December 2020

Potential Parallels Between Pro-Ana and Bodybuilding Content on Social Media

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POTENTIAL PARALLELS BETWEEN PRO-ANA AND BODYBUILDING CONTENT ON SOCIAL MEDIA

by

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A Thesis Submitted in

Partial Fulfillment of the

Requirements for the Degree of

Master of Arts

in Sociology

at

The University of Wisconsin – Milwaukee

December 2020

ABSTRACT

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The University of Wisconsin-Milwaukee, 2020
Under the Supervision of Professor Celeste Campos-Castillo

This thesis examined the relationship between pro-ana and bodybuilding social media content to understand the similarities between these populations' identities and help inform social media content policies. Two interrelated studies were used to investigate this relationship: Study 1 used computational methods which compared the content through machine classification of pro-ana and bodybuilding social media posts on Twitter and Study 2 fielded an online survey experiment to compare the perceptions and human classification of content from these populations on Instagram. The findings from both studies broadly revealed that pro-ana and bodybuilding identities are similar, at least in social media content, which raises concern for the current state of social media censorship policies. The results of this thesis highlight the critical need for social media censorship policies to be cognizant of different populations expressing the same content, creating discrepancies when only one is censored.

To

my mentors,

and especially my parents

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

ACT	Affect Control Theory
SNS(s)	Social Networking Site(s)
Pro-ana	Pro-Anorexic
AN	Anorexia Nervosa
IFBB	International Federation of Bodybuilders
NPC	National Physique Committee
ML	Machine Learning
Fitspo	Fitspiration
Thinspo	Thinspiration
BERT	Bi-directional Encoder Representations from Transformers
GPU	Graphic Processing Unit
TP	True Positive
TN	True Negative
FP	False Positive; Type I Error
FN	False Negative; Type II Error

Introduction

The impact of online content promoting and glorifying eating disorders as a lifestyle is a hotly debated topic within social media policy (Branley and Covey 2017; Argyrides and Kkeli 2015; Syed-Abdul et al. 2013; Yom-Tov et al. 2012). The community of individuals that create and disseminate eating disorder content, referred to as pro-anorexic, “pro-ana”, or “ana” do so to inspire others to maintain or adopt anorexic or bulimic behaviors in the pursuit of thinness (Yom-Tov et al. 2016; Yom-Tov et al. 2012; Harshbarger et al. 2009). The public, health authorities, and academics scrutinize pro-ana content and often argue for the moderation of such content (Gerrard 2018; Yom-Tov et al. 2016; Tong et al. 2013; Yom-Tov et al. 2012; Christodoulou 2012) because it is linked to higher levels of body dissatisfaction and disordered eating (Custers and Van den Bulck 2009; Jett, LaPorte, and Wachisn 2010; Juarez, Soto, and Pritchard 2012; Peebles et al. 2012). The pressure from these entities resulted in major social networking sites (SNSs) censoring the content completely (Facebook 2019; Tumblr 2019; Pinterest 2019) and instituting warning labels (Martijn et al. 2009; Instagram 2019). Despite institutional censorship, regulatory pressures, and social stigma, the presence of pro-ana content on SNSs has not diminished (Casilli, Pailler, and Tubaro 2013).

A similar, but understudied community are bodybuilders. Like eating disorders, specifically anorexia, bodybuilding revolves around body modification (Bulik et al. 2005; Linder 2007). Both populations rely heavily on behaviors of restriction, exercise, and/or starvation to emphasize their physical appearance (American Psychiatric Association 2013; Bulik et al. 2005; Linder 2007). Yet, bodybuilding is idealized and eating disorders medicalized. These similar behavioral patterns and lifestyles produce drastically different social and cultural responses.

From this preliminary account of the intersections between behaviors, bodybuilding is potentially as harmful as eating disorders.

The rise of SNSs affords lifestyles and behaviors associated with pro-ana and bodybuilders to reach a wider proportion of the population. The popular SNS Instagram, which bolsters twice the active users of Twitter, allows users to capture, edit, and share photos, videos, and messages with followers (Muralidhara and Paul 2018; Facebook 2019). Instagram's intent was to allow users to display aspect of their lives through images, videos, and messages, which enables promoting unhealthy behaviors and lifestyles. Other users also publicize their lifestyles via the application and an increasing subset are the bodybuilders and fitness-centered users (Rahbari 2019; Magee 2018). As their lifestyles become more visible to the public, a growing proportion of the population has the potential to idealize these individuals and behaviors. Therefore, there is a need to understand bodybuilding's parallels to eating disorders and their associated consequences to inform the design for social media content policies.

The goal of this thesis is to compare the content and show the similarity of two distinct populations: bodybuilders and pro-ana on social media. The bodybuilding lifestyle has the potential of reframing anorexic behaviors while reaching a wider, unsuspecting audience who may fail to identify the content as harmful. This thesis comprised two interrelated studies to understand the similarities and perceptions of social media posts from bodybuilders and eating disorder (henceforth pro-ana) users. Study 1 used computational methods to compare the content through machine classification of bodybuilding and pro-ana social media posts on Twitter, and Study 2 fielded an online survey experiment to compare the perceptions and human classification of images from Instagram. I used affect control theory (ACT) (Heise 1977, 1979; Smith-Lovin and Heise 1988; MacKinnon 1994) to hypothesize how content and perceptions will be similar for the two populations. This project aimed to demonstrate that (i) while bodybuilding is idealized, it may indicate a medical problem because of its similarities to the anorexic population, and (ii) social media users may be negatively impacted by content that is disguised as "healthy". The findings of this project will help inform the design of social media content policies.

Literature Review

Eating Disorders: Anorexia Nervosa

Eating disorder content online often focuses on anorexia nervosa. Anorexia Nervosa (AN) is associated with visible emaciation, starvation, and increased physical activity (Zipfel et al. 2005; Bulik et al. 2005). The psychological disorder consumes all aspects of an individual's life as their obsession with their outward appearance and weight becomes the center of their self-esteem, which is intertwined with their body-esteem (Bulik et al. 2005). While AN can affect individuals of all ages, sexes, races and sexual orientations, adolescent females and young adult women are disproportionally affected (Zipfel et al. 2005; Bulik et al. 2005; Noetel et al. 2017). Compared to other diagnosed mental illnesses, AN consistently has the highest morality rate (Chancellor, Mitra, and De Choudhury 2016), and in comparison to the general population, the mortality rate for all causes of death is six times higher for individuals with AN (Arcelus et al. 2011; Papadopoulos et al. 2009).

Pro-ana content is an online movement that promotes anorexic behaviors as a lifestyle choice (Rodgers and Meioli 2016; Yom-Tov et al. 2016; Tong et al. 2013; Yom-Tov et al. 2012; Harshbarger et al. 2009; Norris et al. 2006). Individuals in these communities disseminate photos and text on websites and SNSs to inspire others to lose weight and provide advice on how to do so (Yom-Tov et al. 2012; Harshbarger et al. 2009; Norris et al. 2006). As a lifestyle choice, these individuals do not see AN as a serious health condition and maintain behaviors that are medically unhealthy (Chancellor, Mitra, and De Choudhury 2016; Christodoulou 2012; Harshbarger et al. 2009). Pro-ana content is highly prevalent online and on SNSs (Yom-Tov et al. 2012; Teufel et al. 2013) and is frequented by both men and women (Wilson et al. 2006). Increasing proportions of the population use the Internet to find health related information (Fox 2014), which opens the door for users to encounter the pernicious content. While the broader population stigmatizes pro-ana content, engagement is common among teens and women (Arseniev-Koehler et al. 2016).

Exposure to pro-ana content can negatively impact body image concerns and body satisfaction. In female adolescent and college populations, exposure to pro-ana content was associated with increased body dissatisfaction (Custers and Van den Bulck 2009; Jett, LaPorte, and Wachisn 2010; Juarez, Soto, and Pritchard 2012; Yom-Tov et al. 2016) and higher levels of disordered eating (Peebles et al. 2012). Moreover, experimental studies which examined the effects of exposure to pro-ana content on body image revealed participants reported higher levels of body dissatisfaction (Benton and Karazsia 2015; Homan et al. 2012; Taniguchi and Lee 2012), increased weight concerns and dieting intentions (Jin, Ryu, and Muqaddam 2018), and lower perceived attractiveness compared to participants who were exposed to non-pro-ana content (Bardone-Cone and Cass 2006; 2007). Body dissatisfaction can impact an individual's psychological well-being (Sira and White 2010) and in severe cases cause self-harm (Goldfield et al. 2010) and suicide attempts (Presnell, Bearman, and Madeley 2007). These studies support the rationale behind SNSs content policies censoring pro-ana content.

Bodybuilding

Bodybuilding parallels the lifestyle and behaviors of AN, but is not the subject of social media content policies. Competitive bodybuilding is similar to sports like powerlifting, strongman competitions, and Olympic weightlifting, but places emphasis on the overall physical package of the body through muscle mass, symmetry, and definition (Mosely 2009; Siewe et al. 2014). Depending on the division within the sport, the previous factors are weighted differently in judging the overall package of the competitor. The International Federation of Bodybuilders (IFBB), which is the professional governing organization of bodybuilders, and its amateur counterpart, the National Physique Committee (NPC) currently list eight divisions that define different physical aspects within the sport (NPC News Online 2020): Bodybuilding, Women's Physique, Bikini, Fitness, Figure, Men's Classic Physique, Men's Physique, and Wellness.

Bodybuilding as a discipline is directed towards the development of an aesthetically pleasing body, as defined by the division criteria (Linder 2007). The typical image of a bodybuilder is exemplified by Arnold Schwarzenegger through the "aesthetic of bigness", which is a combination of muscle mass, muscle definition, and shape (Linder 2007; Mangweth et al. 2001). However, other divisions cater to different aesthetics that emphasize symmetry over sheer muscularity, like the Bikini division (NPC News Online 2020).

While the weight placed on judgement criteria varies for each division, the behaviors or lifestyle of the competitors are similar and resemble an AN lifestyle. Like AN, bodybuilders compulsively exercise, specifically to create an aesthetically pleasing physique that aligns closely with the criteria of their division. This exercise takes the form of weight training and lifting, which aims to maximize efficient workouts without increasingly heavy weights (Linder 2007; Murray et al. 2016). These regiments vary by athlete, but all follow a compulsive, driven, and structured format (Murray et al. 2016). Bodybuilders aim to train nearly every day of the week by performing sets that range from two to five exercises per body part, with a repetitive movement between eight to 30 within each set (Linder 2007). Bodybuilders penalize their fellow members for skipping or failing to finish a set or training session, as it is detrimental to their overall physical package in the long run (Underwood 2018; Murray et al. 2016). Some members of the community even go as far as verbally harassing other bodybuilders and gym patrons whom they deem as muscularly inferior, exhibiting mental and physical weakness, or training improperly (Smith and Stewart 2012).

Bodybuilders also shape their bodies by manipulating their caloric intake through managing the consumption of a food's protein, carbohydrates, fats, vitamins, minerals, and water (Linder 2007; Mosely 2009; Murray et al. 2016). In this community, individuals commonly reduce their food consumption far below the average daily caloric intake. These diets diverge extremely from healthy nutritional recommendations and use reductionistic scientific language and reasoning to rationalize the deviance (Bazzarre, Kleiner, and Litchford 1990; Elliot et al. 1987; Linder 2007). Mangweth et al.'s (2001) research on bodybuilding men highlights the distorted relationship these individuals have with food in that study participants reported eating habits were determined by schedule rather than hunger, avoided social gathering and restaurants where they could not manipulate their diet, and felt guilt for skipping or eating food outside their diet plan.

Dieting and weight training follow a cycle in which the intensity of exercise and amount of food vary over a course of time. During the prep period(s) of the cycle, bodybuilders exhibit high levels of exercise and consume low amounts of food which has been termed "reverse anorexia" as bodybuilders desire to lose weight but maintain greater musculature (Pope, Katz, and Hudson 1993; Choi, Pope, and Olivardia 2002). Conversely, during the offseason period(s), the emphasis is reversed. The length of time in which the bodybuilder experiences the prep and offseason phase(s) of the cycle varies by division and individual, but the dieting and weight training remain the same.

Despite the parallels to the AN lifestyle, literature on bodybuilding is scarce after 2010 and mostly focuses on the relationships between gender, power, and sexuality (Pickett, Lewis, and Cash 2005; Linder 2007; Meckiffe 2003). There is a critical need to revamp this research area because of the changing media ecosystem. For example, studies examine oversexualization of women who body build in magazines and websites (Meckiffe 2003; Perloff 2014; Hendrickse et al. 2017), but bodybuilders and the general population as a whole favor SNSs (Perloff 2014; Jin, Ryu, and Muqaddam 2018). Traditionally, access to this population's ideals and lifestyles were only obtainable through personal contact or magazine publications (Juarascio, Shoaib, and Timko 2010; Linder 2007; Meckiffe 2003), but the advent of SNSs has exposed bodybuilders to a larger audience not familiar with its content. Many athletes and the broader public who have undertaken this lifestyle are unaware of the pending consequences that follow their choices (Smith and Stewart 2012). As fitness and exercise become more valued in a society and consumed on SNSs (Alberga, Withnell, and von Ranson 2018; Boepple and Thompson 2016; Robinson et al. 2017; Muralidhara and Paul 2018; Tiggemann and Zaccardo 2015), the repercussions and health risks continue to rise if bodybuilding becomes an "ideal" standard.

Hypotheses Development

To understand the affinity between bodybuilder and pro-ana content, I make use of affect control theory (ACT). ACT maintains that identities such as bodybuilder or pro-ana evoke affect that individuals attempt to maintain through their behavior in social interactions (Moore and Robinson 2006; Robinson, Smith-Lovin, and Wisecup 2006). In the case of bodybuilders and pro-ana individuals, the cultural labels that are associated with these identities carry contrasting sentiments. A person who identifies as a bodybuilder, therefore, would unlikely identify as a pro-ana individual as well. Yet, I will argue that these populations exhibit similar behaviors, suggesting the two identities are more closely aligned than presumed and, further, that the social media content from the two populations resemble each other closely.

Despite no research explicitly comparing sentiments towards these two identities, existing research suggests the two should differ sharply. Unlike bodybuilding, the public views AN as a serious health concern (Christodoulou 2012; Harshbarger et al. 2009). When the AN or pro-ana identity is activated within a social context, they receive a rather negative appraisal, while activating the bodybuilding identity receives more positive associations and evaluations. Furthermore, AN is labeled as a "deeply perplexing illness that ravages both the mind and body" (Bulik et al. 2005:1) whereas bodybuilders boast labels such as "Most Perfectly Developed Man" (Magee 2018:7).

Although the identities for pro-ana and bodybuilding likely evoke distinct sentiments, the associated social media content should still resemble each other because of the affinity of the behaviors expressed to affirm the identities. By looking at the *Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM-5)* we can better understand the parallels between bodybuilding and anorexic behaviors. According to the American Psychiatric Association (2013) the revised diagnostic criteria for anorexia consists of three pieces:

> A. Restriction of energy intake relative to requirements leading to a significantly low body weight in the context of age, sex, developmental trajectory, and physical health. Significantly low weight is defined as a weight that is less than minimally normal or, for children and adolescents, less than that minimally expected.

> B. Intense fear of gaining weight or becoming fat, or persistent behavior that interferes with weight gain, even though at a significantly low weight.
>
> C. Disturbance in the way in which one's body weight or shape is experienced, undue influence of body weight or shape on self-evaluation, or persistent lack of recognition of the seriousness of the current low body weight.

Both AN and bodybuilders restrict food to produce similar body responses which align with criterion A. As mentioned above, bodybuilders restrict their dietary intake to enhance their physique and attain a muscular look. While restriction for bodybuilders leads to low body weight as with AN, it also minimizes body fat, which helps to display muscularity. Since low body fat is correlated with low body weight, this creates a bodybuilder who could be diagnosed as anorexic.

Competing causes fear of weight gain and creates persistent behaviors among bodybuilder, aligning with criterion B. During the prep part of their cycle, bodybuilders restrict food and increase exercise to achieve a low body fat and weight. This cycle approximately lasts for 16 weeks and results in behaviors that consistently interfere with gaining weight, even while the bodybuilder at that moment is already at low levels of weight.

Focusing on the latter half of criterion C, bodybuilders fail to recognize the detrimental effects that low body fat and weight have on their health, leading to a host of health problems (Melnik, Jansen, and Grabbe 2007; Mosely 2009; Smith and Stewart 2012). Further, members of the bodybuilding community speculate that those among them have a type of body dysmorphia related to the cycle of competition which maps on to the initial half of criterion C. Research partially affirms this speculation with literature linking the desire for large muscular bodies to body dysmorphic disorder (Choi, Pope, and Olivardia 2002; Mangweth et al. 2001; Mosely 2009).

Thus, although the identities are different, the behaviors used to express them are similar. I therefore expect social media content between the two to also be similar and result in misclassification by machine learning techniques and humans alike.

Hypothesis 1: If bodybuilder and pro-ana content is similar, a machine learning technique will likely report a low accuracy when attempting to classify.

Hypothesis 2: If bodybuilder and pro-ana content is similar, an individual will likely mislabel bodybuilder content as anorexic.

In addition to testing affinity between bodybuilding and pro-ana content, it is pertinent to understand the perceptions of such content. As noted above, the bodybuilding identity receives more positive appraisals and evaluations compared to the pro-anorexic identity. On SNSs, this likely takes the form of social endorsement of bodybuilding content. Research shows that appearance-related imagery on social media receives more engagement in the form of "likes" and comments compared to neutral images (Bakhshi, Shamma, and Gilbert 2014). While pro-ana content often emphasizes appearance (Christodoulou 2012; Syed-Abdul et al. 2013), the censorship constraints placed on them likely limit the engagement these images receive from the general population compared to bodybuilding content. Therefore, it is more likely that bodybuilding images associated with appearance receive higher levels of social engagement.

Increased engagement with content represents acceptance and further indicates popularity, peer attention, and validation (Chua and Chang 2016), which assists in the dissemination of beauty and body ideals (Jong and Drummond 2013). Because of censorship constraints imposed on pro-ana content, bodybuilding related content likely receives more engagement in comparison thereby validating the beauty and body ideals of this population. In tandem with the negative perceptions of anorexic individuals and increased societal emphasis on fitness, bodybuilders are likely perceived as more attractive.

Hypothesis 3: If bodybuilder and pro-ana content is similar, an individual is more likely to label content as a bodybuilder if they deem the person as attractive.

Overview of Studies

Traditional data collection techniques face many barriers when attempting to study hard-to-reach populations through surveys and interviews (Wang et al. 2017). This is relevant for pro-ana users who are hard to detect and reach due to denial of illness, ambivalence of treatment and high drop-out rate (Guarda 2008). Even if the data can be obtained, its reliability and accuracy is suspect because participants conceal their condition and its extent (Wang et al. 2017). The introduction of SNSs as sources of data can overcome some of these limitations because they afford large sample size, a semi-anonymous platform to disclose and socialize, and a naturally occurring flow of data (Wang et al. 2017). These affordances of the platforms help bolster generalizability, validity, and are an unobtrusive way to obtain data. Thus, research points to SNSs as a site to study eating disorders and other mental illnesses (Juarascio, Shoaib, and Timko 2010; Paul and Dredze 2014; Wang et al. 2017; Muralidhara and Paul 2018).

SNSs allow users to document the details of their daily lives as well as express and exchange thoughts (Wang et al. 2017). Many SNSs encourage users to share truthful, personal information (Herring and Kapidzic 2015), thus individuals tend to present their “real identity” through the information they provide about themselves (Zhao, Grasmuck, and Martin 2008). Yet, users can still manipulate their content to create what they consider favorable impressions of themselves (Ellison, Steinfield, and Lampe 2007; Lui 2007; Salimkhan, Manago, and Greenfield 2010), which some researchers have been critical of when analyzing SNS data as representative of truthful information (Herring and Kapidzic 2015). Although SNS users tend to emphasize positive aspects of their lives (Chou and Edge 2012) and self (Valkenburg, Schouten, and Peter 2005), their online self-presentation typically reflects their "true" self (Back et al. 2010). Moreover, it is difficult to regularly skew positive impressions on SNSs because of the power audiences have over a user's content. Marder et al. (2016) theorizes users share content that appeals to their "strongest audience" which constrains one's online behavior to align with the values of that audience. These values, which are largely determined by the perceived social losses and gains that the audience can inflict on the user (Marder et al. 2016), control what users' share. Thus, users cannot consistently present positive impressions because they share control with others about what is posted about themselves online.

Additionally, it is difficult to cultivate multiple self-presentations within the same social media account due to context collapse. Unlike face-to-face interactions, SNS users cannot control the audience who consumes their content and tailor each interaction (Marwick and boyd 2011). Therefore, to avoid context collapse between different audiences, users cannot present multiple selves, or they risk encountering embarrassing and uncomfortable situations (Davis and Jurgenson 2014). While some individuals cultivate multiple self-presentations across different accounts within the same SNS (Molina 2017), users typically present only one self within an account.

Despite SNSs affording users to selectively share personal information and manage multiple accounts with different self-presentations, there is a growing interest in utilizing SNS data to detect and address mental health concerns. Previous studies have shown that SNSs can help researchers infer the mental health state of a user through their content expressed online (Juarascio, Shoaib, and Timko 2010; Wang et al. 2017) and are increasingly being validated with grounded truth from online statements of diagnoses (De Choudhury et at. 2014; Coppersmith, Dredze, and Harman 2014; Coppersmith, Harman, and Dredze 2014), medical records (Eichstaedt et al. 2018), and psychometric instruments (De Choudhury et al. 2014; De Choudhury, Counts, and Horvitz 2013). These efforts that make inferences on users' mental health often rely on machine learning (ML) techniques. One approach, digital phenotyping which relies on passive data (Onnela and Rauch 2016), argues that an individual's health status can be inferred, diagnosed, and subjected to interventions, based on data garnered from interactions with online technologies, like SNSs (Jain et al. 2015; Onnela and Rauch 2016; Torous et al. 2016). The results of ML techniques inferring mental health from SNS footprints suggest promise (Coppersmith et al. 2018; Guntuku et al. 2017; Reece and Danforth 2017; Thorstad and Wolff 2019) and are being adopted by some social media platforms to address self-harm. Facebook's suicide prevention algorithm employs digital phenotyping to detect and address posts indicating suicidal ideation (de Andrade et al. 2018).

Research utilizes various platform, applications, and networks to study pro-ana populations. De Choudhury (2015) relied on Tumblr to examine differences in post content between pro-anorexia and pro-recovery users. Similarly, researchers utilized Tumblr to predict the likelihood of recovery for users who identified as having an eating disorder within the application (Chancellor, Mitra, and De Choudhury 2016). Researchers have also explored in-group and out-group interaction of eating disorder communities on Flickr, Youtube and Facebook (Yom-Tov et al. 2012; Syed-Abdul et al. 2013; Juarascio, Shoaib, and Timko 2010). Recent studies turned to Instagram as an increasingly popular application among younger populations to examine eating disorder content through the application's hashtagging function (Muralidhara and Paul 2018; Chancellor et al. 2016).

Compared to other SNSs, the affordances of Twitter also make the platform an ideal site for studying pro-ana populations. The microblog platform is the most common source of social media data in the academic community (Wang et al. 2017). Among Twitter's advantages is its API, which allows researchers access to one percent of publicly available information about users' account and post(s) information. Twitter's API software can be used to curate, filter, and search a large collection of tweets, re-tweets, and user's accounts in real-time and over the past 7 days (Twitter Developer 2020). While most researchers rely on Twitter's free API, social analytic industries and government entities subscribe to the premium API which allows access to ten percent of the overall Twitter data (Pfeffer, Mayer, and Morstatter 2018). Regardless of the API version, the data garnered can be analyzed to infer the social-behavioral context of users (Wang et al. 2017). Additionally, while other applications have taken precautions to limit the dissemination of pro-eating disorder content, Twitter has made no such attempt (Chancellor, Lin, and De Choudhury 2016). Hence, Twitter is favored in social media research of pro-ana communities.

In review of the pro-ana studies, this research utilized the SNSs Twitter and Instagram. While Twitter is favored among pro-ana academics, reliance on this SNSs as well as Tumblr and Facebook potentially exclude crucial factors of the pro-ana community. Eating disorder populations often base their self-esteem in their outward physical display of extreme thinness or emaciation (Yom-Tov et al. 2012; Harshbarger et al. 2009, Bulik et al. 2005); which is better expressed through images. Bodybuilders also use the physical display of their personal performance or physique through pictures or videos as a form of identity credibility (Smith and Stewart 2012). Although Tumblr and Facebook possess image-based content, a SNS with an image-sharing orientation is preferred as imagery is the normative content. Additionally, research indicates that the photo-based aspect of SNSs is most important for body image (Mabe, Forney, and Keel 2014; Meier and Gray 2014).

Twitter and Instagram users broadly reflect the demographic makeup of the United States population with the exception of age. The race and gender makeup of both SNSs' users are relatively representative of United States population (Smith and Anderson 2018). However, Twitter and Instagram users are typically younger, and more educated than the general population (Smith and Anderson 2018). Despite this skew, Twitter and Instagram are still advantageous for studying pro-ana and bodybuilder populations because their associated content is more relevant for younger populations.

Thus, Instagram is the ideal platform for pro-ana and bodybuilding studies regarding the display of physical appearance and perceptions by users. Hypotheses 2 and 3 will be tested using Instagram. However, Instagram's API is impervious to data collection techniques which limits the amount of data that feasibly can be accumulated (Gonzalez-Bailon et al. 2014; Morstatter et al. 2013). To address this limitation, Twitter is utilized to amass tweets with pro-ana and bodybuilding content to complement the images attained from Instagram and test Hypothesis 1. Utilizing Twitter and Instagram is tandem allows for the study to leverage the advantages of each SNSs and effectively address the hypotheses.

Study 1

To compare bodybuilder and pro-ana content on Twitter, I utilized a relatively new methodology within social science known as computational social science (Lazer et al. 2009). Computational social science is an interdisciplinary approach to studying the social dynamics of society that integrates social science and computer science to investigate vast quantities of data produced online (Oboler, Welsh, and Cruz 2012). In collaboration with computer scientists at the

University at Buffalo, the objective of Study 1 was to investigate that bodybuilding and pro-ana content resembles one another on social media through machine classification.

Data Collection

To compare and investigate the similarities between bodybuilder and pro-ana populations on Twitter, I initially gathered tweets over a four-week time span from May 2019 to June 2019, with each collection occurring once per week using MAXQDA 2018 (VERBI Software 2019). MAXQDA relies on Twitter's standard API to curate publicly available information posted on the platform within the past seven days. I specifically collected tweets using key words or phrase specific to each population. The exhaustive list of keywords and phrases used to identify pro-ana and bodybuilder tweets is presented in Appendix A.

Pro-ana keywords and phrases were selected from previous work (See Wang et al. 2017 or Arseniev-Koehler et al. 2016) as well as my own domain knowledge of the online pro-ana community. The keywords or phrases which were used to amass the bodybuilding data resulted exclusively from my domain knowledge of the field, because to my knowledge there is no classification studies of bodybuilding or recent language studies of the population. Examples of the key words for the pro-ana and bodybuilder populations are presented in Table 1.

Table 1. Examples of Population Search Terms

Pro-ana	**Bodybuilding**
edprobs	anabolic
thighgap	quads
anamia	procard
anorexic	gainz

Tweets related to fitspiration (fitspo) were also collected. With the help of researchers from the University at Buffalo, fitspo tweets were collected retrospectively using Twitter's premium API, which allowed us to gather the tweets during the same time frame in which the bodybuilder and pro-ana tweets were collected. It was necessary for all the tweets to be collected within the same time frame to exclude any temporal effects. The keywords used to collect fitspo tweets were "#fitspo" and "#fitspiration" which were selected based on literature examining this population on SNSs (See Santarossa et al. 2019; Tiggemann and Zaccardo 2015, 2018). The number of tweets by populations is presented in Table 2.

Table 2. Tweets by Population

Population	**# of Tweets**
Pro-ana	7598
Bodybuilder	20212
Fitspo	21569

Fitspo data was used to compare the difference with bodybuilder, and pro-ana tweets to control for possible overlap between populations. Fitspo consists of motivational language and imagery that promotes healthy eating and fitness-related ideals (Tiggemann and Zaccardo 2018). While bodybuilder content is not necessarily motivational, there is probably overlap in SNS content of these two populations because of the focus on fitness and diet. Additionally, researchers note an association between fitspo and pro-ana content. While fitspo has been positioned as a healthy alternative to thinspiration (or thinspo) content, which aligns with pro-ana behaviors (Tiggemann and Zaccardo 2018), analyses suggest both populations contain potentially harmful content emphasizing dietary restriction and thin body ideals for women (Boepple and Thompson 2016; Tiggemann and Zaccardo 2015, 2018). Thus, bodybuilder and pro-ana content are both likely to overlap with fitspo content. However, this overlap in content is not the same as the hypothesized similarities between bodybuilders and pro-anas. Bodybuilder and pro-ana are identities which individuals attempt to maintain through their behaviors, whereas fitspo is a type of aesthetic individuals disseminate online rather than an identity with a set of associated behaviors. Thus, fitspo will likely overlap with bodybuilder and pro-ana content, but this is different compared to the hypothesized link between bodybuilder and pro-ana.

In order to control for this possible overlap, the bodybuilder tweets were separated into two categories: (1) “real” bodybuilding tweets which excluded any tweets that also used #fitspo or #fitspiration and (2) “mixed” bodybuilder tweets which included tweets with #fitspo and #fitspiration. Regardless of overlap, bodybuilder and pro-ana content will be more similar because of the underlying behaviors presented in these identities which fitspo does not possess.

Study Design

I proposed that if bodybuilder and pro-ana content is similar, a machine learning technique will likely report a low accuracy when attempting to classify content. In order to test the hypothesis that their content is similar, we trained a classifier using Twitter content posted by bodybuilders, pro-anas, and fitspo users to differentiate the populations’ tweets. The classifier will rely on the linguistic structure, or words choice, of tweets to separate populations. If the classifier reports a low accuracy when attempting to separate bodybuilder and pro-ana content, it indicates the content likely resembles each other, which would support Hypothesis 1.

A classifier belongs to a broader family of computational techniques known as supervised ML. Supervised ML relies on prior knowledge provided to make predictions about new, unseen datapoints (Schrider and Kern 2018). Supervised ML algorithms obtain the prior knowledge through a training set made up of labeled data examples, which ultimately trains the predictor. Specifically, this study used a binary logistic regression classifier to predict the bodybuilder or pro-ana label by training the classifier through labeled examples of bodybuilder and pro-ana tweets.

Binary logistic classifiers are more advantageous compared to other supervised ML techniques but still face limitations. Binary classifiers are more easily interpretable compared to decision trees or support vector machines and can be easily updated with new data (Tharwat 2018). Additionally, binary logistic classifiers are an alternative to discriminant analysis, which is more complex and carries different assumptions (Caruana and Niculescu-Mizil 2006). Unlike discriminant analysis, binary classifiers do not assume an independent distribution nor a linear relationship between predictors and target variables (Thawart 2018). However, binary classifiers require a large sample size to achieve stable results and often suffer from multicollinearity (Tharwat 2018). Despite these limitations, binary classifiers are still a more suitable supervised ML technique because of its straight-forward interpretability and assumptions.

The goal of Study 1 is to compare bodybuilder and pro-ana tweets based on their linguistic features to investigate whether the content resembles each other. To achieve this goal, seven experiments were designed to validate Hypothesis 1 using a classifier. The classifier conducted tweet classification through two components. The first component is a sentence embedding extractor called Bidirectional Encoder Representations from Transformers (BERT) (Devlin et al. 2019). The goal of sentence embedding extractor is to transform the given tweet to a 716-dimensional vector which is able to capture the linguistic characteristic of the tweet. Typically, training such a model requires multiple computers with powerful graphic processing units (GPUs). Even with this requirement, the model will still need weeks to finish transforming the tweets because they contain millions of parameters and needs to learn the language pattern from the large text corpus. Luckily, previous researchers pretrained a similar model on large text datasets like BooksCorpus (800M words) and English Wikipedia (2,500M words) (Zhu et al. 2015) which can be used instead because the developers made it publicly available online (Devlin et al. 2019). Thus, we leveraged this model to transform tweets using a Python package called *sentence-transformers*. From this first component of the classifier, we are able to embed all the tweets into 716-dimensional feature vectors.

The second phase of the classifier used binary logistic regression to classify the tweets according to the groups (e.g. Pro-ana) of the users who post them. Therefore, the feature vectors of the tweets extracted by BERT served as the data of the regressions and the groups to which tweets belonged are the labels. We used 5-fold cross-validation and report the mean and standard deviation of seven classifier accuracies for five of the experiments. The results of the experiment differentiating the two bodybuilder populations and fitspo are exclude since the experiment did not control for sample size. The sample size for the first three experiments was 7598 and the remaining experiments 3388 tweets. The seven classifiers used to differentiate tweets between bodybuilder, pro-ana, fitspo content are reported in Table 3.

Table 3. Classifiers

Classifier
(1) Fitspo vs. Pro-ana
(2) Fitspo vs. Bodybuilder
(3) Bodybuilder vs. Pro-ana
(4) “Mixed” Bodybuilder vs. Fitspo
(5) “Real” Bodybuilder vs. Fitspo
(6) “Mixed” Bodybuilder vs. Pro-ana
(7) “Real” Bodybuilder vs. Pro-ana

Analytic Plan

Binary logistic regression classifiers estimate the probability of unseen data falling into one of two categories based on labeled examples (Singh, Thakur, and Sharma 2016). The output from a classification model represents the predicted binary class label of the unseen/labeled samples which can be represented in a confusion matrix (Tharwat 2018).

Figure 1. Confusion Matrix

		True Label	
		Positive (P)	Negative (N)
Predicted Label	True (T)	True Positive (TP)	False Positive (FP)
	False (F)	False Negative (FN)	True Negative (TN)

Source: Tharwat 2018

The labeled examples are used to construct the true label, which is either positive (P) or negative (N) for the data. The results of the classifier are the predicted label which can either be true (T) or false (F). True positive (TP) and true negative (TN) represent the correct predictions from the classifier. If the unseen data represents the positive label and is classified as the true label, then the classifier correctly labeled the positive sample (TP). Conversely, if the data is positive but classified as negative, it is considered a false negative (FN) or a Type II error. If the data is negative and classified as negative, it is considered true negative (TN), but if it is classified as positive, it is a false positive (FP) or Type I error.

From these classifications, the confusion matrix is used to calculate the performance of a classifier. The proportion of correct classification by the regression is a measure of classifier accuracy (Singh, Thakur, and Sharma 2016), which is commonly used to assess classification performance (Tharwat 2018). In this study, the classifier reported the accuracy for each tweet being labeled as bodybuilder and pro-ana. If the estimated probability of a tweet is greater than 0.5, meaning it aligns with the true label of a category (T), the tweet is classified correctly (TP) otherwise it is classified into the other category (TN). The proportion of TP and TN classified tweets for a population is divided by the total classification sample to produce the accuracy rating: Acc = TP + TN/(TP + TN + FP + FN) (Sokolova, Japkowicz, and Szpakowicz 2006). Because of its central use in classification performance, the results of the classifiers are analyzed using the reported accuracies.

Results

Table 4. Classification Performance for Predicting the Classes of Bodybuilder, Pro-ana, and Fitspo Tweets.

Classifier	Accuracy
(1) Fitspo vs. Pro-ana	0.822 (0.004)
(2) Fitspo vs. Bodybuilder	0.681 (0.006)
(3) Bodybuilder vs. Pro-ana	0.748 (0.007)
(4) “Mixed” Bodybuilder vs. Fitspo	0.674 (0.007)
(5) “Real” Bodybuilder vs. Fitspo	0.692 (0.01)
(6) “Mixed” Bodybuilder vs. Pro-ana	0.882 (0.003)
(7) “Real” Bodybuilder vs. Pro-ana	0.766 (0.011)

Notes: Standard deviations are in parentheses

Classifier 1-3. The first set of experiments trained three logistic regression classifiers to separate bodybuilder, pro-ana, and fitspo tweets. All three classifiers reported high accuracies when differentiating tweets, meaning all the classifiers could distinguish between each populations’ content. Classifier 1 revealed fitspo and pro-ana content were the least similar for this experiment (Accuracy [Acc] = 0.822, Standard Deviation [SD] = 0.004). Notably, bodybuilder tweets were more easily distinguishable from pro-ana tweets (Acc = 0.748, SD = 0.007) compared to the fitspo (Acc = 0.681, SD = 0.006). This suggests bodybuilder and pro-ana content is less similar than bodybuilder and fitspo content. However, because the bodybuilder and pro-ana classifier yielded a high accuracy rate, Classifier 3 does not support Hypothesis 1.

Classifier 4-7. This next set of experiments incorporated the two categories of bodybuilder tweets to test similarities in bodybuilder, pro-ana, and fitspo tweets. The “real” bodybuilder and fitspo classifier reported a higher accuracy rate (Acc = 0.692, SD = 0.01) than the “mixed” bodybuilder and fitspo classifier (Acc = 0.674, 0.007). The reduced accuracy for both bodybuilder sets of tweets is probably due to a smaller, controlled sample size in these experiments (N=3388).

In terms of pro-ana, the “mixed” bodybuilder and pro-ana classifier had a higher accuracy (Acc = 0.882, SD = 0.003) compared to “real” bodybuilder and pro-ana classifier (Acc = 0.766, SD = 0.011), suggesting the tweets that overlap between bodybuilder and fitspo are more easily separated from pro-ana tweets in comparison to tweets that do not overlap with fitspo. With “mixed” bodybuilder tweets being more similar in terms of content than “real” bodybuilder tweets with fitspo, these results mirror the first classifier where the fitspo and pro-ana results had a higher accuracy than bodybuilder and pro-ana classifier. One could argue that bodybuilder tweets that do not overlap with fitspo (“real” bodybuilder population) are harder to separate from pro-ana than fitspo and tweets that overlap between bodybuilder and fitspo (“mixed” bodybuilder population). Thus, suggesting “real” bodybuilder and pro-ana tweets have more similar content than “mixed” bodybuilder and pro-ana or fitspo and pro-ana tweets. However, the accuracy rates are still relatively high across all experiments.

Discussion

In terms of the overall study objective, the classifiers broadly reported high accuracies which means bodybuilder and pro-ana tweets could be easily separate. Moreover, Classifier 1 reported the highest accuracy of classification which suggests fitspo and pro-ana content is easily distinguishable and therefore not similar. This finding runs counter to literature suggesting fitspo and thinspo, often a proxy for pro-ana (Borzekowski et al. 2010; Ghaznavi and Taylor 2015), share similar content (Boepple and Thompson 2016; Tiggemann and Zaccardo 2018). One explanation is the probable specific linguistic features associated with pro-ana content that allow the classifier to easily separate the tweets, rather than the underlying similar context of the tweets.

However, when the results of the classifiers are interpreted relative to each other, they suggest bodybuilder and pro-ana tweets are similar. In classifiers 4-7, which ultimately controlled for any potential boosts in accuracy from overlap between fitspo and bodybuilder content, the "real" bodybuilder and pro-ana classifier reported a lower accuracy compared to the "mixed" bodybuilder and pro-ana classifier. Meaning, bodybuilder tweets that do not overlap with any fitspo content are harder to separate from pro-ana tweets than bodybuilder tweets that overlap with fitspo. This suggests that bodybuilder and fitspo are similar but once controlled for, reveal bodybuilder and pro-ana content is likely more similar because of the lower accuracy which would support Hypothesis 1.

Interpreting the findings from the classifiers in relative terms is more reasonable compared to absolute terms for this study because this current analysis cannot assess whether the classifiers are performing well. In other words, this study does not provide enough information to determine if the classifier is being conflated due to artifacts of the data or true linguistics differences in populations' tweets. Accuracy can only assess the performance of the classifier in proportion to these rest of the sample, which may contain subsets of which are more easily differentiated from other populations therefore resulting in high accuracy scores. For example, pro-ana tweets likely contain linguistic features that bodybuilder and fitspo tweets do not, which is why the classifier can separate the content easily. This assumption can be tested in the future using topic models to uncover the latent topics with each population. Should the topic model yield themes highly specific to only the pro-ana population, it is likely the classifier is picking up on this information when categorizing the tweets and producing a high accuracy. Similarly, a qualitative analysis of the raw Twitter data should be conducted to understand whether there are any Type I or II errors in classification.

This study is not without limitations. First, the sample size of tweets is relatively small in comparison to the vast majority of Twitter content which likely constrains the population of users whom which we garner tweets from and effects the stability of the classifiers (Tharwat 2018). Furthermore, sampling bias may exist because bodybuilders go through periodic cycles during the year (Hunter 2013; Smith and Stewart 2012) which likely affects the content they share. Future research should increase the sample size of tweets and sample content over a longer time period or at different points in time to account for seasonality of the bodybuilder population. Second, the study does not account for gender difference in tweets which likely affects the content expressed by all populations but specifically pro-ana users who are more likely to be female (Branely 2015; Branely and Covey 2017). Despite methods existing to infer gender from Twitter data (De Choudhury, Counts, and Horvitz 2013; Wang et al. 2017), gender differences were not assessed in this study because of the ethical concerns associated with inferring gender on Twitter (Fink, Kopecky, and Morawski 2012). Lastly, Twitter is favored among SNSs for research on pro-ana communities because of the lack of censorship (Chancellor, Lin and De Choudhury 2016) but whether this is an ideal platform to investigate bodybuilder communities still needs to be determined. Bodybuilders do not face the same censorship constraints as pro-ana users on SNSs which allows them to share their content on different platforms which they may favor or others. Research is needed to investigate whether Twitter content adequately captures bodybuilding communities because physical presentation is a key feature of this identity which is unlikely captured on a textual-based platform. The following study investigated this key aspect of bodybuilder and pro-ana identities through the photo-based platform Instagram to understand similarities in content.

Study 2

To understand how individuals classify bodybuilding and anorexic content on Instagram, I fielded an online survey experiment using Qualtrics. Study 2 sought to assess two main objectives: 1) show that participants mislabeled bodybuilder Instagram posts as pro-ana and 2) investigate perceived attractiveness on labeling bodybuilder and pro-ana content. Objective 1 complements the focus of the first study, which investigated how ML techniques classify bodybuilding and anorexic content on Twitter while objective 2 investigated a potential feature individuals rely on when attempting to categorize content.

Study Design

The rationale of Study 2 is to understand how individuals classify bodybuilding and pro-ana images on Instagram. I proposed that individuals will mislabel bodybuilder images as pro-ana and rely on perceived attractiveness to categorize content. To test this experimentally, I presented participants with non-labeled, partial blurred images that could plausibly come from either population and asked them to classify, rate the attractiveness, and explain why they labeled the image as such in an online survey.

The survey began by having participants review an informed consent document and agreeing to voluntarily participate in the study. After consent, participants responded to demographic questions before moving on to the main survey. The main survey repeatedly presented participants with one of nine randomized images of either a bodybuilder or anorexic and asked them to respond to questions about the classification of the image and why, perceived attractiveness, likelihood of the image depicting a bodybuilder or anorexic, and what type of account would post the image.

At random, participants were presented with two attention check questions to make sure they were not haphazardly skipping through the survey. All participant who failed to meet the attention checks were directed promptly to the end of the survey and informed why they would not be receiving compensation and their results excluded. While participants were informed of the minimal risk involved in internet surveys, they were allowed to skip any questions they deemed as personal or upsetting without penalty. This meant all eligible participants who reached the end of the survey received their entitled compensation and additional bonuses, excluding those who failed the attention checks. However, all incomplete surveys were excluded from the analysis.

Participants were compensated for their answers. The initial compensation for reaching the end of the survey was $0.10, but the compensation was adjusted after 7 days of a low survey response turnover. Only one participant received the initial compensation. With the adjusted compensation, eligible participants who reach the end of the survey received a payment from Amazon of $0.50. Additionally, participants could receive a bonus for providing a detailed response to the open-ended portion of the questions for each image about how the participant identified the type of person in the image. A detailed response constituted identifying a feature of the person and providing a rationale for why that feature led to identifying the type of person in the image. Each feature and corresponding rationale received a bonus of $0.01 with a cap of five features and rationales per image, resulting in a maximum bonus of $0.45. The maximum compensation for reaching the end of the survey with bonuses was $0.95. The survey concluded by thanking the participants for their time and provided them each with a validation code for their compensation. Directions for how to receive compensation were also included.

Stimuli

The experimental stimuli for Study 2 were images depicting bodybuilder or pro-ana content on Instagram. Images were sought out that could plausibly be identified as either bodybuilder or anorexic content by study participants. The plausibility of images was important to elicit participants' mental schema of bodybuilder and anorexic individuals when confronted with label uncertainty. These schemas will force participants to rely on key features they deem as important to bodybuilder and anorexic identities when categorizing content that could plausibly be either population rather than relying on cultural sentiments, and thus make them more accessible during measurement.

To identify pictures, I first utilized Instagram's search function to input a keyword as a hashtag to pull the associated top posts for #bodybuilding and #anorexic. These keywords were chosen based on their direct relation to the content I aimed to identify. Both hashtags were broad enough to capture the majority of related content but also specific enough to exclude direct overlap between the populations. The terms #bodybuilding and #anorexic yielded over 105 million and two million posts respectively. Prior to eliminating any posts, I scanned through each Instagram page to confirm the chosen keywords were accurately pulling content related to bodybuilding and pro-ana and decided it was doing so.

After pulling the associated top posts, I began eliminating content. Instagram's search function presents all public content directly linked to a specific hashtag. Unlike other SNS platforms like Twitter, Instagram does not allow users to also apply search filters to concentrate search results which is why each key term yielded millions of posts. In order to minimize the number of posts to investigate for plausibility, I developed a selection criteria. First, all posts that did not solely focus on a single individual were excluded. This excluded images that depicted individuals but were otherwise obscured by unrelated content or not the central focus on the post. Next, I selected posts for investigation that only depicted females because male-related bodybuilding and anorexic content were not the focus on this study. Finally, I assessed any written content attached to a selected image to verify the post was in line with bodybuilding and anorexic content. This is specifically important for #anorexic as content related to recovery rather than promoting anorexic ideals is difficult to differentiate solely based on an image. The selection criteria yielded an initial 84 possible posts.

The initial posts were then assessed for plausibility using a pilot. First, one female with minimal knowledge of bodybuilder and pro-ana Instagram content classified the 84 images as what she believed were the true labels of the posts. Because she was unaware of the typical nature of these populations' content on Instagram, her classification was unbiased in comparison to a female who regularly viewed bodybuilder and pro-ana content. From her classification, four bodybuilder and five pro-ana images were selected as potentially plausible. Next, three females with limited to expert knowledge on bodybuilding and pro-ana Instagram content were asked to classify the nine images. This was done to understand if the images were still plausible if a study participant possessed knowledge of these populations' content on Instagram and to support the first female's classification. Each individual was provided with the unaltered and unlabeled set of images and asked to classify them based solely on the image. The results of the pilot showed that these individuals were uncertain of the images' label as they could not categorize them correctly. Thus, the nine images were assumed to be plausible of either population.

The selected images were edited using Adobe Photoshop 2020 before being fielded in the online survey. While Instagram allows the fair use of public information, like username and content shared on public accounts for research purposes (Instagram Data Policy 2019), steps were taken to help protect the identifiability of the accounts from which images were taken and the individuals depicted. I removed personally identifiable information such as Instagram handles, captions and comments, and blurred the background for each image. The number of "likes" were also removed from the image as "likes" are known to influence individuals' perceptions of appearance-related imagery in the form of social endorsement (Bakhshi, Shamma, and Gilbert 2014). Additionally, because censorship constraints are placed on pro-anorexic or eating disorder content (Facebook 2019; Tumblr 2019; Pinterest 2019), images derived from #anorexic received substantially less "likes" compared to #bodybuilding. Thus, "likes" were removed to limit any social endorsement and standardized images across populations. The images 1, 2, 3, and 5 denoted the bodybuilder label and images 4, 6, 7, 8, and 9 the anorexic label.

Participants

Because pro-ana content is frequented and shared by young women more often than men (Branely 2015; Branely and Covey 2017) and females are more likely to develop eating disorders (Fairburn and Harrison 2003; Hudson et al. 2007; Preti et al. 2009), participants were required to be 18 years and older and female. Additionally, participants were required to reside in the United States. Eligible participants were recruited through Amazon Mechanical Turk and taken to the Qualtrics survey where they reviewed the informed consent (See Appendix B) and voluntarily agreed to participate in the study. Participants who did not meet the eligibility criteria were directed to the end of the survey and informed why they would not be receiving compensation and their results excluded.

Initially, 74 individuals responded to the survey. However, 63% of these were excluded due to quality controls to confirm participant eligibility and check their attention, resulting in a final sample size of 27 participants.

Measures

The dependent variable for Hypothesis 2 and 3 was constructed from participants' classification of images based on the question, "Is the individual in the picture a/an:" with the response options "Anorexic" coded as 0 and "Bodybuilder" codes as 1. The focal independent variable used to test hypothesis 2 which was the correct label of the image (anorexic images = 0 and bodybuilder images = 1). For Hypothesis 3, attractiveness rating was the focal independent variable and constructed from participants' responses to, "How attractive is the person in this photo?" with responses "Very unattractive", "Unattractive", "Neither attractive nor unattractive", "Attractive", and "Very attractive" codes as 1 through 5 respectively. Additionally, each of the nine images was coded with its corresponding 1 through 9 number derived from the pilot study. All of the survey questions used to construct the measures are presented in Appendix B.

Analytic Plan

In order to control for responses nested within individuals, the data was transformed into individual evaluation, where each response was a separate observation, by reshaping the data from wide to long format in Stata 13. This allowed me to investigate each response to the stimuli rather than participants as a whole. After reshaping the data, the final dataset included 243 individual evaluations.

Hypothesis 2. Hypothesis 2 investigated the relationship between a participants' classification of an image and the image's true label. First, I performed a chi-square test of independence between the dependent label variable and the focal true label variable to investigate the correlation between the two variables. I followed up the bivariate analysis by conducting a mixed-effects regression.

Mixed-effects models allow one to account for interdependencies between observations. Data collected on repeated measures, such as this study, in which one rater evaluates multiple images, are often dependent as responses are nested within participants (Bauer et al. 2013). This correlation violates the independence of observations assumed in many statistical models. Thus, models like logistic regressions are poorly suited to analysis of repeated measures data. However, multilevel or mixed-effects models are well suited for analyzing repeated measurement data because they do not assume independent observations (Bauer et al. 2013; Goldstein 2011). The mixed model approach used in this study was a mixed-effects logistic regression. A mixed-effects logistic regression is a logistic regression containing both fixed and random effects. In the mixed logistic regression model for binary data, the conditional distribution of the responses is assumed to be independent Bernoulli observations dependent on the covariates, fixed effects, and the random effects (Rijmen et al. 2003). While the complexity of mixed-effects logistic regressions sometimes dissuades researchers of their use in favor of more straightforward models (Molenberghs and Verbeke 2004), the ability to assume non-independence and interpret results in the form of odds ratios makes mixed-effects logistic regression highly advantageous for this study.

The mixed-effects Model 1 predicted the odds of labeling an image as bodybuilder based on the associated image's true label as bodybuilder. In this model, the fixed effect was true image label variable and the random effect the participants identifier. The choice of the variable for fixed and random effects were based on modeling the dependence between responses for labeling of the same participant.

Hypothesis 3. Hypothesis 3 investigated the relationship between a participant's classification of an image and perceived attractiveness. This was first achieved by performing a t-test to investigate the difference between the means of labeling an image as bodybuilder or anorexic by attractiveness rating. The bivariate analysis was then followed by the mixed-effects model's 2 and 3. Model 2 predicted the odds of labeling an image as bodybuilder based on attractiveness rating and Model 3 which added the variable for the true image label as bodybuilder to Model 2. In both models, the random effect was participants' identifier whereas for Model 2 the fixed effect was attractiveness rating and Model 3's fixed effects were the attractiveness rating and true image label variables.

Additionally, I performed a secondary analysis to disaggregate effects by image. Using mixed-effects models, Model 4 predicted the odds of labeling an image a bodybuilder based on each specific image and Model 5 added the attractiveness variable to Model 4. The results of the regressions were further elaborated by calculating predicted probabilities of being labeled a bodybuilder. Lastly, open-ended responses to each question about why participants labeled an image as bodybuilder or anorexic were open coded using MAXQDA 2020 (VERBI Software 2019) to investigate how participants perceived the content of each image.

Results

Table 5. Sample Demographics (N=27)

	Mean	Percent	Range
Age	39.41		23-67
Marital Status	1.7		1-4
(1) Married		55.56	
(2) Unmarried (Cohabitating)		25.93	
(3) Never Married		11.11	

(4) Divorced		7.41	
US Born	0.89		0-1
(1) Yes		88.89	
(2) No		11.11	
Income	4.07		1-6
(1) $0 to $19,999		3.7	
(2) $20,000 to $34,999		3.7	
(3) $35,000 to $49,999		18.52	
(4) $50,000 to $74,999		40.74	
(5) $75,000 to $99,999		22.22	
(6) $100,000 or more		11.11	
Latino or Hispanic	0.11		0-1
(1) No		88.89	
(2) Yes		11.11	
Race	1.3		1-3
(1) White		81.48	
(2) Black or African American		7.41	
(3) Asian		11.11	
Education	2.56		1-4
(1) Some college, no degree		22.22	
(2) Technical/Associates/Junior College (2-year)		11.11	
(3) Bachelor's Degree (4-year)		55.56	
(4) Graduate Degree		11.11	
Employment Status	1.22		1-4
(1) Employed		88.89	
(2) Retired		3.7	
(3) In school		3.7	
(4) Unemployed/Other		3.7	

Sample Demographics. Table 5 displays the sample demographics for Study 2. All participants were female and resided in the United States with only 3 respondents (11.1%) having been born in a foreign country. 81.5% of the respondents identified as White, followed by 11.1% identifying as Asian and 7.4% as Black or African American. Most respondents identified as non-Hispanic or Latino/a (88.9%) and the mean age of respondents was 39. Over half of respondents were married and completed a bachelor's degree (55.6%). The mean annual (combined) household income of respondents was $50,000 to $74,000.

Hypothesis 2. My first objective with this study was to investigate that participants would mislabel bodybuilder content as anorexic due to similarities. To empirically investigate this objective, I proposed Hypothesis 2 which states, "If bodybuilder and pro-ana content is similar, an individual will likely mislabel bodybuilder content as pro-ana."

Table 6. Chi-Square Test of Independence

	True Label		
Participant's Label	**Anorexic**	**Bodybuilder**	**Total Misclassified**
Anorexic	23 (58.9)	83 (47.1)	106
Bodybuilder	112 (76.1)	25 (60.9)	137
Total Correctly Labeled	135	108	243

Chi^2 (1) = 87.2881 Pr = 0.000

Notes: Expected values in parentheses.

A chi-square test of independence was performed to examine the relationship between participants' classification of an image and the image's true label. The results indicated participants overwhelming mislabeled bodybuilder and pro-ana content X^2 (1, N=27) = 87.29, $p <$ 0.000. Specifically, participants underreported the correct label for both populations. The patterns in Table 6 revealed participants consistently labeled bodybuilder content as pro-ana and notably, pro-ana content as bodybuilder. The chi-square analysis supports Hypothesis 2, which was further investigated in a mixed-effects model to account for interdependencies between observations.

Table 7. Mixed-Effects Logistic Regression for Predicting the Odds of Labeling an Image as Bodybuilder (N=243)

Variables	Model 1	Model 2	Model 3
True Image Label: Bodybuilder	0.042*** (0.017)		0.078*** (0.032)
Attractiveness Rating		2.931*** (0.499)	2.034*** (0.379)

*Notes: *** p<0.001, ** p<0.01, * p<0.05; Standard deviations in parentheses.*

The results from a mixed-effects logistic regression predicting the odds of labeling an image as bodybuilder based on the image's true label as bodybuilder is presented in Table 7 under Model 1. The predicted odds of labeling an image as bodybuilder (versus anorexic) is

0.042 smaller for the true image label being bodybuilder than they true image label being anorexic ($p < 0.000$). In other words, the predicted odds of labeling an image as bodybuilder rather than anorexic is reduced by 95.8% [(1-0.042) x 100 = 95.8] when the true image label is bodybuilder versus the actual image label being anorexic. This model reveals true bodybuilder images are less likely to be labeled as bodybuilder whereas true pro-ana images are more likely to be labeled as bodybuilder. Model 1 confirms the results of the chi-square test, which found participants overwhelmingly mislabeled each population and supports the classification patterns by participants that consistently labeled bodybuilder images as pro-ana and vice versa. Together, the results of Model 1 and the bivariate correlation provide support for Hypothesis 2.

Hypothesis 3. The second objective of this study was to show that participants had a preference towards bodybuilder Instagram posts, compared to anorexic, based on attractiveness. When an individual is uncertain of an image's label and the images are similar, participants need to rely on other characteristics to determine the label. One such characteristic is attractiveness, where bodybuilders are suggested to be perceived more attractive than anorexics. Thus, this analysis allows me to understand the labeling of each image after removing a suggested feature for classification. I proposed Hypothesis 3 to empirically test this objective which stated, "If bodybuilder and pro-ana content is similar, an individual is more likely to label an image as a bodybuilder if they deem the person as attractive."

An independent t-test was performed to determine if there were differences in attractiveness rating between participants' classification of an image as bodybuilder or anorexic. The results showed images labeled as bodybuilder had significantly higher attractiveness ratings (*Mean* = 3.92, *SD* = 0.08) compared to images labeled as anorexic (*Mean* = 2.80, *SD* = 0.11) [$t(28) = -8.61$, $p < 0.000$]. Specifically, bodybuilder-labeled images were on average perceived as “attractive” while anorexic-labeled images perceived as “neither attractive nor unattractive”. The results of the t-test support the notion that bodybuilders are perceived as more attractive compared to anorexics and that attractiveness is a possible feature participants relied on to categorize content when they are uncertain of the image’s label. The bivariate analysis lends support to Hypothesis 3, which was further investigated in Model 2 and 3.

The results of Model 2 and Model 3 are presented in Table 7. Model 2 predicted the odds of labeling an image as bodybuilder based on attractiveness rating. The predicted odds of labeling an image as bodybuilder (versus anorexic) is 2.93 larger for each increase in attractiveness rating ($p < 0.000$). In other words, the predicted odds of labeling an image as bodybuilder is 193% greater for each increase in attractiveness rating [(2.93-1) x 100 = 193]. Model 2 supports Hypothesis 3 as images perceived as more attractive were more likely to be labeled as bodybuilder rather than anorexic.

Model 3 added the true label variable to Model 2 and predicted the odds of labeling an image as bodybuilder based on attractiveness rating and the true image label. Even after controlling for true bodybuilder images, the predicted odds of labeling an image as bodybuilder were twice as large for each increase in attractiveness rating compare to anorexic ($OR = 2.03$; $p < 0.000$). While the results of Model 3 show images perceived as more attractive are more likely to be labeled as a bodybuilder, thus supporting Hypothesis 3, a true bodybuilder image is still less likely to be labeled as bodybuilder when controlling for attractiveness. Therefore, participants likely invoke other features besides attraction when attempting to label bodybuilding images.

Image Detail. As a follow-up to the main analyses, I employed another set of models to disaggregate the effects of labeling an image as bodybuilder by each image. This set of models allowed for additional details to surface as to what image(s) were more or less likely to be misclassified by participants and to partial out the effects of perceived attractiveness on participants' classification. This allows me to understand how other features besides attractiveness effect each image's predicted odds of being labeled as a bodybuilder.

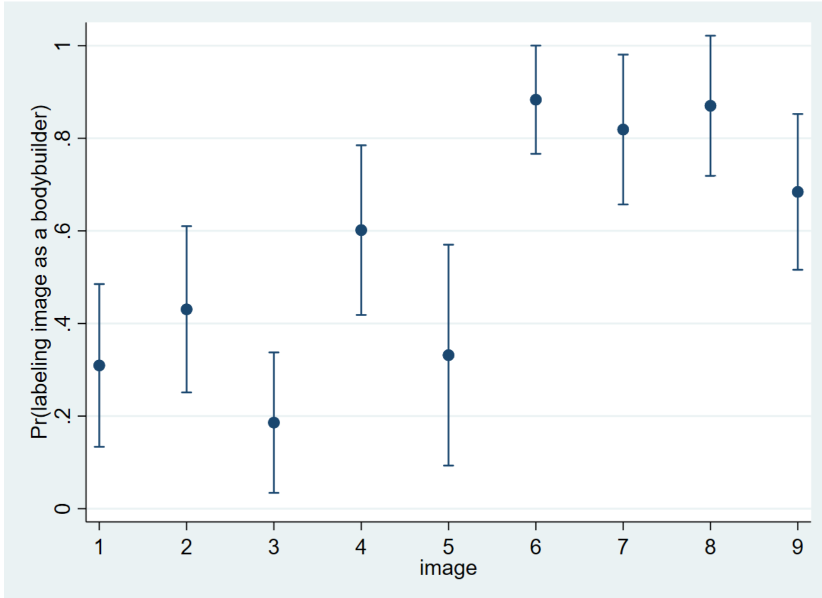
Table 8. Mixed-Effects Logistic Regression for Predicting the Odds of Labeling an Image as Bodybuilder by Image (N=243)

Variables	**Model 1**	**Model 2**
Image		
2	1.854	1.956
	(1.202)	(1.330)
3	0.444	0.436
	(0.334)	(0.335)
4	9.762**	4.861*
	(6.669)	(3.466)
5	0.444	1.138
	(0.334)	(0.931)
6	38.381***	37.534***
	(32.143)	(33.293)
7	38.381***	20.000***
	(32.143)	(17.015)
8	62.077***	32.439***
	(58.179)	(31.185)
9	12.096***	7.804**
	(8.445)	(5.607)
Attractiveness Rating		2.297
		(0.510)

*Notes: *** $p<0.001$, ** $p<0.01$, * $p<0.05$; Standard deviations in parentheses.*

The results of the mixed-effects logistic regressions which disaggregated the effects of images are presented in Table 8. Model 1 estimated the predicted the odds of labeling an image as bodybuilder for each specific image while Model 2 estimated the same predicted odds but included the attractiveness rating variable. I used these models to estimate and graph the predicted probability of labeling an image as bodybuilder to further elaborate the effects of each image.

Figure 2. Margins Plot for the Predicted Probabilities of Labelling an Image as Bodybuilder



Next, I compared the predicted probabilities between each image which are displayed graphically in Figure 2. In order to compare the predicted probabilities of labeling an image as bodybuilder, I conceptualized relatively high, moderate, and low predicted probabilities based on the marginal predicted mean. A high predicted probability was conceptualized at or above 0.8, meaning respondents are "good" at labeling an image as a bodybuilder. A moderate predicted probability is between 0.79 and 0.4, meaning respondents are "adequate" at labeling an image as a bodybuilder. A low predicted probability is below 0.39 and suggests respondents are "good" at labeling an image as not a bodybuilder. The greater the predicted probability for an image, the more likely the image depicts characteristics similar to participants' bodybuilder schemas. These predicted probabilities were used to infer which of the bodybuilder or pro-ana images were more or less likely to align with bodybuilder schemas, and the identify other key features besides attractiveness guiding classification.

The anorexic images 6 and 8 have the highest probability of being labeled as bodybuilder whereas anorexic image 4 as the lowest predicted probability relative to the other anorexic images. This suggests image 6 and 8 likely feature the most characteristics similar to participants schema of bodybuilders and therefore more likely to be labeled as a bodybuilder. Image 4, while still possessing perceived characteristics of bodybuilders, likely does not depict all the characteristics image 6 and 8 feature which resulted in a lower predicted probability of being classified as bodybuilder. The bodybuilder images 1 and 3 reported the lowest predicted probabilities whereas the bodybuilder image 2 highest probability relative to the other bodybuilder images. While as a collective the bodybuilder images were less likely to be labeled as bodybuilder and therefore less likely to align with participants' bodybuilder schemas, image 1 and 3 can be inferred as presenting the least amount of similarities relative to the other bodybuilder images.

This secondary analysis continues to support the previous findings that bodybuilder and pro-ana content is mislabeled by participants and supports the consistent mislabeling of pro-ana content as bodybuilder. What this analysis further suggests is the probability of mislabeling the content varies between images, where certain images are more or less likely to align with participants' bodybuilder schemas.

These findings are further elaborated in participants' responses to the open-ended questions about their chosen label. In response to the chosen label participants assigned to each image, they were asked to explain, "…how do you know the individual is a/an anorexic or bodybuilder?" and their responses open coded to identify broad themes. Participants often described why they labeled an image as bodybuilder or anorexic by denoting how they did not appear as the opposite label. Specifically, participants would use bodybuilder attributes to describe how an image they labeled as anorexic lacked those characteristics and vice versa. For example, when describing why they labeled an image as a bodybuilder, one participant responded, "The person has abdominal muscles, which I've never seen in someone who's anorexic. They're thin but have somewhat larger/proportionate breasts, which people who are anorexic don't have because they don't have enough fat. This person is clearly healthy." Here the participant notes that the individual depicted in the post lacked a non-defined mid-section and flat chest often associated with anorexics. When asked to describe why they labeled an image as a bodybuilder, one participant reported, "No lanugo, thick hair, well-defined abs. No sagging skin. It is assumed this person eats healthily, exercises and has sufficient protein intake. Their thin / defined waist could be a result of caloric restriction, but they look too healthy & muscular to have full anorectic behavior." Like the previous response, this participant used the lack of characteristics associated with the opposite label to describe the individual in the image. These responses align with the previous findings and further suggest participants likely see bodybuilder images as anorexic and anorexic images as bodybuilder.

Not all participants believed the images were indicative of either a bodybuilder or anorexic. Participants were only allowed to label an image as either a bodybuilder or anorexic which some suggested as constraining their classification. While none of the participants offered a label to capture what they believed the individual depicted should be classified as, they simply denoted that neither label was appropriate. For example, one participant responded, "For her height; she appears to be underweight. If she were a bodybuilder she would probably be more muscular. If there were more options, I may have picked differently." Another reported, "I don't think they're a body builder, but I don't think they're anorexic." Yet, not every participant expressed this concern in their open-ended response suggesting that the majority of participants believed images were either bodybuilder or anorexic in nature.

Another broad theme that emerged from the open-ended responses was the positive appraisal of bodybuilder images compared to anorexic images. Participants commonly used language like “healthy”, “attractive”, and “proud” when describing bodybuilder images. Conversely, participants described anorexic images as “unhealthy”, “too thin”, and “disturbing”. Moreover, participants noted the presence of muscles positively as “well defined” and “shapely”. The positive appraisal of female bodybuilders by these participants lends support to Hypothesis 3.

The open-ended responses also revealed participants cited body language, specific body parts, and overall appearance when explaining why they labeled an image as bodybuilder or anorexic. 40% of participants discussed an individual’s body language in their explanation for their chosen label. Participants noted an individual’s muscle presences (85%), mid-section (78%), and legs (56%) in their response. Lastly, a majority of participants discussed the overall appearance of the individual by commenting on whether they appeared to be proportional (59%), fit or toned (67%), and thin or skinny (85%). The reliance on body language, specific body parts, and overall appearance by participants when explaining why they labeled an image as such suggests that these are some of the key features participants used to identify bodybuilder and anorexic identities.

Discussion

The present study compared and investigated the similarities between bodybuilder and pro-ana social media content in Instagram posts through human classification. The results clearly indicated bodybuilder and pro-ana content is overwhelmingly mislabeled and notably, pro-ana content is more likely to be labeled as bodybuilder by participants. These findings remain unchanged when perceived attractiveness is accounted for in participants’ classification. In addition, perceived attractiveness had a significant effect on participants’ chosen label but was not the only feature used to categorize bodybuilder and pro-ana content.

The finding that bodybuilder and pro-ana images were mislabeled was not as surprising as the finding that both sets of images were consistently labeled as the opposite population. Bodybuilder and pro-ana identities evoke cultural labels with contrasting sentiments which would suggest individuals perceive their associated social media content differently and therefore would be unlikely to be label as the opposite identity. Yet, this study reports the converse: bodybuilder images are consistently and more likely to be categorized with the anorexic label and vice versa. This suggests individuals indeed possess two distinct schemas of bodybuilder and anorexic identities but overwhelmingly apply them incorrectly. Future research examining individuals perceived certainty of an image's identity is needed to investigate why participants routinely misapplied their bodybuilder and anorexic schemas.

This study also tested a hypothesized feature participants relied on to distinguish bodybuilder and pro-ana content. As discussed, bodybuilder and pro-ana identities carrying contrasting sentiments where bodybuilders are perceived as more attractive compared to anorexics. Perceived attractiveness is therefore likely a distinguishing feature in participants' schemas they used to categorize bodybuilder and pro-ana identities when presented as similar. Bodybuilder-labeled images were reported as more attractive compared to anorexic-labeled imaged by participants which confirmed the attractiveness sentiment associated with bodybuilder identities. Yet, additional analyses which disaggregated the effects of each image and attractiveness on labeled bodybuilder images suggested the effect of perceived attractiveness on labeling an image as bodybuilder varies for each image. Thus, while perceived attractiveness is likely a key feature used to distinguish bodybuilder and pro-ana content, each image likely possessed other features participants more or less relied on when categorizing the content.

The next logical step to understanding the features participants used to classify bodybuilder and pro-ana Instagram content is to link the features noted in the open-ended responses by image to the quantitative data and conducted another series of models that account for these features similar to the perceived attractiveness models. Perhaps perceived muscle mass or body shape could account for more variation in labeling an image as bodybuilder. A qualitative assessment of the open-ended responses suggested that body language, physical attributes, and overall appearance were other features participants noted as important when labeling an image.

The present findings need to be interpreted in the context of the study limitations. First, the sample size was small and limited to predominately a white female population, which inhibits the ability to generalize the findings to other populations. Future research should increase the number of individuals sampled and investigate the perceptions of bodybuilder and pro-ana content in males who are more demographically representative of the bodybuilding community (Mosely 2009) and view pro-ana content as well (Wilson et al. 2006). Additionally, while bodybuilder and pro-ana content largely depict white individuals (McGrath and Chananie-Hill 2009), research should also investigate how perceptions vary in racial and ethnically diverse samples. Second, the study only presented one of the many possible types of female bodybuilders which limits the findings to only this demographic of bodybuilders. While this was done deliberately to elicit label uncertainty in participants and control for cultural sentiments, this excluded other possible types of female bodybuilders individuals may encounter on SNSs which would likely elicit different responses from participants. A similar study to the present could include other divisions of female bodybuilder to investigate how participants perceive the different features of these females and whether their visual content is still similar to pro-ana.

Lastly, the physical features presented by bodybuilders vary depending on their behavioral cycle which likely effects how participants perceive them and how similar they are to pro-ana individuals. Future research should investigate at what point in the cycle do bodybuilders present physical features similar to pro-ana individuals and how social media content posted at different phases of the cycle are more or less similar to pro-ana content. Despite these limitations, the present study clearly demonstrates bodybuilder and pro-ana Instagram posts are similar and more notably, bodybuilder images are consistently labeled as pro-ana and pro-ana images labeled as bodybuilder.

Conclusion

The goal of this thesis was to compare bodybuilder and pro-ana content and show how similar the two populations are through SNSs. Bodybuilder and pro-ana identities carrying contrasting cultural sentiments which is highlighted by the idealization of bodybuilding and medicalization of eating disorders. Problematically, the intersections between these populations' behaviors propose bodybuilder and pro-ana identities are more similar than previously thought, potentially setting unsuspecting individuals up to adopt harmful behaviors. With SNSs affording bodybuilders to publicize and disseminate their behaviors unlike ever before, this thesis investigated the potential parallels between bodybuilder and pro-ana social media content.

While this research is not the first to discuss the link between bodybuilding and anorexia, to my knowledge this thesis represents the first explicit comparison of bodybuilder and pro-ana social media content which can help inform social media content policies. Currently, pro-ana content is widely censored on SNSs (Facebook 2019; Tumblr 2019; Pinterest 2019), which limits users' exposure and access to this harmful content. However, the broad finding that bodybuilder and pro-ana social media content resembles one another suggests current censorship policies need to be revised because pro-ana ideals, lifestyles, and behaviors can be re-framed through bodybuilding content, thus exposing unsuspecting users to harmful content. Additionally, with bodybuilder and pro-ana content being similar, it would be discriminatory to only censor one of these populations. While I am not advocating for the complete censorship of either population, steps could be taken to construct less discriminatory policies which censor only the most harmful topics, as opposed to an entire population.

Topics within bodybuilder and pro-ana content can be classified and tested to identify the most problematic and harmful content to be censored. A classifying algorithm could be trained to learn the broader context of the pro-ana population, which would then gather data only for this population to construct a dataset that is then subjected to topic modeling. Topic modeling uncovers the structure within a dataset without any prior knowledge by assuming there are latent topics within the human language (Schrider and Kern 2018). The topic model would expose subtopics within the pro-ana populations. Researchers could then conduct an experiment, with content representing each subtopic, to identify which one(s) raise body dissatisfaction among users and the likelihood at which they adopt problematic behaviors. Based on the contextual information of the subtopics, they can potentially be labeled as problematic or benign and be used to categorize the harmful topics within populations. Such examination can help construct less discriminatory policies in which only the most harmful topics are censored, as opposed to entire population.

While beyond the scope of this study, more research is needed to understand bodybuilder and pro-ana contents effects on body dissatisfaction. To date there is a plethora of work on mass media's effects on body concept (Scharrer 2013; Bell and Dittmar 2011; Tiggeman 2011; Morgan et al. 2009; Hogan and Strasburger 2008; Thompson et al. 1999). Often these studies posit the exposure to body image standards imposed by mass media as central to the internalization of unrealistic ideals (i.e. magazines, movies, and television) (Stice and Shaw 2002; Cusumano and Thompson 1997). For women, the ideal physique emphasized by the media is thin and athletic, which is virtually impossible for most women to attain (Low et al. 2003; Cusumano and Thompson 1997). Exposure to this unachievable standard portrayed by the media is positively associated with body dissatisfaction and eating disorder behaviors in both correlational, longitudinal, and experimental studies (Bardone-Cone and Cass 2006, 2007; Benton and Karazsia 2015; Homan et al. 2012; Jin, Ryu, and Muqaddam 2018; Smolak and Thompson 2009; Taniguchi and Lee 2012; Vaughan and Fouts 2003; Harrison 2001; Stice, Spangler, and Agras 2001). However, these studies have overwhelmingly focused on traditional mass media, which has experienced a steep decline in utilization, especially among young adults (Perloff 2014). This is problematic as young adults are more vulnerable to media influence (de Vries, Vossen, and van der Kolk-van der Boom 2019; de Vries et al. 2016; Rousseau et al. 2017; Holland and Tiggeman 2011) and have since migrated to contemporary forms of media consumption (Perrin 2015).

Overall, the findings from Study 1 and 2 suggest bodybuilder and pro-ana identities are similar, at least in social media content. Moreover, these similarities are present on two distinct social media platforms which strengthens this finding. This highlights the critical need for social media censorship policies to be cognizant of different populations expressing the same content, when only one is censored. These findings also have implications for research on body image as bodybuilding content may exert the same or increased negative effect on body dissatisfaction as reported in exposure to pro-ana content. Accordingly, this thesis can contribute to social media content policies and advance the current state of bodybuilding, pro-ana, and body dissatisfaction research.

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Appendix A: *Study 1 Search Terms*

Bodybuilder	Pro-ana	Fitspo
wbff	thinsp	fitspo
npc	thinspiration	fitspiration
ifbb	meanspo	
nanbf	bonespo	
ocb	legspo	
inbf	proana	
wnbf	anabuddy	
flexfriday	anorexia	
bodybuilding	anorexic	
bodybuilder	pro-ana	
girlswholift	proanorexic	
swoll	anorexianervosa	
flexfriday	proanatips	
shredded	anacoach	
gainz	proanaandpromia	
swole	promia	
gymfreak	mia	
legday	bulimia	
quads	bulimic	
booty	pro-mia	
abs	probulimia	
prepcoach	probulimic	
peakweek	proed	
anabolic	pro-ed	
physique	ednos	
figure	eatingdisorder	
classicphysique	ed	
mensphysique	edprobs	
wpd	edtwt	
npcbikini	fatty	
roadtopro	skinny	
procard	skinnier	
ifbbbikini	thin	
	hipbones	
	backbone	
	bones	
	collarbone	
	hips	
	thighgap	
	thyghgap	
	bikinibridge	
	GW,CW,LW,UGW	
	bodycheck	
	ABCdiet	
	projectthin	
	binge	
	bloated	
	laxatives	
	bingeeating	
	triggerwarning	

Appendix B: *Study 2 Survey Documentation*

Document 1. Informed Consent

University of Wisconsin-Milwaukee
Informed Consent to Participate in Research

Study title: Impressions of Instagram posts

Researcher[s]: Katherine Craig and Celeste Campos-Castillo

Study Description: The purpose of this research study is to understand how people differentiate content on Instagram. Approximately 1,000 subjects will participate in this study. If you agree to participate, you will be asked to complete an online survey that will take approximately 10 minutes to complete. The questions will present you Instagram pictures and then ask you identify the type of person in the image and how you came to that conclusion. They will also ask you about your demographic background.

Risks / Benefits: Risks to participants are considered minimal. Collection of data and survey responses using the internet involves the same risks that a person would encounter in everyday use of the internet, such as breach of confidentiality. While the researchers have taken every reasonable step to protect your confidentiality, there is always the possibility of interception or hacking of the data by third parties that is not under the control of the research team. However, questions may be personal and upsetting. You may skip any question you are not comfortable answering without penalty.

There will be no costs or individual benefits to participants in this study. We believe that understanding how individuals identify social media content will provide a societal benefit.

Eligibility and compensation

Eligible participants who reach the end of the survey will receive payment from Amazon of \$0.50 However, participants can receive a bonus of \$0.01 with a cap of \$0.05 per question for a maximum bonus of \$0.45. The bonus will be rewarded for providing a detailed response to the open-ended portion of each question about how you identified the type of person in the image. A detailed response constitutes identifying a feature of the person and providing a rationale for why that feature led to identifying the type of person in the image. Each feature and corresponding rationale receive a bonus of \$0.01 with a cap of five features and rationales per question. The maximum compensation for reaching the end of the survey with bonuses is \$0.95. Participation is contingent on you meeting the following requirements:

· You are at least 18 years old

· You are female

· You live in the United States

· You correctly answer attention check questions that check to see if you read and understand the instructions

Limits to Confidentiality: Researchers will have access to your MTurk worker ID which may be able to be linked to your personal information including your Amazon public profile page. Amazon will have access to your MTurk ID and personal information (social security number, IP address, bank account information, etc...). MTurk worker IDs will not be shared with anyone and will be used solely for the purposes of distributing compensation. Your MTurk Worker ID will only be stored on Amazon's servers and will not be stored in the same dataset as your responses. Instead, you will be assigned a unique ID, distinct from the MTurk worker ID, which you will receive while completing the Qualtrics survey. Qualtrics IDs will be removed from the dataset in 5 years. Data will be retained on the Amazon and Qualtrics servers for 5 years and will be deleted by the research staff after this time. However, data may exist on backups or server logs beyond the time frame of this research project. Data transferred from the survey site will be saved on a password protected computer for 5 years. Only the PI listed above and research staff will have access to the data collected by this study. However, the Institutional Review Board at UW-Milwaukee or appropriate federal agencies like the Office for Human Research Protections may review this study's records. All study results will be reported without worker ID so that no one viewing the results will ever be able to match you with your responses

Future research: De-identified data (all identifying information removed) may be shared with other researchers. You won't be told specific details about these future research studies.

Voluntary Participation: Your participation in this study is voluntary. You may choose to not answer any of the questions or withdraw from this study at any time without penalty. Your decision will not change any present or future relationship with the University of Wisconsin Milwaukee or Amazon.

Who do I contact for questions about the study? For more information about the study or study procedures, contact Katherine Craig at kcraig@uwm.edu or Celeste Campos-Castillo at camposca@uwm.edu.

Who do I contact for questions about my rights or complaints towards my treatment as a research subject? Contact the UWM IRB at 414-229-3173 or irbinfo@uwm.edu

Research Subject's Consent to Participate in Research:

By entering this survey, you are indicating that you have read the consent form, you are age 18 or older and that you voluntarily agree to participate in this research study. Please make sure that you have read and agree to Amazon's Mechanical Turk participant and privacy agreements as these may impact the disclosure and use of your personal information.

Thank you!

Document 2. Demographic Questions

Q5 What year were you born?

▼ 1920 (587) ... 2005 (672)

Skip To: End of Survey If What year were you born? = 2003
Skip To: End of Survey If What year were you born? = 2004
Skip To: End of Survey If What year were you born? = 2005

Q6 What is your current occupational status?

- ◯ Employed (1)
- ◯ Unemployed (2)
- ◯ Retired (3)
- ◯ In school (4)
- ◯ Homemaker (5)
- ◯ Other (6) ____

Q7 Were you born in the United States?

- ◯ No (1)
- ◯ Yes (2)

Q9 Are you Hispanic or Latino/a?

- No (1)
- Yes (2)

Q10 What race or races do you consider yourself to be (check all that apply)?

- White (Caucasian) (1)
- Black or African American (2)
- Asian (3)
- American Indian or Alaska Native (4)
- Native Hawaiian or other Pacific Islander (5)
- Other (6) ____

Q11 What is the highest grade or level of schooling you've completed?

- No diploma (1)
- High School Diploma/GED (2)
- Some college, but no degree (3)
- Technical/Associate/Junior College (2 yr, LPN) (4)
- Bachelor's Degree (4 yr, BA, BS, RN) (5)
- Graduate Degree (Masters, PhD, Law, Medicine) (6)

Q12 What is your marital status?

- ◯ Married (1)
- ◯ Married, living apart (2)
- ◯ Unmarried partner (cohabitating) (3)
- ◯ Never married (4)
- ◯ Divorced (5)
- ◯ Separated (6)
- ◯ Widowed (7)

Q13 What is your (combined) annual household income?

- ◯ $0 to $9,999 (1)
- ◯ $10,000 to $14,999 (2)
- ◯ $15,000 to $19,999 (3)
- ◯ $20,000 to $34,999 (4)
- ◯ $35,000 to $49,999 (5)
- ◯ $50,000 to $74,999 (6)
- ◯ $75,000 to $99,999 (7)
- ◯ $100,000 to $199,999 (8)
- ◯ $200,000 or more (9)

End of Block: Default Question Block

Document 3. Survey Questions

Please rate the following image from an Instagram account.

<IMAGE>

QX. How attractive is the person in this photo?

- Very unattractive (1)
- Unattractive (2)
- Neither attractive nor unattractive (3)
- Attractive (4)
- Very attractive (5)

QX. Is the individual in the picture a/an:

- Anorexic (1)
- Bodybuilder (2)

QX. In response to your answer above, how do you know the individual is a/an anorexic/bodybuilder? (A bonus can be earned for providing a detailed response. A detailed response constitutes identifying a feature of the person and providing a rationale for why the feature led to identifying the type of person in the image. Each feature and corresponding rationale receive a bonus of $0.01, up to $0.05 for this specific person in the image.)

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QX. What type of Instagram account would post this picture?

- ○ Thinspiration (thinspo) (1)
- ○ Fitspiration (fitspo (2)

QX. How likely do you think this person is a bodybuilder?

- ○ Very likely (1)
- ○ Likely (2)
- ○ Somewhat likely (3)
- ○ Neither likely nor unlikely (4)
- ○ Somewhat unlikely (5)
- ○ Unlikely (6)
- ○ Very unlikely (7)

QX. How likely do you think this person is an anorexic?

- Very likely (1)
- Likely (2)
- Somewhat likely (3)
- Neither likely nor unlikely (4)
- Somewhat unlikely (5)
- Unlikely (6)
- Very unlikely (7)