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Familiar faces, familiar spaces: Social similarity and co-presence in non-relational behavioral convergence

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Abstract

Social influence is frequently measured through an ego's direct ties. Although influence may also stem from an ego's indirect ties, reference group, and casual contacts, it is difficult to capture their impact using existing network methods. We identify and trace the influence stemming from an ego's "familiar others," consisting of those socially similar individuals with whom the ego comes in contact at school, but does not necessarily share a relationship. To evaluate the role of familiar others, we investigate unhealthy weight behaviors in adolescence using data from the National Longitudinal Study of Adolescent to Adult Health. Our results demonstrate that familiar others' unhealthy weight-related behaviors are strong predictors of the ego's own weight behaviors, net of immediate alters' behaviors, and individual-level characteristics. Further, we find that this relationship is stronger and more robust than that between egos and their direct ties. These results suggest that familiar others constitute a key source of social influence that is distinct from the influence of network alters.

Keywords: *social influence, behavioral convergence, non-relational contagion, weak ties, methodology, health, weight, social networks*

1 Introduction

How is our behavior influenced by those we encounter, but do not really know? Much social networks research investigates the flow of social influence through an individual's direct relationships. This influence is strongest when the transmitter resembles the receiver (Centola, 2011; McAdam & Rucht, 1993), in part because homophilous alters may serve as more salient references for the ego (Festinger, 1954; Hyman, 1942; Merton & Kitt, 1950; Shibutani, 1955). However, an ego's salient references may extend beyond their[1] immediate, direct ties, such as those named in the core discussion network (e.g., Marsden 1987). Indirect ties and "negligible" ties, such as "a 'nodding' relationship between people living on the same street, or the 'tie' to the vendor from whom one customarily buys a morning newspaper" (Granovetter, 1973, 1361), can similarly serve as conduits for the flow of influence. Likewise, those who are co-present in our environment, even if we have no prior relationship, can still provide a reference for our own behavior. Despite the important role of weaker ties, casual contacts, and other types of "familiar others" in behavioral diffusion, our theory regarding and ability to capture these influences has been limited. Much as a woman entering a gym may notice that women similar to her spend more time on cardiovascular exercises than weight training and feel pressure to do likewise, we may often respond to social influence derived from individuals with whom we lack ongoing relationships. In this paper, we explore this theoretical lacunae, introduce a method for capturing this type of influence, and investigate how the set of co-present individuals who resemble the ego, but to whom the ego is not necessarily tied, influence the ego's behavior.

Within an ego's network, one way that influence flows is via the direct sanctioning or reinforcement from alters (Portes, 1998). Network alters monitor the ego and encourage (or dissuade) the ego to engage in particular behaviors. This mechanism of influence requires direct interactions between the ego and their alters (i.e., direct ties) in order for information to travel. However, influence can also flow from others who lack a strong tie, or any tie at all, to the ego (i.e., "untied" to the ego by conventional network methods). A growing body of research demonstrates that untied others who are structurally equivalent (Burt, 1987; Fujimoto & Valente, 2012) or who share foci with the ego (Browning et al., 2017; Crosnoe et al., 2008; Frank et al., 2010) influence the ego's behavior. This work underscores the significant influence of individuals with whom the ego comes into contact without sharing a conventional tie. For example, when a shared social space (e.g., class, organizational meeting) provides opportunities for the ego to observe the behaviors of co-present others, these "untied" others' actions provide information to the ego about behavioral expectations, even though they do not necessarily have a relationship with each other. Social comparison, (Festinger, 1954) rather than direct sanctioning and reinforcement, guides the ego's behavior. Thus, an ego may be influenced indirectly when these co-present individuals serve as models for observational learning and social comparison.

Drawing on theories of social comparison, observational learning, and behavioral modeling, we introduce an ego's "familiar others" as a previously unmeasured source of influence. We designate an ego's familiar others as those individuals who are (1) socio-demographically similar to the ego and (2) co-present with the ego at the same school, but (3) who do not necessarily share a conventional friendship tie. Familiar others may be indirect ties who are unaccounted for by most network measures, second-order network members, untied peers at even greater removes, or an ego's "potential friends" (e.g., desired friends within the wider social network; Giordano, 2003). Even when a direct tie is absent, however, structurally induced homophily

[1] We use "their" as a singular, non-gendered pronoun to refer to the ego throughout this paper.

drives similar individuals into the same spaces at school, producing the exposure necessary for observation and behavioral contagion. Individuals are more likely to compare themselves to (Erickson, 1988; Festinger, 1954), and adopt the behaviors of, homophilous others (Centola, 2011; Mueller et al., 2010). Therefore, individuals who resemble the ego serve as an important reference group, and provide the closest, and potentially most accurate, social comparisons for the ego (Festinger, 1954). We argue that these co-present individuals who resemble the ego constitute a salient, but frequently overlooked, aspect of an ego's social environment.

Using data from the National Longitudinal Study of Adolescent to Adult Health, we demonstrate a new method, Blau bubble analysis, for identifying an individual's familiar others based on McPherson's model of Blau space (McPherson, 1983; 2004; McPherson & Ranger-Moore, 1991). We then use this novel method to demonstrate empirically how familiar others' behaviors are related to those of the ego. Using the case of unhealthy weight behaviors (medically unnecessary weight loss and weight gain) among respondents in the Add Health, we find that egos' engagement in unhealthy weight gain is strongly predicted by unhealthy weight gain among their familiar others', even after controlling for the behavior of their direct alters. Our analyses provide evidence that familiar others are an important source of social influence that is complementary to that of network alters. We conclude with the health implications of our findings, discuss methodological limitations in our approach and recommend extensions of Blau bubble analysis for future work.

2 Background

2.1 *Flows of influence*

Social network research has long been interested in the flow of influence through an ego's ties. Findings from this work provide ample evidence that individuals adjust their behaviors based on cues from their alters. Patterns in smoking (Christakis & Fowler, 2008; Ennett et al., 2006), obesity (Christakis & Fowler, 2007), and risky sex (Latkin et al., 2003), for example, have all been attributed to network-based influence.

A key criticism of network analysis is that social networks capture a specific rather than comprehensive scope of an ego's social environment. Most social network methods rely on exhaustive measurement of bounded groups (e.g., workplaces) or name generators that capture a limited, often stronger, subset of a respondent's ties (e.g., the core discussion network). But the number of relationships that are measured in this way usually falls far short of the total number of relationships maintained by individuals, estimated as ranging from a few hundred (DiPrete et al., 2011; McCarty et al., 2001; Roberts et al., 2009) to nearly two thousand (Killworth et al., 1990). The ego's salient social environment almost always extends beyond those individuals captured as direct ties and thus standard network methods cannot capture the full range of potential social influences.

Unmeasured influences in networks can derive from several sources. First, second-order networks, populated by those who are tied to ego's associates but not directly to ego, are often ignored despite their impact on ego by proxy. In bounded networks, these second-order ties can be identified, but only for relationships falling within the scope of the original network item. For example, if a tie is measured as an advice relation, one can only identify second-order *advice relation* ties with socio-centric data, even if other types of (unmeasured) ties may be meaningful for the outcome at hand. Meanwhile, second-order relations usually cannot be identified when using ego-network methods. Second, most network studies rely on respondent recall of contacts, which tends to be biased by human cognitive processes (e.g., Brashears 2011; 2013) and therefore often fail to accurately measure weak ties. This is also often the de facto case for studies relying on automatically generated network data (e.g., email archives) as some minimum threshold is often used to separate "real" ties from those that result from incidental contact. This is a reasonable practice, but likely inadvertently discards real weak ties along with contacts that are not associated with ongoing relationships. Third, individuals are often surrounded by others with whom they do not share a direct tie as typically conceived, but who nevertheless condition the local social environment. These unmeasured relationships may be what Granovetter (1973) referred to as "negligible ties," (p. 1361, fn. 4), or ties entailing regular contact that fails to elevate the relationship to even the level of a "weak" tie (e.g., daily contact with a barista at work). However, these individuals can also include casual contacts (e.g., Brashears et al., 2017), potential friends (Giordano, 2003), or individuals inhabiting the same loose social circles (Simmel, 1955) and/or sharing the same foci (Feld, 1981) as the ego. Below, we explore in greater detail why omitting such contact from consideration is problematic.

2.1.1 Influence from indirect and untied others

Although many of the unmeasured relationships described above are weak, or even viewed as absent, recent research demonstrating regular patterns of interaction and influence between individuals who are not directly tied suggests that they are nevertheless important. For example, Shakya et al. (2012) find that the parenting style of adolescents' friends' parents influences their level of drinking, as well as cigarette and marijuana smoking, highlighting the role of indirect influence in adolescent substance use behaviors. They suggest that the repeated encounters an individual has with their friends' parents may foster spillover to the individual's behaviors, net of their friends' behaviors and parents' own parenting style. Especially noteworthy, the parents of friends would be very likely to be omitted from even the second-order network in most full network studies (e.g., would be missed by "who are your friends" type items), but still exert an influence on the respondent. Likewise, Burt's (1987) study of antibiotic adoption behavior among physicians demonstrates that diffusion tends to occur between structurally equivalent doctors even though they do not share a direct tie. This result likely stems from the similar opportunities given to those in similar structural positions as well as competing individuals tracking each other's behavior through other means (but see also Van den Bulte & Lilien, 2001). Thus, social similarity in the form of structural similarity can lead to behavioral convergence across untied egos.

Both of the above cases show how second-order and structurally equivalent individuals can influence ego, but we are particularly interested in the influence of those in the social environment who would never appear in a network inventory at

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all. For example, using smart card data from the Singapore public transit system, Sun et al. (2013) find regular patterning in individuals' commuting routes. These patterns mean that commuters routinely encounter the same set of fellow commuters, leading to the emergence of informal, time-specific communities. Such communities would be missed on network inventories simply because they are composed of individuals who are essentially untied though not unknown to each other. Similarly, Browning et al. (2017) find that households can be linked via their common participation in physical locations (e.g., workplaces) and that frequent encounters with others in these domains have a positive impact on perceived social closure and support. In this case, while the households may be known, it is repeated contact in other contexts, something that is typically unmeasured, that appears to define the social environment. Frank et al. (2010) combine co-presence in physical settings with affiliations by investigating the role of co-presence in social influence through their identification of "local positions." Using data on adolescent course taking schedules, they demonstrate that adolescents conform to the norms promoted by the larger group of students with whom they take the same combination of classes (i.e., other students who occupy the same local position). Local positions capture both a social and an academic space in schools, such that the students who share an individual's local position represent potential friends, reference groups, and weak but instrumentally important support ties. Moreover, a student's local position strongly predicts their math advancement, net of the advancement of their immediate friends (Frank et al., 2010). In this way, repeated exposure to a set of untied others can facilitate behavioral convergence. Finally, Brashears et al. (2017) use the Add Health data to find that individuals are more likely to adopt the behaviors characteristic of groups that inhabit their local social space, even while controlling for membership, and the membership and behaviors of direct ties. This work indicates that the local social environment can impact individual behavior in ways not typically accounted for by conventional network studies. In total, the above papers demonstrate that even thorough, high-quality network studies are often unable to fully map the social influences impinging on the individual, and point to the key role of individuals who are present in the social environment, but untied to the ego.

We build on these prior studies, proposing that an additional source of unmeasured influence is the ego's "familiar others," or those individuals with whom the ego comes in contact, but to whom the ego is either unconnected or weakly connected. Such familiar others may be weak or negligible ties, or even fail to qualify as ties by any definition, but are regularly encountered by the individual and thus exert a consistent influence over individual behavior. In the following sections, we elaborate the theory of familiar others' influence, as well as describe a method, Blau bubble analysis, for identifying familiar others.

2.2 Familiar others and non-relational influence transmission

Familiar others consist of those individuals with whom the ego comes in regular contact while remaining untied. Given that most individuals are routinely present in a limited, but stable, set of physical settings (e.g., neighborhood, workplace, and recreational facilities), they will be placed into proximity to the same others who populate those settings at the same time. As demonstrated by Sun et al. (2013), this

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leads to a predictable and consistent set of others who will be routinely co-present with the individual. As a result, this limited set of others will be "familiar" and, most important, will have the opportunity to exert a consistent influence on the individual.

In order for familiar others to influence the individual, information and expectations must travel to the individual. Whereas ties promote this information flow in networks, familiar others do not share the same direct connection with the ego. The ego is unlikely to have a targeted interaction (e.g., direct sanctioning) with their familiar others that guides their behaviors. However, not all influence requires the presence of a tie to flow. Theories of social comparison and observational learning emphasize that social similarity and repeated exposures can facilitate an ego's behavioral adoption (Festinger, 1954). Combined, they suggest that the ego is particularly likely to adopt a behavior from a socially similar individual with whom they come in frequent contact, regardless of the existence of a tie. While this mechanism of social influence is not exclusive to familiar others, we argue that the identification and measurement of familiar others allows us track this form of influence as it extends beyond an ego's immediate network alters.

2.2.1 Social similarity and co-present others

Social similarity is key to the identification of familiar others because of its relationship with co-presence. Population distributions and stratification drive demographically similar individuals into the same social spaces (e.g., neighborhoods, workplaces, and schools), culminating in the baseline homophily observed in networks (Blau, 1977; Marsden, 1987). Consequently, individuals are more likely to be exposed to demographically similar others, regardless of whether they share a tie (McPherson *et al.,* 2001). Relationships formed in this way may lead to additional exposures to similar others due to the generation of additional shared foci (Feld, 1981) or by way of organizations recruiting members from the same pool (McPherson, 1983). Although the ego will not befriend all the potential alters who share their foci, these untied but socially similar individuals remain co-present.

Critically, an ego may spend more time with their familiar others than with strong ties because they may be co-present with the ego across a greater number of settings. Although we may prefer to spend time with our strong ties, much of our day is dominated by co-workers, peers, and commuters on the same schedule (Sun et al., 2013; Young & Lim, 2014). This co-presence increases the likelihood of observational learning, wherein egos model their behaviors based on those they see around them (Bandura, 1977). Bandura (1977) explains, "The people with whom one regularly associates delimit the types of behavior one will repeatedly observe and hence learn most thoroughly," (p.6). Mere exposure to behaviors can affect an ego's attitudes and increase the likelihood of behavioral adoption (Brockner & Swap, 1976; Moreland & Zajonc, 1982; Saegert et al., 1973; Zajonc, 1968). For example, children exposed to characters smoking in movies are more likely to smoke themselves, net of smoking behavior among their ties (Dalton et al., 2003; Sargent, 2005). Thus, even without a direct tie, the ego and their familiar others' shared contexts provide opportunities for observational learning.

The effect of this regular co-presence is enhanced by the finding that social learning is most likely to occur among socially similar individuals. Network-based studies of influence demonstrate that behavioral adoption is highest when the ego resembles the transmitter (Centola, 2011; McAdam & Rucht, 1993). While the precise mechanism behind this pattern remains unclear, these higher adoption rates suggest that homophilous alters serve as more salient references. Through a combination of repeated exposures and shared social similarity, an ego may view their familiar others as a reference group and adjust their own behaviors accordingly. Social similarity undergirds individuals' choice of reference in social comparison because they will obtain the most useful gauge of their standing by comparing themselves to their equals (e.g., a Michelin star chef compares herself to other Michelin star chefs, not to at-home cooks) (Erickson, 1988; Festinger, 1954). When comparative self-evaluation yields discrepancies between the reference group and the individual, individuals will either adjust their own attitudes to align with those of the group or choose another group to use as a reference (Festinger, 1954; Hyman & Singer, 1968; Shibutani, 1955). The influence mechanism is psychological, such that the impetus to change behavior stems from the individual's perspective taking (e.g., "I think they think I should work out more.") rather than direct evaluation (e.g., "Paul said that I should work out more") (Turner, 1956).

Thus, while co-present others in general exhibit a set of behaviors the ego *could* engage in, socially similar familiar others signal a set of behaviors the ego *should* engage in. Giordano (1995; 2003) suggests that these untied or weakly tied references may constitute a more critical social audience precisely because they do not have a strong or supportive relationship with the ego. In this way, the ego may turn to their familiar others for behavioral direction, especially when behavioral expectations are unclear or subjective. Beyond direct ties, familiar others' behaviors signal to the ego what is appropriate or expected from someone like them. Take the example of a gym. Even without knowledge of gendered body weight norms, a woman could observe the gender-normative expectations set for her based on the segregation of women on cardiovascular machines and men in the weight lifting area. Without knowing any patron specifically, an ego may adopt or adjust her behavior based on the behaviors demonstrated by the patrons who demographically resemble her (e.g., similar gender, age, socio-economic status, and race individuals). The adopted behavior may become engrained as the norms about fitness, appearance and physique for "someone like her" become increasingly clear through repeated exposures. Or, more directly, one visit to the gym might produce minimal impact, but repeated exposure to familiar others engaging in consistent patterns of behavior over many visits to the gym will exert a consistent influence. To this end, as the exercise behaviors of those who resemble her change over time (ex: increasing popularity of weight lifting among women), an individual's behaviors may also change to align with the new behavior(s) exhibited by her familiar others. We depict the role of familiar others in this non-relational behavioral convergence in Figure 1.

A key contribution of familiar others to this literature is the minimal data it requires for computation. While the work on indirect influence and local positions is an excellent line of scholarship, the methods in these studies rely on detailed data on temporal co-presence (Sun et al., 2013; Frank et al. 2010; Crosnoe et al., 2008) or global networks (Burt, 1987). In contrast, familiar others require neither time

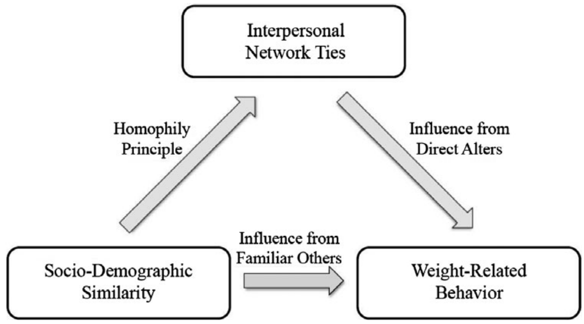

Fig. 1. The role of socio-demographic similarity in flows of social influence.

schedules nor network data for identification. The identification of familiar others thus represents a valuable tool for tracing social influence when more expensive network data are unavailable. Below, we describe our method of identifying familiar others even in cases when physical co-presence is not directly measured.

3 Data and methods

3.1 Identifying familiar others

We draw on theories of Blau space to identify an ego's familiar others. Blau space is a multi-dimensional space wherein axes are defined by socio-demographic parameters salient for social interaction (McPherson, 1983; 2004; McPherson & Ranger-Moore, 1991). Each coordinate within Blau space represents a unique combination of socio-demographic characteristics along the chosen dimensions, and the individual's position is determined by their unique set of characteristics. The more similar two individuals are on the set of demographic parameters that define the space, the more proximate they will be to one another within the space. For example, a 30-year old, college educated, middle income person would be closer to a 40-year old, college-educated, middle income person in Blau space than they would be to a 20-year old, low income, high school graduate. Based on the homophily principle, individuals closer to one another in Blau space are more likely to come into contact and/or form a tie. Blau space thus allows researchers to *approximate* an individual's social network – especially when network data are limited or unavailable. Previous studies of organizational ecology have employed Blau space to identify an organization's pool of potential members and to model the dynamics when organizations compete for members in the same pool (McPherson, 1983; 2004; McPherson & Ranger-Moore, 1991). In our research, we redirect the focus from organizations to individuals.

In our new method, Blau bubble analysis, we identify an individual's set of familiar others and compute their average score on the behavior of interest to track influence. Blau bubble analysis consists of two stages. In the first stage, we identify familiar others who serve as the ego's reference group. To do this, we first construct the Blau space using salient demographic attributes as the axes. We then position individuals within the space based on their unique combination of characteristics across these attributes (Figure 2). Although we use three continuous variables for the purpose of visualization, the space can include categorical variables and exceed three dimensions.

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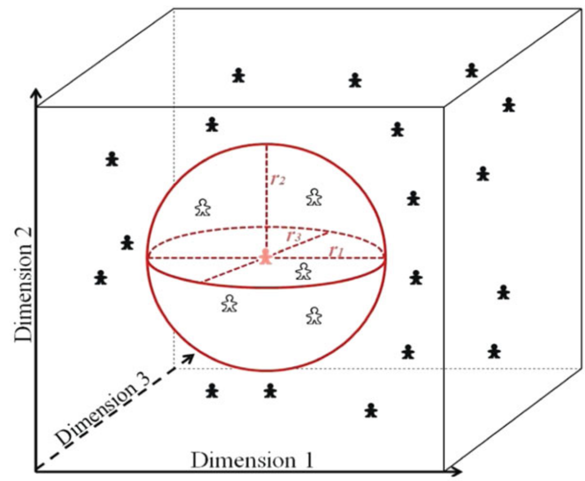

Fig. 2. Identifying familiar others in a three-dimensional Blau space. (Color online)

Within this space, close neighbors are more similar to each other than to individuals located farther away. Drawing on reference group theories that emphasize the role of social similarity in social comparison, *we identify an individual's familiar others as an individual's spatial neighbors*. To define this "neighboring" within the space, we delineate familiar others as those individuals who are situated within a specific distance from the individual. We calculate the Euclidean distance of the ego i from any given respondent j within the Blau space, denoted as Dij, as follows:

$$D_{ij} = \sqrt{\frac{\sum_{p=1}^{k} \left(X_{pi} - X_{pj}\right)^2}{k}}$$

where X is the value on a given dimension and k is the number of dimensions in Blau space. For categorical dimensions, individuals who share the same category (e.g., both female) have a score of zero; dissimilar individuals have a score of one. Continuous variables are standardized to the unit interval. Consequently, all dimensions range from zero to one.

In the equation above, the distance is computed between the ego and all other individuals in the same Blau space. Put differently, if there are 200 individuals in the Blau space, the distance from the respondent to another individual is calculated 199 times so that the respondent has a difference score between themself and every other individual in their space. The number of dimensions, k, may differ depending on the parameters chosen and the number of attributes for which both i and j have valid data.[2] A score of zero on D indicates perfect similarity between individuals i and j, while a score of one indicates perfect dissimilarity.[3]

After calculating the ego i's distance (i.e., dissimilarity) to every other individual within the space, a radius must be defined as a distance (similarity) threshold to identify the ego's familiar others. Because the distance score increases as dissimilarity

[2] For example, if there is a missing value on one of the six parameters for either i or j, the Euclidean distance between the two individuals is computed using five parameters ($k = 5$).

[3] All attributes are valued equally, though given theoretical justification that one dimension is more important than others, different weights may be given to each dimensions.

increases, individuals who fall below the radial cutoff are designated as the ego i's familiar others. We term the designated radial space the "Blau bubble," such that familiar others can be identified as those individuals within an ego's Blau bubble. In Figure 2, familiar others are represented as those white-shaded individuals who fall within the ego's Blau bubble. Conversely, individuals above the cutoff (e.g., outside of the radius used to define the Blau bubble) are designated as too dissimilar to serve in the reference group. If the radius is set to 0, only those individuals whose characteristics completely match with the ego will be classified as familiar others; if the radius is set as 1, all individuals in the Blau space will be captured. We adopt a value of 0.333 for identifying familiar others. In a hypothetical two-dimensional Blau space wherein individuals are evenly distributed throughout the space, this radius would identify approximately 1/3 of individuals as familiar others.[4] Alternative thresholds ranging from 0.1 to 0.9 are explored in the "Robustness" section.

In principle, it ought to be possible to replace our threshold with an inverse square law-like decay function that reduces the influence a familiar other exerts on the individual as the distance between them increases. We do not attempt such for two reasons. First, while we suspect that some decay function is operative, we have no specific theoretical basis for constructing it. As a result, we would either be forced to select its form essentially arbitrarily, or to rely on induction from this specific dataset, which would increase the risk of over-fitting. We prefer instead to use a threshold as a less arbitrary method that invites less intensive tuning to specific data. Second, by using a threshold we are able to use our robustness checks to identify the radii at which social influence from familiar others declines, thereby providing insight into the "range" over which this process operates. Therefore, we think it is more conservative theoretically, and more informative substantively, to rely on a threshold approach at this time.

In the second stage, we measure the mean value of the dependent variable among the ego's familiar others. We formalize this step and calculate the Blau Proximity Index scores as follows:

$$\mathrm{BPI}_i = \left(\frac{\sum_{j=1}^{n} Y_j}{n} \middle| D_{ij} \leqslant r \right)$$

where r is the threshold (i.e., radius) under which familiar others are designated, Y is the dependent variable, and n is the number of familiar others (i.e., individuals who are within the ego i's Blau bubble). Using the scores of the Blau Proximity Index as the key independent variable, we measure whether the behavioral patterns of familiar others indeed predict those of the ego.

As we outline above, conventional network analysis is often confronted by significant challenges in acquiring data. Indeed, it has sometimes proven difficult simply to identify who should be considered a part of the network in the first place (i.e., the "boundary specification problem"; see Laumann et al., 1992), much less to properly measure their relations. Responses to this challenge have often proceeded by either seeking out more detailed data, or drawing inferences from affiliation. Efforts using the former strategy (e.g., Frank et al. 2010; Crosnoe et al., 2008; Sun

[4] In a two-dimensional space, where the dimensions span from zero to one, the total area of the Blau space is 1 and the area of a circle with a radius of 0.333 is 0.348 ($= \pi \times 0.333^2$).

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et al. 2013) have identified familiar others using transit data or highly detailed data on class schedules within a school. These approaches are highly effective and useful, and should be employed when possible, but are also intrusive and limited by the need for such highly detailed data. Efforts using the latter strategy include studies of affiliation networks (e.g., Breiger 1974; Suh et al., 2016) that define relatedness in terms of co-membership or co-location in similar neighborhood spaces (e.g., Browning et al., 2017). Such approaches broaden the definition of what can be counted as a network, and have inspired efforts to understand more traditional forms of data in relational terms (e.g., Breiger & Melamed, 2014). Our Blau bubble analysis extends both of these approaches. Like the first approach, we try to identify those individuals who are routinely, and repeatedly, present in the same physical settings as the ego, allowing them to exert a behavioral influence. And like the second approach, we essentially infer the existence of influence relationships, in our case relying on the homophily principle to identify those others who are most likely to be co-present with the ego, and most likely to serve as significant others for social comparisons. The advantage of our method is that it can identify this set of familiar others with less detailed data than either of the previous approaches, requiring neither information on co-presence in specific locations, or formal affiliation data. As such, while Blau bubble analysis is explicitly inferential, and probably does not need to be used when more detailed data are available, it provides a flexible and data inexpensive approach to identifying the most influential persons likely to be in ego's environment, but who will remain stubbornly invisible to standard network inventories. We thus see our approach as a worthwhile addition to existing methods, rather than as a replacement for any one.

3.2 Case study: Unhealthy weight behaviors in adolescence

Much research points to the role of social influence in individuals' engagement in health protective and destructive behaviors (see Berkman & Glass, 2000; Smith & Christakis, 2008). Weight-related behaviors have emerged as an important site for influence studies in light of the rising rates of obesity and eating disorders. Though seemingly medical (Willett et al., 1999), defining what constitutes a "healthy weight" has become a political, social, and cultural issue (Oliver, 2006; Ornstein, 2010; Spurgas, 2005; Yancey et al., 2006). Despite medical research identifying the negative health effects of under- and overweight statuses, (Rome & Ammerman, 2003; Van Gaal et al., 2006), advertising, popular culture and social movement campaigns have provided myriad, competing idealized body types that challenge medical standards. Perhaps due to the subjectivity surrounding desirable body weights, both network members and reference groups have been shown to exert significant influence on an individual's overweight status (Christakis & Fowler, 2007), body dissatisfaction (Hargreaves & Tiggeman, 2004), and engagement in weight control behaviors (Hutchinson & Rapee, 2007; Paxton et al., 1999).

Building on this prior literature, we examine the case of unhealthy weight behaviors among adolescents to test whether familiar others indeed exert influence on the ego. We focus on weight-related behaviors due to their health implications and subjectivity. Unhealthy weight behaviors in adolescence, such as unnecessary dieting or unhealthy weight gain, have important health implications later in the life course (Neumark-Sztainer et al., 2006; 2012; Sinaiko et al., 1999), making them substantively important to study. Additionally, the conflicting recommendations for healthy, appropriate, or attractive weight status create an environment of variable expectations, prompting individuals to turn to others for guidance. Social comparison theory emphasizes that an ego is most likely to turn to their reference group when the attribute being evaluated is subjectively ranked or the behavioral norm is unclear (Festinger, 1954; Shibutani, 1955), making this an especially appropriate domain for us to evaluate our new method. Prior work by Mueller et al. (2010) demonstrates that adolescent girls' same gender, same weight status peers act as salient references in their decisions of whether to attempt weight loss. This work highlights the important role of school context and, more specifically, of individuals who resemble the ego within that context for the ego's engagement in weight loss behavior. Because there are varied norms surrounding what constitutes a desirable body weight and judgments of weight status tend to be correspondingly subjective (Maximova et al., 2008), we expect that individuals will turn to socially similar others, defined by similarity on a *range* of socio-demographic attributes, in deciding what type of weight-control (if any) behavior to engage in.

3.3 Hypotheses

We investigate whether the ego's behavior resembles that of their familiar others. More formally, we hypothesize that familiar others' weight control behaviors will influence the ego's weight control behaviors. Because we believe that familiar others exert an influence that is complementary (rather than antithetical or identical) to network alters, we predict that this relationship will not be reducible to the ego's direct ties. Although we cannot test our proposed mechanisms directly, identifying the predicted effects would provide a general proof of concept for familiar others as an important, but previously unmeasured, source of influence. Given that prior social network studies demonstrate robust findings for network-based weight outcomes and behaviors (Leahey et al., 2011; Valente et al., 2009), the role of familiar others for this same outcome demonstrates the extent to which behavioral influence requires a tie to flow. Indeed, previous work suggests that familiar others may be an especially salient source of influence for weight control behaviors in adolescence (Mueller et al., 2010).

3.4 Data

We use data from Wave I of the National Longitudinal Study of Adolescent to Adult Health (Add Health) to investigate the effects of social influence on body weight behavior. The Add Health provides rich detail on adolescents' health behaviors, friendship networks, and socio-demographics. While the study utilizes a clustered sampling design to sample students nested within high schools, the data can be weighted and clustered by school during analysis to produce unbiased population estimates (Chen & Chantala, 2014). The Add Health's clustered sampling design provides a robust test of our hypotheses because each school can be utilized as an independent Blau space, allowing us to generalize the role of familiar others beyond the dynamics of a specific school. Additionally, the Add Health's extensive friendship network data allows us to test the influence of familiar others while controlling for the impact of direct alters.

Wave I of the Add Health includes both an in-school survey, a self-administered questionnaire that all students in attendance completed between September 1994 and April 1995, and a longer, in depth in-home interview, which a subsample of respondents and their parents completed in April–December 1995. To rule out interviewer and parental effects in the in-home interview, adolescents were asked sensitive health and risk behavior questions using an audio computer-assisted self-interview (A/CASI) format (Turner, 1998). We limit our analysis to the 16 "saturation schools" in which all enrolled students were selected to complete the in-home questionnaire. These schools contain complete network data, enabling a more rigorous test of familiar others and social network influence. The saturation schools include two large schools with enrollment over 800 and 14 smaller schools with enrollments under 200. Our final sample consists of 2,579 students spread across the 16 saturation schools.

3.5 Dependent variable

To construct measures of weight behavior, we draw on the Add Health item that asks respondents "Are you trying to lose weight, gain weight, or stay the same weight?" Respondents are also given the option of "not trying to do anything about weight," which we collapse with "stay the same weight." Then, we compare these behaviors against the respondent's objective BMI using established cutoffs of underweight, healthy weight, and overweight status based on weight, height, and age. We define overweight, underweight, and normal weight status according to the CDC's BMI-for-age growth charts for children and adolescents (Kuczmarski et al., 2000), which account for natural periods of rapid growth during adolescence. Raw BMIs were converted to percentiles based on these charts, which designate weight percentiles based on an individual's height, weight, age, and gender. In line with these guidelines, underweight status is designated for respondents in the fifth percentile or less, normal weight status is assigned for respondents with weights between the fifth and 85th percentile, and overweight status is assigned for respondents with weights greater than the 85th percentile for their age and gender.

Comparing the respondent's behavior with their objective BMI status, we construct a dependent variable, yielding three categories: healthy weight behavior, unhealthy weight loss, and unhealthy weight gain. We describe respondents' actions as "healthy" or "unhealthy," based on whether the respondent's weight action moves them in or out of the CDC's "healthy weight" category for their age, height, and gender. Healthy weight behavior includes all actions that bring the respondent's weight to a healthy level. These include weight gain for underweight respondents, weight maintenance for healthy weight respondents, and weight loss for overweight respondents. Unhealthy weight loss is recorded for those underweight and normal weight respondents reporting that they are trying to lose weight, as well as for underweight respondents who report trying to stay at the same weight. Unhealthy weight gain is recorded for those normal weight and overweight respondents who report trying to gain weight and for overweight respondents who report maintaining weight. Unnecessary weight loss is coded as −1, healthy weight action is coded as 0, and unhealthy weight gain is coded as 1.

While our dependent variable is somewhat broad, we prefer it as the most informative option. While eating disorders and disordered eating behaviors (ex: forced vomiting) are important health outcomes in their own right, the goal of our paper is to understand *more broadly* how people's behavior is affected by their familiar others. By examining more extreme and rarer behaviors like eating disorders, we would limit ourselves to small population of affected individuals and a potentially non-generalizable proof of concept of familiar others' influence. Alternatively, we could simply rely upon the respondent's report that they are attempting to lose, maintain, or gain weight, but the meaningfulness of these answers varies depending upon their weight status. An overweight individual who is attempting to lose weight may be following the advice of their physician, whereas an underweight individual engaging in the same behavior may be doing so against such advice. Failing to distinguish by weight status thus runs the risk of mixing individuals who are experiencing very different weight control trajectories. Finally, we cannot simply rely upon adult BMI categories because adolescents are still experiencing significant, sometimes rapid and dramatic, growth. As a result, BMI values that might be unreasonable for adults may be developmentally appropriate for many of our respondents. Our dependent variable thus makes the best use of our data to allow apples-to-apples comparisons of respondent weight behavior.

Figure 3 illustrates trends in weight-related behavior among adolescents, differentiated by gender. Engagement in unhealthy weight behaviors is prevalent among adolescents in the Add Health, with nearly half of respondents exhibiting problematic weight behaviors. The figure also illustrates a striking difference in the types of weight behaviors across males and females. Females are more likely to lose weight unnecessarily or maintain their underweight status (34.1% among all females), while males are more likely to fall into the category of unhealthy weight gain (41.8% among all males). The average score of weight-related behavior is −0.264 for females and 0.331 for males.

3.6 Key independent variables

We use Blau bubble analysis (detailed above) to identify familiar others and to calculate the score for their average weight-related behaviors. We define the Blau space using six socio-demographic parameters that structure social interactions and shape individuals' reference groups: gender, race, language spoken at home (as a proxy for ethnic minorities), grade level, parents' income, and Add Health Picture Vocabulary Test[5] score (as a measure of intelligence). We utilize these socio-demographic variables as dimensions of the Blau Space because they impact patterns of association. Adolescents display friendship and contact homophily based on ethnicity, gender (Brashears, 2008), family socioeconomic status (SES) (Bearman et al., 2004; Schaefer et al., 2011), and intelligence (Barnes et al., 2014; Bearman et al., 2004; Schaefer et al., 2011). Moreover, grade level, intelligence, and SES influence students' assigned academic tracks (Gamoran & Mare, 1989), further structuring

[5] The PVT test is an abridged, age-standardized version of the Peabody Picture Vocabulary Test.

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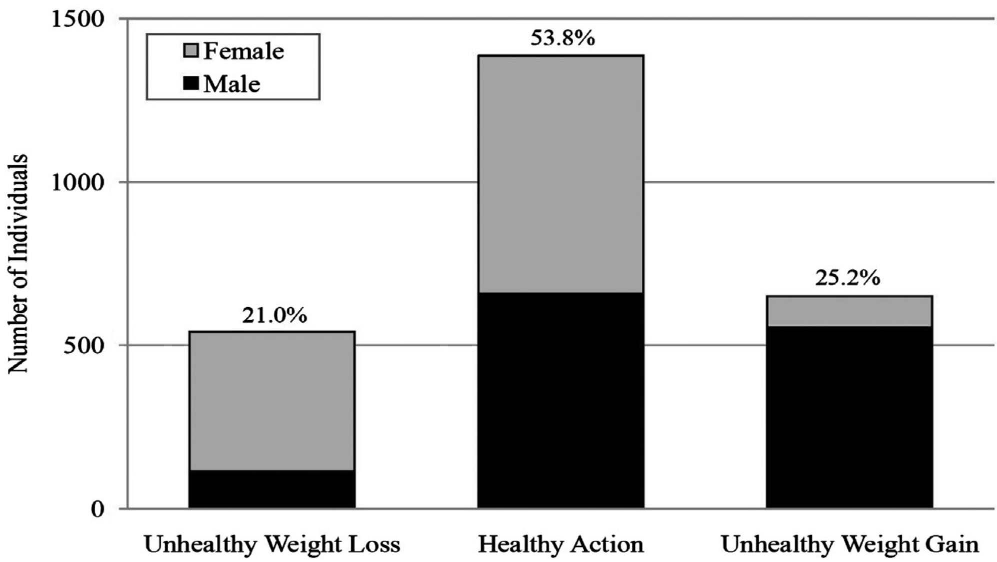

Fig. 3. Weight-related behavior by gender.

interaction patterns among adolescents (Hallinan & Williams, 1989; Kubitschek & Hallinan, 1998). The distance from the ego to all other individuals within the space is calculated by school. We identify familiar others as those individuals who fall within the 0.333 radius in the individual's school-defined Blau space (i.e., the difference score between the ego and the other is less than or equal to 0.333).[6]

We then calculate the average weight behavior of the ego's familiar others. Since each school has its own ecology within which students interact, we bound the Blau Proximity Index *by school* such that the identification of an individuals' familiar others is limited to the population of other students within their school. This bounding by school co-attendance enables repeat opportunities for the ego to interact with their familiar others. Familiar others' weight behavior is coded in the same way as the dependent variable (-1 = unhealthy weight loss, 0 = healthy weight action, 1 = unhealthy weight gain). For example, an average familiar others weight behavior of 0.62 indicates the individual's familiar others' tend to engage in unhealthy weight gain, whereas an average of -0.43 indicates they display more engagement in unhealthy weight loss. This process is repeated for all students included in our sample. Weighted by school size, the average proportion of the school that is identified as an individual's familiar others is 22.9%. The correlation between

[6] Direct alters who are located inside the radius are included as familiar others. Rather than removing direct alters in the computation process, we include the behaviors of direct alters as an independent variable in the analysis. We also do not remove familiar others who are also direct alters when computing the average behaviors of direct alters. On average, there are 149 students inside a radius of 0.333. While the average number of direct alters is 2.48, the average number of friends who are also identified as familiar others is 1.10 (44.2%). The striking numeric difference between an ego's total familiar others and the small number of familiar others who are also direct ties makes it highly unlikely that an observed effect from an ego's familiar others is miscapturing an effect from their direct ties.

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the respondent's weight-related behavior and the average behavior of their familiar others is 0.43 ($p < 0.001$) (see Table A1 in the Appendix for the full correlation matrix).

To examine the effect of peer networks on the respondent, we average the aforementioned weight-related behavior variable across all members of ego's first-degree alters with available data. During the in-home survey, respondents were asked to nominate up to ten friends, five of each gender. If a student reports friends who attend the same school, the friend is selected from a roster of students within the school so that the data may be compiled into the saturation school global network. Respondents may also nominate friends outside of school; however, the average number of nominations to out-school-friends is small (Haynie, 2001), and we are unable to account for their behaviors due to missing data (i.e., they were not part of the sampling frame). Because we rely on in-school students to compute the familiar others' behavioral average, we do not believe this reliance on in-school direct alters biases our results. The correlation between the ego's weight-related behavior and the average behavior of their direct alters is 0.16 ($p < 0.001$) (Table A1).

3.7 Control variables

In addition to the key independent variables, we include 15 control variables in our comprehensive model. First, we control for the possibility that BMI will influence the likelihood of falling into one of the categories of unhealthy behavior. We include the respondent's BMI, the average BMI of their familiar others, and the average BMI of their network alters as controls. Because certain socio-demographic characteristics may be directly associated with unhealthy weight behavior, we control for the parameters that are used to place the familiar others within Blau space. These adjustment variables include a binary gender variable (female=1), a binary variable of racial minority status that includes Black, Hispanic, and Asian race (white=0),[7] a binary variable for a language other than English spoken at home as a measure of ethnic minority status, parental income,[8] PVT score, and grade level. Based on the literature (Serdula et al., 1993) and descriptive statistics, we expect that gender will have a strong effect on the type and risk of unhealthy weight behavior adolescents engage in.

We also include a number of individual-level attributes as controls. Since body weight can increase dramatically during pregnancy, we adjust for whether the respondent is currently pregnant. We also adjust for whether the respondent has been in a romantic relationship in the last 18 months, as this status may be independently

[7] We use a single binary variable for racial minorities in the regression models due to the high multi-collinearity problem that arises when we use separate race variables for Black, Hispanic, and Asian. We are able to keep the VIF under seven with the substitution of one binary race variable (white vs. non-white). We suspect that the problematic VIF in models with all three race variables is the result of the strong correlation between familiar others' behaviors, female, and Black.

[8] Parental income is the only variable that is derived from the in-home parent questionnaire. Because the response rate is much lower for the parent questionnaire than the student questionnaire, potential biases might be influencing our analyses. Therefore, we impute missing values on the variable using multiple imputation (MI) techniques in the statistical package Stata. The parental income variable is imputed by the respondent's racial minority status, PVT score, use of a language other than English at home, and grade level. We retrieve 691 cases as a result of multiple imputation. The results are not qualitatively different from the analyses without imputation.

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Table 1. Descriptive statistics of dependent and independent variables.

Variables	Mean	S.D.	Min.	Max.
Ego's weight-related behavior	0.04	0.69	−1	1
Familiar others' behavior	0.06	0.32	−1	1
Direct alters' behavior	−0.13	0.53	−1	1
Ego's BMI	23.02	4.61	11.75	46.20
BMI of familiar others	23.03	1.12	15.29	26.57
BMI of direct alters	22.59	3.09	14.14	41.98
Female	0.49	–	0	1
Racial minorities	0.45	–	0	1
Parental income (thousand)	45.04	27.44	0	284
PVT score	99.81	13.61	41	138
No English at home	0.16	–	0	1
Grade level	10.37	1.37	7	12
Pregnancy	0.02	–	0	1
Romantic relationship	0.58	–	0	1
Physical attractiveness	3.59	0.84	1	5
Sports team membership	0.48	–	0	1
Physical exercise	3.54	2.08	0	9
Sedentary activity	20.57	19.00	0	228

related to unhealthy weight behaviors (Halpern et al., 2005). Additionally, we include an ordinal variable of the respondent's physical attractiveness as rated by the interviewer. Given prevailing weight norms, attractiveness may indicate prior engagement in weight control behaviors or influence the respondents' current weight control behaviors net of the behaviors of their direct alters or familiar others.

Further, we control for the individual's sports team memberships and levels of physical and sedentary activity. We calculate a count of the individual's sports club memberships based on the respondent's participation in the 13 athletic organizations we identify in the data. These athletic organizations include cheerleading/dance, baseball/softball, basketball, field hockey, football, ice hockey, soccer, volleyball, swimming, tennis, track, and wrestling. These organizations may encourage healthy behaviors (e.g., healthy eating) that act as a protective factor in the individual's risk of unhealthy weight behavior (Pate et al., 2000) or foster unhealthy weight norms that function as a risk factor (Taub & Blinde, 1992). Additionally, we compute an index of physical exercise by summing respondent's self-reported engagement in the following physical activities: (1) jogging, walking, karate, jumping rope, gymnastics, or dancing, (2) rollerblading, roller-skating, skate-boarding, or bicycling, and (3) baseball, softball, basketball, soccer, swimming, or football. Higher index scores indicate more physical activity. We finally generate an index of sedentary activity based on the total number of hours the respondent (1) watched television, (2) watched videos, and (3) played computer/video games. In addition to sedentary activity, this variable may proxy the respondent's exposure to media, which may serve as an additional source of influence (Agliata & Tantleff-Dunn, 2004). Table 1 shows the descriptive statistics of the dependent and independent variables we use in our analyses.

3.8 Method

To test whether the weight-behaviors of familiar others influence the ego, we employ a multinomial logistic regression model. Because the dependent variable is categorical, we predict the likelihood that an individual will engage in unhealthy weight behaviors (unnecessary weight gain (p_1) or unnecessary weight loss (p_2)) relative to the reference category of taking the healthy action for their weight (p_3). The multinomial logistic regression model takes the following form:

$$\log\left(\frac{P_j}{P_3}\right) = \alpha_j + \beta_{1j}\text{ Familiar Others} + \beta_{2j}\text{ Direct Alters}$$
$$+\beta_{3j}\text{ Controls}\,(j = 1, 2; p_1 + p_2 + p_3 = 1)$$

where both logits, $\log(p_1/p_3)$ and $\log(p_2/p_3)$, have their own α_j and independent coefficients for each covariate (Long & Freese, 2006). The coefficients estimate the effect of the independent variables on the log odds of falling into one of the unhealthy categories, controlling for adjustment variables. We present the *relative risk ratios* of the coefficients, which should be interpreted as the relative risk of the respondent falling into either the category of unnecessary weight gain (p_1) or the category of unnecessary weight loss (p_2) relative to being in the reference category of healthy weight behavior (p_3). In all models, we also use robust standard errors to adjust for school clustering. Finally, we include sample weights to adjust for unequal sampling probabilities in the Add Health data. Since the level of interest is each school, within which students interact with each other, we only use the individual-level within-school weight component to correct for design effects within schools (Chantala & Suchindran, 2011). This allows us to make locally representative statements at the school level.

4 Results

4.1 Multinomial logistic regressions

Do familiar others serve as a source of influence for weight-related behavior? Models I–IV (Table 2), provide strong evidence that they do.

In Model I, we test the relationship between familiar others' weight behaviors and the individual's behaviors. The results demonstrate that familiar others' behaviors are significantly related to those of the ego, both with regard to unhealthy weight gain and weight loss. A one unit increase in the familiar others' average weight-related behavior (i.e., toward unnecessary weight gain) is associated with 0.09 times the relative risk ($p < 0.001$) of unhealthy weight loss (i.e., the risk decreases) and 18.92 times the relative risk ($p < 0.001$) of unhealthy weight gain relative to being in the reference category of healthy weight behavior.

In Model II, we include an independent variable controlling for direct alters' weight control behaviors. Direct alters' weight behaviors are significantly related to those of the ego only in case of unhealthy weight gain. The relative risk of the ego engaging in unnecessary weight gain is expected to increase by a factor of 1.31 ($p < 0.05$) for a one unit increase in direct alters' behavior (i.e. average shifts toward unnecessary weight gain). However, the inclusion of the direct alters' weight behaviors does not reduce the significance of the familiar others' weight

Table 2. Multinomial logistic regression analyses on weight-related behavior.

	Unhealthy weight loss				Unhealthy weight gain			
	I	II	III	IV	I	II	III	IV
Social environment:								
Familiar others' behavior	0.09***	0.09***	0.12***	0.65	18.92***	16.92***	21.58***	9.43***
	(0.03)	(0.02)	(0.02)	(0.35)	(3.17)	(2.69)	(3.48)	(5.93)
Direct alters' behavior		0.89	0.89	0.89		1.31*	1.28†	1.29*
		(0.20)	(0.17)	(0.18)		(0.16)	(0.17)	(0.16)
BMI status:								
BMI of respondent	0.90***	0.90***	0.89***	0.89***	0.93***	0.93***	0.93***	0.93***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)
BMI of familiar others	1.21***	1.21***	1.03	1.04	1.18***	1.18***	1.01	0.96
	(0.05)	(0.05)	(0.06)	(0.06)	(0.04)	(0.03)	(0.04)	(0.05)
BMI of direct alters	1.00	0.99	0.98	0.98	1.01	1.03†	1.02	1.02
	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)
Blau parameters:								
Female				3.11***				0.53†
				(0.87)				(0.20)
Racial Minorities			1.04	1.01			1.38†	1.53*
			(0.11)	(0.16)			(0.23)	(0.26)
Parental income			1.00	1.00			1.00	1.00
			(0.00)	(0.00)			(0.00)	(0.00)
PVT score			0.99	1.00			0.99	0.99
			(0.00)	(0.00)			(0.01)	(0.01)
No English at home			1.30***	1.52***			0.95	0.85*
			(0.08)	(0.08)			(0.07)	(0.07)
Grade level			1.28***	1.30***			1.16***	1.17***
			(0.06)	(0.06)			(0.05)	(0.05)

Table 2. Continued.

	Unhealthy weight loss				Unhealthy weight gain			
	I	II	III	IV	I	II	III	IV
Controls:								
Pregnancy	0.95	0.96	0.96	0.88	1.83	1.70	1.31	1.46
	(0.23)	(0.19)	(0.22)	(0.22)	(0.96)	(0.96)	(0.69)	(0.72)
Romantic relationship	1.36***	1.36***	1.29*	1.30*	1.39**	1.38**	1.29**	1.27**
	(0.12)	(0.12)	(0.14)	(0.15)	(0.15)	(0.14)	(0.11)	(0.11)
Physical attractiveness	1.04	1.04	1.02	1.01	0.81†	0.81†	0.80†	0.80†
	(0.05)	(0.04)	(0.04)	(0.04)	(0.10)	(0.10)	(0.11)	(0.11)
Sports team membership	0.98	0.98	1.09	1.09	1.12	1.11	1.18	1.17
	(0.08)	(0.09)	(0.10)	(0.10)	(0.14)	(0.14)	(0.14)	(0.14)
Physical exercise	1.06**	1.06*	1.09**	1.10***	1.06*	1.06*	1.09**	1.08**
	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Sedentary activity	1.00	1.00	0.99	1.00	0.99***	0.99***	0.99***	0.99***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	0.03**	0.03*	0.28	0.08*	0.04*	0.03**	0.54	2.23
	(0.03)	(0.04)	(0.34)	(0.08)	(0.05)	(0.04)	(0.56)	(3.50)
Pseudo R^2	0.15	0.15	0.17	0.17	0.15	0.15	0.17	0.17
Observations	2,653	2,652	2,479	2,479	2,653	2,652	2,479	2,479

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.1$; Coefficients reported as relative risk ratios.

behaviors relationship with the individual's. The relative risk of unnecessary weight loss decreases by a factor of 0.09 ($p < 0.001$), and the relative risk of weight gain increases by a factor of 16.92 ($p < 0.001$), per one unit increase in the familiar others' average weight behavior.

In Models III and IV, we include Blau space parameters as additional adjustment variables. These socio-demographic variables are used as dimensions in Blau bubble analysis because they are salient factors in structuring interpersonal interactions among adolescents. By including these variables in the regression analyses, we adjust for the possibility that the significant effect of familiar others is a mere artifact of the individual's socio-demographic characteristics. In other words, we ensure that the importance of proximity in social space is not a spurious result of the direct effect of the variables used to define social space. In Model III, respondent's racial minority status, parental income, PVT score, use of a language other than English at home, and grade level are included in the model. After controlling for these covariates in Model III, a one unit increase familiar others' average weight behavior remains significantly, positively associated with the both individual's increased risk of engaging in unnecessary weight gain (RRR = 21.58, $p < 0.001$) and decreased risk of engaging in unnecessary weight loss (RRR = 0.12, $p < 0.001$). Additionally, the direct alters' weight behaviors are predicted to marginally significantly increase the individual's relative risk of unhealthy weight gain by a factor of 1.28 ($p < 0.1$).

In Model IV, the gender variable is included as a final control. The inclusion of the female dummy variable makes our test very conservative due to the high correlation between female sex and the familiar others' weight behavior variables ($r = -0.89$, $p < 0.001$). The high negative correlation indicates that females are much more likely to be surrounded by familiar others, mostly other females, who engage in unnecessary weight loss. The results in Model IV reflect this overwhelming demographic effect. The relationship between familiar others' behavior and individual's risk of unhealthy weight loss loses significance, while the relationship between familiar others and the individual's risk of unhealthy weight gain remains positive and statistically significant (RRR = 9.43, $p < 0.001$). Similarly, a one unit increase in the behavior of direct alters increases the relative risk of engaging in unnecessary weight gain by a factor of 1.29 ($p < 0.05$). In sum, after controlling for the respondent's socio-demographic characteristics, including gender, familiar others' weight behaviors still predict the individual's engagement in unhealthy weight gain, though not in unhealthy weight loss. As for unhealthy weight loss, gender appears to be the strongest risk factor. Females have 3.11 ($p < 0.001$) times higher relative risk of engaging in unnecessary weight loss, even after adjusting for the behaviors of their direct ties and familiar others.

Among the adjustment variables, the analyses indicate that the higher the BMI of the respondent, the less likely they are to engage in unhealthy weight loss. However, this may be by virtue of the fact that it is impossible to lose weight unnecessarily if the individual is already overweight according to our construction of the variable. Additionally, familiar others' average BMI is positively associated with the likelihood of falling into both categories of unhealthy behavior in Models I and II, but the relationship disappears with the inclusion of additional control variables. In other words, the BMI of familiar others fails to significantly predict the ego's weight-related behavior once the ego's own demographic characteristics are taken into account.

Respondents are more likely to exhibit unhealthy behaviors as they advance to higher grades. An increase of one grade is related to approximately 1.30 times ($p < 0.001$) the relative risk of unnecessary weight loss and 1.17 times the relative risk ($p < 0.001$) of unnecessary weight gain. We observe a similar relationship with previous romantic relationships, wherein relationship status increases the relative risk of both unnecessary weight loss and unnecessary weight gain.

We additionally adjust for the roles of sports team membership and physical and sedentary activity levels on the individual's risk of unhealthy weight control. Physical and sedentary behavior levels are more consistently related to the individual's engagement in unhealthy weight behaviors than the individual's number of sports team memberships. In the final model, a one unit increase in the physical exercise variable is related to a 1.10 ($p < 0.001$) times the relative risk of unnecessary weight loss, as well as a 1.08 ($p < 0.01$) times the relative risk of engaging in unnecessary weight gain. Conversely, more sedentary adolescents, those who report higher levels of TV, video and computer game usage, are slightly less likely to gain weight unnecessarily than to demonstrate healthy weight behaviors (RRR = 0.99, $p < 0.001$).

In sum, our analyses provide support for our hypothesis that familiar others exert influence on individuals that is complementary to that of network alters. Even after controlling for friends' behaviors, familiar others' behaviors more strongly and consistently predict the individual's risk of unhealthy weight-related behavior. This finding withstands the inclusion of the respondent's own socio-demographic characteristics that determine the individual's position in Blau space. In other words, it is behaviors of the familiar others themselves, not the absolute position of the individual in Blau space, that predict the individual's risk of unhealthy weight behavior.

4.2 Robustness

To test the robustness of our results, we repeat our analysis with (1) familiar others thresholds of varying size, (2) longitudinal models, and (3) separate models by gender. In our identification of familiar others, we utilize a radius of 0.333 in the Blau bubble analysis to distinguish an individual's familiar others from non-familiar others. To test the robustness of our finding that the familiar others' weight behaviors are related to those of the ego, we repeat our Model IV analysis (full model) with radii varying in size from 0.1 to 0.9. Figure 4 presents the relative risk ratio of the familiar others variable in predicting the ego's unnecessary weight gain. This figure also illustrates average percentage of students who are identified as an individual's familiar others across varying radii in the 16 saturation schools.[9]

Figure 4 illustrates that the weight-related behavior of familiar others has a statistically significant effect when the radius is set to 0.4 or lower. While we use 0.333 as the familiar others designation threshold in our main analyses, the radius of 0.4 demonstrates the strongest relationship between the individual's and their familiar

[9] The average school size is 237 students. When we compute the average percentage of familiar others, the number of familiar others who are inside the radius is divided by total possible number of familiar others, which is N (school size) – 1 (the respondent).

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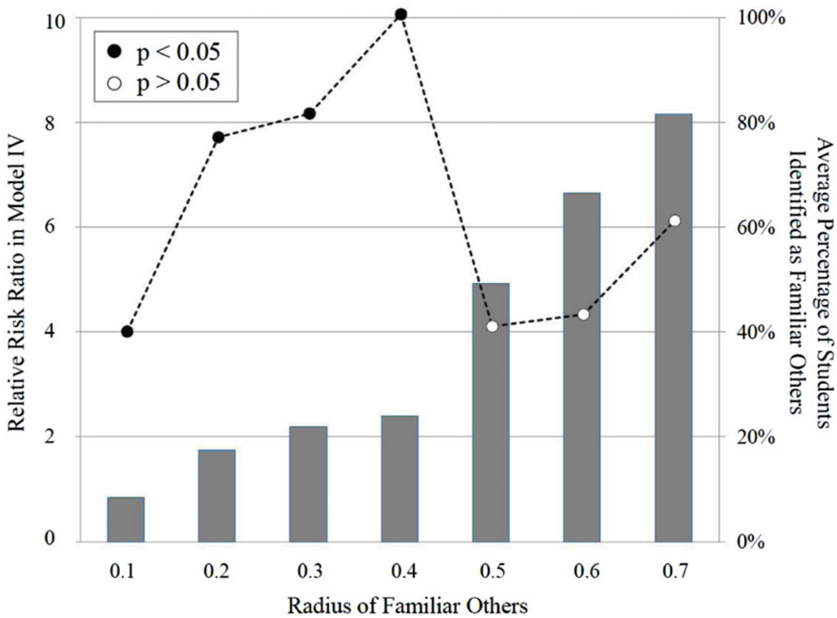

Fig. 4. Predicting unhealthy weight gain with different radii of familiar others. (Color online)

others' weight-related behaviors. When the radius is 0.5 or higher, the magnitude of the prediction relationship drops dramatically and the relationship loses statistical significance ($p > 0.05$). In addition, the average percentage of students who are identified as familiar others in 16 schools more than doubles from 23.9% of school's population when the radius is defined as 0.4, to 49.2% of the school's population when the radius is set at 0.5.[10] These supplementary results demonstrate that familiar others' behavior is strongly related to the individual's behavior when less than 50% of the school's total students are identified as familiar others. This finding makes theoretical sense as we would expect the influence of familiar others to decrease as the group of familiar others consists of less salient references for the individual.

We additionally test our Models III and IV results longitudinally by creating a Wave II dependent variable using the same variable specifications as Wave I. We use the individual's weight behavior (unnecessary weight loss, healthy weight action, and unnecessary weight gain) at Wave I as an additional control variable in the test of whether familiar others' behavior predicts the individual's weight behavior at Wave II. We also utilize the Wave II within-school sampling weight to control for differential sampling probabilities. Due to decreased response rate in Wave II, our sample size drops to 1,836 observations. The results of this conservative test provide partial support for the enduring effect of familiar others' weight behaviors on the individual's own weight behaviors. In the longitudinal version of Model III, familiar others' average weight behaviors in Wave I significantly predict the individual's weight behaviors in Wave II. A one unit increase in familiar others' behavior

[10] The figure does not include the radii of 0.8 and 0.9 because the percentage of students exceeds 95% when the radius reaches 0.8 and the behavior of familiar others essentially captures the average weight-related behavior of all students.

at Wave I (i.e., toward unnecessary weight gain) predicts a 0.25 times reduced relative risk ($p < 0.001$) of unhealthy weight loss and 4.13 times greater relative risk of ($p < 0.001$) of unnecessary weight gain in Wave II. Direct alters' weight behavior at Wave I is only marginally significant in predicting the individual's relative risk of unnecessary weight gain (RRR =1.27; $p < 0.1$). However, these significant relationships do not withstand the inclusion of the gender variable in the longitudinal equivalent of Model IV. Neither familiar others' nor direct ties' Wave I behaviors predict the individual's Wave II behavior after adjusting for gender. This result demonstrates that gender, and the differential norms it proxies, is a more robust predictor of the ego's weight behavior than the behaviors of their tied and untied references. Whereas an ego's direct alters and familiar others may change across waves, gender remains a static identity for the vast majority of respondents. Consequently, social influence from Wave I may be a weaker predictor of current activity if Wave II alters exhibit different or more varied weight behaviors than Wave I alters or familiar others. In this case, influence would be better understood as contemporaneous, rather than durable, phenomenon.

Finally, we test whether the influence of familiar others is differentiated by gender. We replicate the Wave I, Model III regression with analyses separated by gender. As in our main analysis, we find that familiar others' weight behaviors are strongly associated with the ego's unhealthy weight gain behaviors, but not with unhealthy weight loss. This relationship between familiar others' unhealthy weight gain and the ego's is larger in magnitude and statistically stronger than that between the ego and their direct alters. Among females, a one unit increase in familiar others' average weight behavior (average shifts toward unnecessary weight gain) is associated with 13.58 times the relative risk of unnecessary weight gain ($p < 0.01$). This result is replicated to smaller extent among males where a unit increase in familiar others' behavior is associated with 6.18 times the relative risk of unnecessary weight gain ($p < 0.001$). Although the coefficient magnitude is larger for females, the effect size should be treated with some caution due to the small number of females who report engaging in unhealthy weight gain. Nonetheless, these results suggest that familiar others are a significant source of influence for both males and females.

5 Discussion and conclusion

Previous studies of behavioral convergence have traced the flow of influence through an ego's direct ties. Our work shows that this method overlooks an important, complementary source of non-relational influence: an ego's familiar others. Using unhealthy weight behaviors as our case, we demonstrate the relevance of familiar others. We show that individuals' weight behaviors are more often and more strongly predicted by those of their familiar others than by those of their direct network ties. These findings corroborate prior work on social influence from untied others who nevertheless are part of a relevant reference group (e.g., Burt, 1987; Crosnoe et al., 2008; Frank et al., 2010; Mueller et al., 2010; Shakya et al., 2012) and suggest that Blau bubble analysis is a promising method for measuring non-network based influence on individual-level behaviors.

A key finding from our study is that familiar others' behaviors more strongly and more consistently predict the ego's behavior than the behaviors of their direct ties. This result may stem from an individual's relatively greater number of familiar others than confidants. Whereas an individual may maintain a relatively small number of close relationships, familiar others encompass a larger group of people. Even if each familiar other exerts less influence than a direct tie, the sum influence of familiar others may be greater simply because familiar others represent a wider swathe of the social environment. Relatedly, familiar others' influential strength may be a function of the greater time individuals spend with their familiar others relative to direct ties. Although we may prefer to spend time with our close ties, much of our day is dominated by the presence of familiar others, who may encompass coworkers, peers, and fellow commuters (see Sun et al., 2013; Young & Lim, 2014). Given that the data surveys high school students, much of respondents' time is spent in classrooms or in extracurricular activities where they may be separated from the friends they nominate as direct ties. When individuals spend more time in the presence of their familiar others than their direct ties, these increased encounters provide ample opportunities for observational learning and social comparison.

Familiar others' weight behavior is also more strongly related to individuals' risk of unhealthy weight gain. This finding may proxy the reduced effort required to gain weight than to lose weight. Individuals, especially adolescent boys, may be motivated to gain weight when they medically do not need to in an effort to "bulk up." Although building muscle requires dietary attention and physical exercise, individuals may shortcut these steps by simply gaining weight to appear larger. In this way, the cost of adopting the unhealthy weight gain behavior is relatively low. Conversely, weight loss may have a higher cost of adoption because of the more severe (and potentially unpleasant) dietary and exercise regime it requires. When behavioral adoption is inexpensive, social influence may play a stronger role.

In addition to the role familiar others play, we find that gender is a strong predictor of unhealthy weight behaviors. Female adolescents are over four times more likely to engage in unhealthy weight loss, regardless of the behaviors of their direct ties and familiar others. Although we lose significance for the role of familiar others in predicting unhealthy weight loss when we control for the ego's gender, both our main and supplemental analyses demonstrate that familiar others significantly predict unhealthy weight gain among both males and females. Put differently, it is not that females are immune to the influence of familiar others, but rather our results suggest that engagement in unhealthy weight loss is effectively part and parcel with being female in adolescence, rather than shaped by behavioral action in the social environment. This finding echoes Nichter's (2009) work on "fat talk" among adolescent girls. She finds that discussion of one's excess body weight serves as a type of communal glue and a signal of solidarity among adolescent girls, even when it is divorced from behavioral efforts to lose weight. Our gender finding does not jeopardize the theoretical or empirical implications of familiar others. Rather, it suggests that female respondents should be surveyed at younger ages while weight norms are still elastic if we wish to understand how social influence, from familiar others and direct alters alike, impacts the development of internalized unhealthy weight loss norms. Although healthy weight females who report trying to lose weight may do so for different reasons than overweight females (e.g., medical recommendation vs. social norms of "attractiveness"), the saying "You can never be too rich or too thin," speaks absolutely, and so its broader pressure may similarly be felt across women and girls of varying weight statuses.

While our results are intriguing, we cannot claim to be able to establish causality in the concordance of behaviors we observe between an individual and their familiar others. Our results align with previous work documenting the role of social relationships for unnecessary weight gain (e.g., Christakis & Fowler, 2007) and provide an important step toward measuring potential sources of social influence beyond an individuals' immediate ties. At the same time, establishing causality in network influence studies has proven to be conceptually and methodologically challenging (e.g., Bramoulle et al., 2009; Shalizi & Thomas, 2011) and many well-known examples of contagion and influence (e.g., Christakis & Fowler, 2007; Coleman et al., 1966; Fowler & Christakis, 2008a) have subsequently faced stiff challenges (e.g., Cohen-Cole & Fletcher 2008a; 2008b; Van den Bulte & Lilien, 2001; But see also Fowler and Christakis, 2008b). Advanced methodological approaches, including Stochastic Agent Based Models (Snijders et al., 2010) and Exponential Random Graph Models (Lusher et al., 2013), are partial solutions but are not wholly effective. It is therefore no surprise that we are unable to demonstrate causation to our complete satisfaction. Likewise, with so many of the familiar others captured in our data also serving as egos in the same analysis, our models likely suffer from an unpleasant degree of collinearity. We do not regard this state of affairs as ideal, but note that the goal of Blau bubble analysis is to take a critical aspect of the social environment of individuals, their familiar others, and allow it to be added to conventional analyses. Much as criticisms have been leveled at efforts to demonstrate causal influence through networks, similar criticisms have been leveled at efforts to causally link individual level variables to outcomes (e.g., McPherson, 2004). Indeed, analyses show that many such apparent causal links may be the spurious result of homophily and influence (e.g., DellaPosta et al., 2015). Or, more simply, conventional variable-based models may often be critically biased by their failure to account for interpersonal influence and network effects. We therefore acknowledge the faults in our approach, but think that its contribution to integrating previously unmeasurable elements of the social context outweighs them. Future efforts should concentrate on overcoming these deficiencies, particularly since our Blau bubble analysis can be employed as a means of integrating social influence effects into more conventional survey-based research.

While we find strong cross-sectional support for familiar others' influence, more research is needed to examine the role of familiar others' influence over time. We find modest support for an enduring effect of familiar others' weight behaviors on the individual's weight behavior. Although familiar others' exhibit a more consistent longitudinal influence on individuals than direct alters, this effect does not hold with the inclusion of the gender control variable. This inconsistency may reflect the contemporaneous nature of familiar others' influence on the ego. Familiar others' weight behaviors at Wave I may not carry as much clout a year later because comparative self-evaluations are made in the moment. An ego may be more likely to alter their behaviors based on the *current* rather than prior actions of their familiar others. Testing the influence of familiar others using longitudinal data measured in shorter intervals would shed light on the durability of this effect. Nonetheless, people effectively live in the present, and thus the impact of familiar others will still be felt psychologically by the respondent.

Although we use the case of unhealthy weight behaviors in this study, familiar others and Blau bubble analysis have the potential to be applied across a wide range of social scientific analyses. Firstly, Blau bubble analysis is an easily accessible method because individual-level survey data can be used to identify and calculate the influence of familiar others. This liberal data requirement represents an important development, as dyadic data has frequently been required to examine whether individuals with socially similar characteristics demonstrate similar behavioral patterns. This method is a parsimonious means of measuring social influence within the environment, a key interest of networks researchers, even when network data is absent. Additionally, unlike the original conception of Blau space (McPherson, 1983), *categorical variables* can be used as parameters when creating the individual-level socio-demographic space in Blau bubble analysis. This innovation allows the researcher to account for critical categorical respondent characteristics, such as race and gender, when calculating the distance between individuals within the space. Finally, Blau bubble analysis could be extended to predict the formation of interpersonal networks. Because of the prevalence of the homophily (Lazarsfeld & Merton, 1954), two individuals who are adjacent to each other within the space are more likely to be tied to each other. In this way, networks researchers can use a conservative radius in Blau bubble analysis to predict an individual's potential or future friends. Researchers who wish to try these methods for themselves should download our BlauNet package for the R statistical environment,[11] which is able to compute Blau bubbles as well as execute a variety of other analytic and plotting functions. Though beyond the purview of this study, future work comparing the role of local positions (Frank et al., 2010) to familiar others for individuals' behaviors would be especially interesting.

In conclusion, our analyses provide support for our hypothesis that familiar others influence the ego's behavior. This work contributes to the extant research on social influence by introducing and measuring a previously overlooked source of influence in the social environment. Our results have strong implications for understanding and accounting for the role of interpersonal influence on behavior, namely that influence within the social environment is better captured by familiar others than by immediate ties. We do not suggest that conventional social network methods are in some sense wrong, but rather add our approach as a way of measuring interpersonal influence that is normally difficult or impossible to capture. Future influence studies would benefit from the addition of familiar others, who exhibit influence that is distinct from that of direct alters. Our research suggests that individuals may be more strongly influenced by those homophilous individuals who they see, but do not know.

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[11] Available at https://cran.r-project.org/web/packages/Blaunet/index.html.

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Conflicts of interest

The authors report no conflicts of interest.

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Appendix

Table A1. Pairwise correlation matrix of dependent and independent variables.

Variables	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII	XIII	XIV	XV	XVI	XVII	XVIII
I. Weight-related behavior	1.00																	
II. Familiar others' behavior	0.43^{**}	1.00																
III. Direct alters' behavior	0.16^{**}	0.24^{**}	1.00															
IV. Ego's BMI	0.07^{**}	0.10^{**}	−0.05	1.00														
V. BMI of familiar others	0.17^{**}	0.37^{**}	0.08^{**}	0.15^{**}	1.00													
VI. BMI of direct alters	0.04	0.06^{*}	-0.41^{**}	0.33^{**}	0.17^{**}	1.00												
VII. Female	-0.43^{**}	-0.89^{**}	-0.22^{**}	-0.05^{**}	-0.36^{**}	-0.05^{*}	1.00											
VIII. Racial minorities	0.03	0.05^{**}	0.02	0.07^{**}	0.32^{**}	−0.01	0.02	1.00										
IX. Parental income (thousand)	−0.03	−0.03	0.02	-0.07^{**}	-0.08^{**}	-0.07^{**}	−0.01	-0.13^{**}	1.00									
X. PVT score	0.04	0.05^{*}	0.06^{*}	-0.04^{**}	-0.08^{**}	-0.05^{*}	-0.05^{**}	-0.32^{**}	0.22^{**}	1.00								
XI. No English at home	-0.07^{**}	-0.13^{**}	-0.08^{**}	0.02	0.11^{**}	0.04	0.02^{*}	0.25^{**}	-0.14^{**}	-0.30^{**}	1.00							
XII. Grade level	−0.01	0.00	0.00	0.15^{**}	0.42^{**}	0.21^{**}	0.00	−0.01	0.07^{**}	0.09^{**}	0.05^{**}	1.00						
XIII. Pregnancy	−0.03	-0.14^{**}	0.02	0.04^{**}	−0.01	0.00	0.16^{**}	0.04^{**}	-0.03^{**}	-0.02^{*}	-0.03^{**}	0.08^{**}	1.00					
XIV. Romantic relationship	−0.01	−0.03	−0.02	-0.05^{**}	0.10^{**}	0.06^{*}	0.04^{**}	-0.07^{**}	0.05^{**}	0.09^{**}	-0.10^{**}	0.25^{**}	0.12^{**}	1.00				
XV. Physical attractiveness	-0.12^{**}	-0.17^{**}	0.01	-0.17^{**}	-0.09^{**}	-0.07^{**}	0.13^{**}	-0.05^{**}	0.07^{**}	0.10^{**}	−0.00	0.04^{**}	0.00	0.09^{**}	1.00			
XVI. Sports team membership	0.05^{*}	0.08^{**}	0.08^{**}	-0.04^{**}	−0.03	−0.04	-0.05^{**}	-0.03^{**}	0.08^{**}	0.10^{**}	-0.10^{**}	-0.09^{**}	-0.05^{**}	0.01	0.07^{**}	1.00		
XVII. Physical exercise	0.08^{**}	0.19^{**}	0.04	-0.09^{**}	−0.03	−0.03	-0.21^{**}	-0.03^{**}	0.05^{**}	0.03^{**}	-0.04^{**}	-0.24^{**}	-0.12^{**}	-0.02^{*}	0.05^{**}	0.20^{**}	1.00	
XVIII. Sedentary activity	0.06^{**}	0.20^{**}	0.04	0.05^{**}	0.04^{*}	0.02	-0.12^{**}	0.15^{**}	-0.10^{**}	-0.08^{**}	-0.03^{**}	-0.14^{**}	0.00	-0.06^{**}	-0.08^{**}	-0.02^{*}	0.02^{*}	1.00

Note: $^{**}p < 0.001$, $^{*}p < 0.01$.