it has also been employed in non-clinical settings (e.g., Rogoza, Brytek-Matera, & Garner, 2016). In our study, we used the German short version of the scale (EAT-13D; Berger et al., 2012), which has been described as a risk screening of problematic dietary behavior by its authors. All 13 items (e.g., “I like my stomach to be empty,” “I display self-control around food”) had to be answered in a 5-point format (1 = never, 5 = always). We observed excellent internal consistency for the EAT-13D, Cronbach’s $\alpha = .92$.

**Control variables.** Apart from participants’ age and gender, we kindly requested them to disclose their body height and weight so that we could calculate individual body mass indices (BMI; defined as body mass divided by the square of the body height). Next, we subtracted participants’ actual BMI from the value 21.7—which marks the “perfect” midpoint of the healthy weight range suggested by the World Health Organization (2008)—and only used the absolute result of this subtraction in our later analyses. This specific procedure was chosen in order to account for the possibility that both under- and overweight could have had notable effects on our dependent variables—a finding that would have been clouded by simply using the BMI in our linear regression procedure.

**Results**
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Table 1 gives a descriptive overview of all measured variables, while Table 2 summarizes the zero-order correlations between them. Corresponding to our five hypotheses, we conducted a total of five hierarchical linear regression analyses with IBM SPSS 20 software—exploring the prediction of participants’ factual estimations (H1 and H2), self- and other-related attitudes (H3 and H4), and self-reported disordered eating behavior (H5). In each of these analyses, participants’ age, gender, and deviation from a perfect BMI were entered in the first step of the hierarchical procedure. Then, in the second step, we added the obtained measures of Instagram use: Use duration (in hours) and browsing activity (as assessed by our self-developed browsing index). If either of these two variables emerged as a significant predictor, we further calculated a third, moderated regression model, which included interaction terms between the significant Instagram use variable(s) and participants’ gender (i.e., “gender × Instagram use duration” or “gender × Instagram browsing activity”). This third step served to give an informed answer to our additional research question on the moderating role of gender for the proposed cultivation effects. For readers’ convenience, Tables 3 through 7 present an overview of all calculated regression models.

First-order cultivation: Estimations

Our first hierarchical regression focused on participants’ estimations of the national overweight prevalence as a potentially cultivated real-world assumption (H1). Using participants’ estimations as a criterion and entering the three sociodemographic predictors, the first step of our model accounted for approximately 11% of the observable variance, $F(3,223) = 8.81, p < .01$. Specifically, we found that all three demographic variables significantly predicted participants’

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3 As required for this kind of procedure, non-binary variables such as age or Instagram use duration were mean-centered before calculating the interaction terms for the moderated regression.
estimations of the overweight prevalence: Age ($\beta = .25, t[223] = 3.67, p < .01$), gender ($\beta = -.24, t[223] = 3.48, p = .03$), and deviation from a perfect BMI ($\beta = .19, t[223] = 2.98, p < .01$).

Considering the orientation of the beta values and our dummy coding of the gender variable, this means that both higher age and female gender were related to higher estimations of the national overweight prevalence. In terms of BMI, the positive coefficient indicates that participants with an increased deviation from a healthy body weight expected a higher percentage of people in the general population to be obese. Proceeding to the second step of our regression model, however, no significant increase in $R^2$ could be observed, $\Delta R^2 < .01, p = .79$. As such, we note that participants’ Instagram use remained mostly unrelated to their perceptions of the weight distribution in the general population (Tab. 3).

To explore H2, we conducted a hierarchical linear regression using participants’ assumed prevalence of body satisfaction in Germany as the criterion. Our first step led to a significant regression equation, $F(3,223) = 2.93, p = .03$, albeit with a rather low coefficient of determination, $R^2 = .04$. Among the entered predictors, only participants’ gender became significant, $\beta = .21, t(223) = 2.95, p < .01$, indicating that male respondents believed a higher percentage of Germans to be satisfied with their own body. Again, adding our Instagram variables to the regression model did not lead to a significantly higher $R^2$ ($\Delta R^2 = .02; p = .09$), suggesting that more intense usage of Instagram did not connect to changed estimations of prevalence in a statistically noteworthy way (Tab. 4). In conclusion, we have to reject both H1 and H2.

**Second-order cultivation: Attitudes**

Our next hierarchical regression addressed participants’ attitudes about their own body as measured by the BESAA weight satisfaction index (H3). An initial model using only the three demographic predictors resulted in a significant equation, $F(3,223) = 13.24, p = .00, R^2 = .15$. 
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More precisely, both age ($\beta = -0.17, t(223) = 2.49, p = .01$) and gender ($\beta = 0.22, t(223) = 3.28, p < .01$), as well as deviation from a perfect BMI ($\beta = -0.34, t(223) = 5.43, p < .01$) could be linked to the outcome variable in a significant way. Whereas the difference between participants’ BMI and the perfect value of 21.7 actually emerged as the strongest predictor—a less ideal BMI went along with higher body dissatisfaction—we also observed that older age and female gender predicted unfavorable self-perceptions. In our regression’s second step, however, adding the two Instagram use variables did not reveal the effects that we had anticipated (Tab. 5). With no significant increase in $R^2 (\Delta R^2 = .01, p = .24)$ and two insignificant beta coefficients, we cannot report a meaningful connection between usage of the photo-sharing platform and individuals’ body esteem, leading to a rejection of H3.

A different picture emerged from our forth regression analysis, using participants’ averaged weight rating for the 36 presented full-body photographs as a criterion. In this case, the first regression model containing only the sociodemographic predictors did not turn out significant, $F(3,223) = 1.48, p = .22, R^2 = .02$. However, having added the two Instagram use variables during the second step of the procedure, a significant increase in $R^2$ occurred ($\Delta R^2 = .04, p = .02$). The resulting five-predictor model now explained nearly 6% of the criterion’s variance, $F(5,221) = 2.59, p = .03$. In particular, we examined that only the Instagram browsing index—not participants’ weekly use duration—was found to be a significant predictor, $\beta = .24, t(221) = 2.89, p < .01$. Accordingly, a stronger tendency to browse through the profiles of other Instagram users actually went along with a higher averaged weight rating in our photo rating task. As such, we conclude that our data do not support H4a, but present evidence in favor of H4b.

Since Instagram browsing had emerged as a significant predictor for participants’ views on strangers’ weight, we calculated a third regression model, which further included the interaction term “gender × Instagram browsing” (addressing our exploratory RQ). Indeed, this
third model explained significantly more variance than the second, $\Delta R^2 = .02$, $p = .02$, allowing a slightly better prediction of participants’ weight ratings, $F(6,220) = 3.05$, $p < .01$, $R^2 = .08$.

Considering the negative coefficient of the interaction term, $\beta = -.50$, $t(220) = 2.89$, $p < .01$, and inspecting the slopes for women and men, we examined that Instagram browsing was only related to stricter weight ratings among female participants. Among men, this specific type of SNS use could not be linked to a different assessment of strangers’ weight.

**Third-order cultivation: Behavior**

In our final regression analysis, we investigated participants’ self-reported disordered eating behavior as a criterion (Tab. 7). A first model with the three demographic predictors explained approximately 7% of the observable variance, $F(3,223) = 5.66$, $p < .01$. Surprisingly, only age ($\beta = .19$, $t(223) = 2.67$, $p < .01$) and gender ($\beta = -.25$, $t(223) = 3.55$, $p < .01$) were found to be highly relevant from a statistical perspective, whereas BMI deviation ($\beta = .12$, $t(223) = 1.76$, $p = .08$) slightly missed the conventional threshold of statistical significance. Entering Instagram use duration and Instagram browsing in the procedure’s second step, however, led to a significant increase in $R^2$ ($\Delta R^2 = .04$, $p < .01$). In the resulting five-predictor model, it was again participants’ interest in browsing through Instagram which emerged as a significant predictor of problematic dietary behavior, $\beta = .17$, $t(221) = 2.09$, $p = .04$. As such, we report that participants’ self-reported tendency to pursue disordered eating was related to higher age, female gender, and—in line with our assumption H5—a stronger interest in Instagram browsing. Regarding the potential role of gender as a moderator of the observed Instagram effect, we again added a third step to the regression model, entering the interaction term “gender × Instagram browsing”.

Interestingly, this did not result in a significant increase of the model’s determination coefficient ($\Delta R^2 < .01$, $p = .79$), so that we can report a similar effect of Instagram browsing on the eating behavior of both women and men.
Discussion

A large body of media psychological research has demonstrated that frequent SNS use can severely affect people’s self-worth, happiness, and general psychological well-being. Beyond these self-related aspects, however, the research field has focused much less on the various other, body-related changes that might occur by repeatedly looking into social media’s distorted mirror of reality. To remedy this shortcoming, the current study conducted a structured investigation of cognitive, attitudinal, and behavioral facets of people’s body image, using the well-established framework of CT. Doing so, we observed that a stronger tendency to browse the social network Instagram predicted stricter views on the weight of strangers (especially among women), as well as an increased risk for disordered eating (among both genders). To our surprise, these relationships were examined despite the fact that stronger Instagram browsing could not be linked to a reduced satisfaction with the own body—the only assumption that mirrored the findings of previous studies.

Providing a possible explanation for our results pattern, we suggest that frequent explorations of strangers’ social media content (the specific activity operationalized in our “browsing index”) could be related to the cultivation of a “third-person gaze,” in that the frequent exposure to the appearances of strangers exerts a stronger influence on other-related than on self-related body schemata. Arguably, this paints a picture different from the one offered by SCT, which postulates that the perception of others provides a very important basis for the evaluation (and adjustment) of the self. We would like to point out, however, that several studies on social comparisons have stressed the particular role of peer comparisons (e.g., Chou & Edge, 2012; Corcoran & Mussweiler, 2009; Lubbers, Kuyper, & van der Werf, 2009) as routine standards in daily life. Hence, it might be possible that young SNS users simply prefer the profiles of their friends and colleagues as a resource for their self-evaluation, whereas browsing public Instagram
profiles might serve to modify future impressions of others. In this sense, CT can indeed complement SCT as an explanatory approach to SNS effects—even though additional work is clearly needed to scrutinize our newly formed assumptions. Most of all, it has to be noted that the results of our hierarchical regression analyses are correlational in nature, making it impossible to interpret the yielded insight as evidence for causal relationships. Eventually, many different explanations or currently neglected variables might account for the observed effects. Therefore, we ask readers to interpret the reported findings with appropriate caution.

Despite this important restriction, however, we consider it a noteworthy empirical finding that Instagram browsing emerged as a significant predictor of dietary restraint—whereas neither participants’ actual body mass nor their individual weight satisfaction could be connected to this criterion in a meaningful way. As such, we come to the conclusion that platforms such as Instagram may indeed play a notable role in promoting disordered eating among young adults. At the same time, it is important to note that the mere time spent on Instagram showed no significant connection to our behavioral measure (or to any other outcome variable). Therefore, we think it may be wise not to demonize social media from the outset, but to differentiate between the specific uses and gratifications young users pursue when accessing SNS. Similar to the results reported by recent meta-analyses (e.g., Marker, Gnambs, & Appel, 2017; Verduyn et al., 2017), our study indicated that it might be much less important how often people use social media than what they use it for. Thus, we believe that future interventions aimed at improving young people’s body image might be more successful if they address the way social media are used, other than rallying against them altogether. As a potential starting point, institutional health initiatives may find a good opportunity in picking up the “body positivity,” “fat acceptance,” and “self-compassion” movements that have emerged on social networks in recent years (e.g., Retallack, Ringrose, & Lawrence, 2016; Slater, Varsani, & Diedrichs, 2017).
EVERY (INSTA)GRAM COUNTS?

Last but not least, we want to highlight our findings in terms of gender roles. In accordance with most previous studies, our regression analyses indicated that females were more likely to overestimate the frequency of body satisfaction in the general population, to hold an unfavorable view on their own body, and to indulge in risky eating behavior (corresponding to all three orders of cultivation). Moreover, the observed relationship between Instagram browsing and the weight ratings assigned to strangers was much more pronounced among female than among male participants. Without wanting to detract from the experience of young boys and men, our results do support the notion that body perceptions and their consequences are still a particularly female burden. On the other hand, we would like to acknowledge that sexual orientation might play a sensitive role in this regard, as previous studies suggest a much higher impact of media-transmitted body images on gay than on heterosexual men (e.g., McArdle & Hill, 2007).

**Future Work and Limitations**

Reflecting on the value of CT in the social media context, we still consider the framework a formidable guideline to address various aspects of human experience after the extensive use of SNS. After all, formulating our hypotheses along the lines of CT allowed us to uncover effects that might have remained hidden in a study applying a more narrow theory such as SCT.

At the same time, our data indicate that in order to uncover the full impact of social media as a cultivation system, it may be advisable to conduct further longitudinal studies that assess people’s thoughts, feelings, and behaviors beyond a single observational point. Of course, any future research on the presented topic would also benefit from more diverse study samples in order to grasp the generalizability of our results. Then again, recent literature suggests that the international success of a few selected media providers—in particular US-based services such as Netflix, Instagram, and YouTube—has invoked a notable *media globalization* in recent years, blurring the preferences and experiences of digital citizens all over the world (e.g., Cunningham
EVERY (INSTA)GRAM COUNTS?

& Craig, 2016; Lule, 2018). Still, we want to underscore that the presented study can only speak to the experience of young adults in Germany, which might turn out differently in other cultures or stages of life. In a similar vein, we would like to emphasize that our findings might be very characteristic for the “Instagram experience,” yet not apply to the many other SNS available at the current time. As indicated by previous research (e.g., Lee et al., 2015; Phua et al., 2016), social media users seem to agree rather strongly on the distinct affordances of a particular SNS, which may explain both the homogenization within, as well as the diversification between existing social media platforms. Thus, we deem it possible that our results relied on very specific characteristics of Instagram (e.g., the high prevalence of fitness and dietary advice on the website, or the fact that users are shown the most popular hashtags when preparing new uploads); using other SNS such as Snapchat or Pinterest, on the other hand, might lead to very different outcomes. Lastly, we would like to put it up for discussion whether the “browsing index” used in this study should be complemented by other, even more specific measures of social media use. For instance, it might make sense to conceive some form of a multiplicative index that combines use time and use quality into a singular index. Furthermore, it might be a valuable idea to assess users’ actual interest in different topics on SNS (e.g., by asking for the number of subscriptions to fitness channels) to increase the value of any follow-up studies. Doing so, future research could also scrutinize the idea that specific thematic interests or sub-cultural “niches” on social media play an important role in promoting a dysfunctional body image (Cohen, Newton-John, & Slater, 2017; Ging & Garvey, 2017). As such, we invite our peers to expand upon the presented work by conducting a more comprehensive exploration of Instagram users’ activities and personal interests. Last but not least, it might be worth the effort to take a closer look at dispositional factors that moderate the discussed effects, considering that media recipients have a different trait-like inclination to internalize media-transmitted ideals (Yamamiya et al., 2005).
EVERY (INSTA)GRAM COUNTS?

together, there are still many open questions on how social media affect people’s views on themselves and others. In order to give valid answers to them, it might be a good idea to build a theoretical foundation beyond the usual social psychological approach—and cultivation might be one important piece of the puzzle.
 EVERY (INSTA)GRAM COUNTS?

References


EVERY (INSTA)GRAM COUNTS?


EVERY (INSTA)GRAM COUNTS?

Ging, D., & Garvey, S. (2017). ‘Written in these scars are the stories I can’t explain’: A content analysis of pro-ana and thinspiration image sharing on Instagram. *New Media & Society, 20*(3), 1181–1200. https://doi.org/10.1177/1461444816687288


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https://doi.org/10.1080/10810730.2014.904022


https://doi.org/10.1177/2056305116640559


https://doi.org/10.1016/j.paid.2017.03.037


https://doi.org/10.1002/ejsp.475


https://doi.org/10.1007/s10648-017-9430-6


EVERY (INSTA)GRAM COUNTS?


Slater, A., Varsani, N., & Diedrichs, P. C. (2017). #fitspo or #loveyourself? The impact of fitspiration and self-compassion Instagram images on women’s body image, self-
EVERY (INSTA)GRAM COUNTS?


https://doi.org/10.1016/j.bodyim.2017.06.004


https://doi.org/10.1016/j.bodyim.2018.07.002


https://doi.org/10.1002/eat.22141


https://doi.org/10.1177/1359105316639436

EVERY (INSTA)GRAM COUNTS?


https://doi.org/10.1016/j.chb.2008.02.012
Table 1. *Means and standard deviations for the measured variables.*

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<th>Maximum</th>
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<td>37.9</td>
</tr>
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<td>3.60</td>
<td>0.01</td>
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<td>1.00</td>
<td>1.00</td>
<td>4.25</td>
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</table>

**first-order cultivation measures**

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<th></th>
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<td>33.4%</td>
<td>15.2%</td>
<td>5%</td>
<td>73%</td>
</tr>
<tr>
<td>estimation of body satisfaction prevalence</td>
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<td>13%</td>
<td>87.5%</td>
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**second-order cultivation measures**

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</thead>
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<td>BESAA weight satisfaction sub-scale$^1$</td>
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<td>0.99</td>
<td>1.00</td>
<td>5.00</td>
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<tr>
<td>Average weight ascribed to strangers' bodies$^1$</td>
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<td>0.19</td>
<td>2.72</td>
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**third-order cultivation measure**

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<td>EAT-13 scale for disordered eating$^1$</td>
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<td>0.88</td>
<td>1.00</td>
<td>4.77</td>
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</tbody>
</table>

*Notes. $N = 228$. $^1$ Scale range 1–5.*
Table 2. Zero-order correlations between measured variables.

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<th>7</th>
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<td>3</td>
<td>BMI</td>
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<td>.26**</td>
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<tr>
<td>4</td>
<td>weekly Instagram use</td>
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<td>–.22**</td>
<td>.07</td>
<td>–</td>
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<td></td>
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<td></td>
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<tr>
<td>5</td>
<td>Instagram browsing</td>
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<td>–.39**</td>
<td>.05</td>
<td>.53**</td>
<td>–</td>
<td></td>
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<td>.18**</td>
<td>–.12</td>
<td>.08</td>
<td>.05</td>
<td>.01</td>
<td>–</td>
<td></td>
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<td>7</td>
<td>estimation: national body satisfaction prevalence</td>
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<td>.17**</td>
<td>–.04</td>
<td>.09</td>
<td>.04</td>
<td>–.23**</td>
<td>–</td>
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<td>personal weight satisfaction</td>
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<td>.12</td>
<td>–.43**</td>
<td>–.13</td>
<td>–.12</td>
<td>–.09</td>
<td>.17*</td>
<td>–</td>
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<td>–.05</td>
<td>–.18**</td>
<td>.00</td>
<td>.16*</td>
<td>.19**</td>
<td>.03</td>
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<td>.28**</td>
<td>.18**</td>
<td>.23**</td>
<td>.10</td>
<td>–.08</td>
<td>–.67**</td>
<td>.14*</td>
</tr>
</tbody>
</table>

Notes. * \(p < .05\), ** \(p < .01\). \(^1\) Gender coded with “0” = female, “1” = male.
Table 3. Hierarchical regression with participants’ estimations of the national overweight prevalence as a criterion.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th>β</th>
<th>t</th>
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<th>R²</th>
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<td>8.81**</td>
<td>.11</td>
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<tr>
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<td>-.24*</td>
<td>3.48</td>
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<td></td>
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<tr>
<td></td>
<td>difference from perfect BMI</td>
<td>.19**</td>
<td>2.98</td>
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<tr>
<td>2</td>
<td>age</td>
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<td>3.57</td>
<td>5.34**</td>
<td>.11</td>
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<tr>
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<td></td>
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<td>2.96</td>
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<td>Instagram browsing</td>
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<td>0.63</td>
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Notes. * p <.05, ** p < .01. ¹ Gender coded with “0” = female, “1” = male.

Table 4. Hierarchical regression with participants’ estimations of the national body satisfaction prevalence as a criterion.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th>β</th>
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<th>F</th>
<th>R²</th>
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<td>2.93*</td>
<td>.04</td>
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<td></td>
<td>gender</td>
<td>.21**</td>
<td>2.95</td>
<td></td>
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<tr>
<td></td>
<td>difference from perfect BMI</td>
<td>-.04</td>
<td>0.61</td>
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<tr>
<td>2</td>
<td>age</td>
<td>-.07</td>
<td>1.03</td>
<td>2.76*</td>
<td>.06</td>
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<td></td>
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<td>.26**</td>
<td>3.43</td>
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<td>Instagram browsing</td>
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<td>0.91</td>
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</table>

Notes. * p <.05, ** p < .01. ¹ Gender coded with “0” = female, “1” = male.
Table 5. Hierarchical regression with participants’ personal weight satisfaction as a criterion.

<table>
<thead>
<tr>
<th>Regression</th>
<th>Variables</th>
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<th>$R^2$</th>
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<td>13.24**</td>
<td>.15</td>
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<td>difference from perfect BMI</td>
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<td>5.43</td>
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<td>8.54**</td>
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</table>

Notes. * $p < .05$, ** $p < .01$. $^1$ Gender coded with “0” = female, “1” = male.
Table 6. *Hierarchical regression with participants' average rating of strangers' weight as a criterion.*

<table>
<thead>
<tr>
<th></th>
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<th>t</th>
<th>F</th>
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<td>1.08</td>
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*Notes.*  
* p < .05, ** p < .01. \(^1\) Gender coded with “0” = female, “1” = male. In the \( R^2 \) column, asterisks indicate a significant \( R^2 \) change compared to the previous model.
Table 7. *Hierarchical regression with participants' self-reported disordered eating behavior as a criterion.*

<table>
<thead>
<tr>
<th></th>
<th></th>
<th>( \beta )</th>
<th>( t )</th>
<th>( F )</th>
<th>( R^2 )</th>
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<td>age</td>
<td>.21**</td>
<td>3.04</td>
<td>5.50**</td>
<td>.11**</td>
</tr>
<tr>
<td></td>
<td>gender (^1)</td>
<td>-.17*</td>
<td>2.39</td>
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<tr>
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<td>1.03</td>
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<td>2.09</td>
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<tr>
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<td>age</td>
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<td>3.05</td>
<td>4.58**</td>
<td>.11</td>
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<tr>
<td></td>
<td>gender (^1)</td>
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</table>

*Notes.*  
* \(* p < .05, ** p < .01. \(^1\) Gender coded with “0” = female, “1” = male. In the \( R^2 \) column, asterisks indicate a significant \( R^2 \) change compared to the previous step.*