Social Networks 72 (2023) 151–164

Contents lists available at ScienceDirect

Social Networks

journal homepage: www.elsevier.com/locate/socnet

Kudos make you run! How runners influence each other on the online social network Strava

Rob Franken [a,*], Hidde Bekhuis [b], Jochem Tolsma [a,c]

[a] Radboud University Nijmegen, Department of Sociology, P.O. Box 9104, 6500 HE Nijmegen, the Netherlands
[b] Radboud University Nijmegen, Department of Orthopedagogics: Learning and Development, P.O. Box 9104, 6500 HE Nijmegen, the Netherlands
[c] University of Groningen, Department of Sociology, Grote Rozenstraat 31, 9712 TG Groningen, the Netherlands

ARTICLE INFO

Keywords:
Social network analysis
Sports
Social support
Social influence
Strava
SAOM

ABSTRACT

Strava is the largest online social network for athletes. We used Strava's big data to investigate how runners in the same virtual Strava club influenced each other's running behavior. We hypothesized that receiving kudos on recorded activities would spur exercise rates, and that the running behavior of clubmates to whom ego gave kudos would serve as a motivational example. We focused on five different Strava clubs that functioned as a virtual extension of real-life Dutch running clubs with a total of 329 members. Using data on kudos and recorded activities, we constructed a longitudinal dataset of complete networks and behavior over 11 periods with a one-month time window. We tested our hypotheses using SIENA. We found that receiving kudos induced runners to run more and more often. Moreover, athletes tended to adjust their running behavior to that of their 'kudos-friends' (i.e., those to whom they gave kudos). Contrary to our expectation, kudos-friends who ran more and more often than ego were not the most influential. If anything, the reverse was true; athletes were more likely to come to resemble the running behavior of their kudos-friends who ran less and less often.

Introduction

Western societies have reached a pinnacle in physical inactivity (Pratt et al., 2020). Promoting sports participation has therefore become an important element of increasing physical activity levels among populations (WHO, 2019). Researchers and practitioners have tried several individual-level strategies to stimulate behavior change towards greater physical activity (for a review, see Murray et al., 2017). However, despite numerous efforts, the effects of current interventions proved rather short-lived. The real challenge seems to be *keeping* people active and the failure of individual-level behavior approaches in this respect has urged researchers to shift their focus to social influences (e.g., Hunter et al., 2019).

The people we do sports with can provide various types of social support and other resources beneficial for keeping active. Peer influence processes may induce us to try to mimic the activity patterns of our sports partners. Sports partners may *actively* try to persuade us to keep exercising, by inviting us to co-participate or by explicitly encouraging us, or they may *passively* serve as peer models (Bandura, 2001). The more we become aware of the sports activities of our peers, the more likely we are to perceive their sports behavior as a normative example (Ajzen, 1991). This may motivate us to try to mimic the observed activity patterns, resulting in more or fewer sports activities depending on the sports behavior of our peers.

Social networks are known to influence aspects of health, ranging from the patterns of infectious disease spread (Keeling and Eames, 2005), over the diffusion of obesity (Smith et al., 2020), to smoking and drinking behaviors (McMillan et al., 2018). However, owing predominantly to data and methodological limitations, little research has examined the extent to which, and the mechanisms by which, social networks influence sports behavior. Previous findings that certain characteristics, such as network size and the activity levels of alters, correlate with an individual's physical activity – while *consistent* with the idea of peer influence – do not provide empirical *support* for a causal assertion (Shalizi and Thomas, 2011). We need to control for shared social contexts (e.g., the same neighborhoods or sports clubs) and peer selection processes, in order to progress beyond just documenting that people who are more closely related to each other tend to have more similar sports behaviors.

Social media platforms and the digital data traces they produce have provided researchers with rich data in recent years. Unlike conventional datasets, based on questionnaires, these new digital data sources often

* Corresponding author.
E-mail addresses: rob.franken@ru.nl (R. Franken), hidde.bekhuis@ru.nl (H. Bekhuis), jochem.tolsma@ru.nl (J. Tolsma).

https://doi.org/10.1016/j.socnet.2022.10.001

Available online 13 October 2022
0378-8733/© 2022 The Author(s). Published by Elsevier B.V. This is an open access article under the CC BY license (http://creativecommons.org/licenses/by/4.0/).

provide copious information on the evolution of online social networks as they unfold (Edelmann et al., 2020). Digital trace data support innovative research on various aspects of health. For instance, using data from social media, researchers have studied mortality (Hobbs et al., 2016), the dissemination of health information about vaccines (Salathé et al., 2013), and problem drinking (Moreno et al., 2012).

Alongside general social media platforms, such as Facebook and Twitter, online fitness communities for people to interact and influence each other's exercise motivation have risen to prominence. Popular sport apps, such as Strava, Zwift, and Garmin Connect, draw on social network services and have received special attention from sports academics and professionals (Koivisto and Hamari, 2019). The emergence of online fitness communities presents an important resource for addressing the shortcomings of previous network studies in the field of sports and active living. Previous studies in this field are subject to several limitations. They are often studies of friendship networks among adolescents in school classes (e.g., de la Haye et al., 2011; Fujimoto et al., 2018; Shoham et al., 2012; Simpkins et al., 2013). The specificity of such samples limits their generalization to a broader (adult) population. Moreover, these studies relied on self-monitoring networks and self-reported sports and physical activity via surveys. However, the reliability of self-monitoring networks remains a subject of sharp debate (e.g., Bernard and Killworth, 1977). Likewise, self-report measures of sports and physical activity are notoriously unreliable and known to suffer from cross-sectional misclassification bias based on gender, age, and educational level (e.g., Dyrstad et al., 2014).

Online fitness communities provide tools that solve these issues. One of the things that set these communities apart, is that they operate almost exclusively through biometric data. Sports activities are generally uploaded onto the platform automatically, and since the majority of its members self-track their activities using GPS-enabled devices, activity posts typically include precise and reliable exercise data. Moreover, most social interactions on these platforms leave a digital trace, and therefore a signification of some type of social relationship. The availability of such trace data, together with detailed information on individuals' day-to-day exercise behaviors, form a golden opportunity for researchers interested in the social dynamics of sports. These new technologies provide not only novel resources for analyzing social influences with respect to sports behavior, but ultimately also empirically grounded avenues for mobilizing the motivational power embedded in social networks to promote sustainable exercise behaviors.

Taking a field experiment approach, Zhang and colleagues (2015, 2016) created their own online fitness communities to evaluate the effect of social influence mechanisms on changes in sports activity. Zhang and colleagues (2016) used a randomized controlled trial to compare the effects on sports participation of online communities in which anonymous peers interacted in either a supportive or competitive online community. They found that social comparison in online networks provided a significantly greater source of social influence on exercise class attendance than social support. The experimental approach is appealing because it avoids possible confounding effects of exogenous social environments and eliminates the selection or homophily problem that "birds of a feather flock together" (McPherson et al., 2001). Such experiments can, in many cases, help researchers circumvent network endogeneity issues of observational studies, and therefore constitute a powerful approach for assessing peer influence. However, in real life you often select interaction partners yourself, who may *then* influence you. Therefore, omitting selection processes by randomly assigning individuals to peer groups may lead to a wrong assessment of influence. We suspect naturalistic networks to be stronger sources of a more effective generation of social support than experimental networks consisting of anonymous, non-chosen 'peers'.

In this contribution, we exploit the new opportunities provided by social media to investigate social influences on sports behavior. Specifically, we analyze big data from the online fitness community Strava. Strava is a web-based platform and mobile app used by recreational and professional athletes, mainly in running, cycling, and triathlon. Strava provides users a means to keep track of their sports activities by automatically uploading their sports sessions, which are recorded by smart devices. Via Strava, users can connect and interact with online friends, mainly by giving kudos or commenting on recorded activities. Users can also compare their performance to that of friends.

We investigate to what extent receiving kudos – a virtual thumbs-up – and the sports activity of 'kudos-friends' (i.e., alters who ego gave kudos) influence sports behavior. We focused on the networks formed by kudos relationships between Strava users in the same virtual club and their monthly running behavior (in terms of running frequency and volume). Our dataset comprises five Strava clubs, 329 athletes, 12 monthly time points, 19,026 kudos relationships, and 10,037 recorded activities spanning a total volume of 10,027 h. We used the stochastic actor-oriented model (SAOM) implemented in R as the Simulation Investigation for Empirical Network Analysis (RSiena) to identify social influences on running behavior within the kudos networks of these virtual clubs (Ripley et al., 2022). We tested the extent to which (1) receiving kudos motivated users to run more and more often and (2) if and how the running activity of kudos-friends influenced running frequency and volume. We controlled for multiple factors that affect who users interact with on Strava (structural network and selection effects) and factors influencing sports activity (e.g., gender, seasonal effects, shared club environments).

In sum, we pioneer the use of Strava's big data to study social influence among runners in Strava clubs. Unlike prior SAOM studies, which focus on very specific groups (adolescents in school classes), our focus is on a broader population of adults across diverse running clubs. Instead of using survey instruments, we measured sports behavior more reliably by, for the most part, automatically recorded activities. We conceptualized a new type of social network, the kudos network, which is constructed with digital trace data of actual interactive behavior within the club. New social influence operationalizations are introduced and tested to better understand the mechanisms by which friends influence one another's activity levels (see methods section). While prior studies exploiting the opportunities offered by social media employ experimental networks, our study investigates naturalistic networks. Lastly, we followed Strava-users for a relatively long one-year time window, during which we observed the network and behavioral outcomes 12 times.

Theory

Theoretical considerations of previous research

A body of evidence shows that social networks help enable the pursuit of sports over time (e.g., Fitzgerald et al., 2012; Franken et al., 2022; Keegan et al., 2011). Two major mechanisms through which the people we do sports with can motivate us to stay active are related to social support and social comparison. Social support is a long-established strategy for promoting healthy behavior in social networks, both offline and online. It refers to [the] "aid and assistance exchanged through social relationships and interpersonal transactions" (Heaney and Israel, 2008, p.191). Social support encompasses various categories, such as informational support (i.e., providing advice or guidance), esteem support (i.e., bolstering a sense of competence), and instrumental support (i.e., concrete instrumental assistance). Social support from network partners in a sporting context has been shown to be an important resource for athletes (Sheridan et al., 2014).

An alternative approach to encouraging continued sports participation utilizes social comparisons (Diel et al., 2021a). Using others as a reference standard is at the core of many different sports (Walton et al., 2020). The activity levels of our sports partners might serve as goals for our own activity. Social comparison and social learning theory (Bandura, 2001; Goethals and Darley, 1977) posit that individuals evaluate the 'desirability' of their behavior using their peers' behavior as a yardstick, leading them to match their behavior to that of their peers. They may intentionally try to imitate peers' behaviors to promote their relative standing or to avoid rejection by peers. Thus, this refers to the principle of assimilation, according to which "network actors adapt their own individual characteristics to match those of their own social neighborhood" (Steglich et al., 2006, p. 51).

A fundamental assumption of this principle is that ego estimates his ranking within the group based on the characteristics of a 'generalized other' (Marsh et al., 2008). In other words, ego is assumed to evaluate his position compared to the behaviors of all ties, and to act upon this evaluation [i.e., by maximizing the (average) similarity to all actors to whom ego is tied]. This implies that all peers are equally important comparison targets and subsequently equally important sources of influence. However, since the first formulation of social comparison theory, it was conjectured that this may not be the case: from ego's perspective, peers may differ in their attractiveness as comparison targets and the extent to which their behaviors are desirable. In line with Festinger's early work, we expect that different sports abilities and performances have intrinsically different values (Festinger, 1954, p. 124). This succinctly captures much of what is often understood as 'social status' (Sauder et al., 2012), which is to say the prestige accorded to an individual based on the position he or she occupies in the group. From this perspective, it can be expected that sports activity has an aspiration effect, meaning that more active athletes are more attractive as interaction partners, but simultaneously, it can be expected that sports partners that are relatively more active are subjectively more meaningful comparison targets and consequently greater sources of influence.

Thus, according to the literature, support provided via social ties can improve an individual's sports participation; social comparison processes may stimulate athletes to try to resemble their co-athletes, and athletes may especially try to mimic the sports behavior of co-athletes with a higher status.

Strava

The empirical context in which we will investigate these general ideas is Strava. Strava is a social platform for athletes to track their activities and gain insight into their performance. Strava uses smart, often GPS-enabled devices (e.g., smartwatches) to map routes and log training metrics such as pace and duration. After completing a workout, data is generally automatically synced across the platform.

While sports activity tracking has become mainstream practice (Lupton, 2016), Strava has managed to successfully bridge the gap between activity-tracking utilities and traditional social media (e.g., Facebook), hence establishing itself as a global leader in the 'social fitness' industry. Strava had more than 74 million active users in 195 countries in 2021 and recorded over one billion activities in 2020. Like traditional social media, Strava uses a system of 'following' other users. When you finish a workout, your exercise data appears in your personal feed (activity log), as well as in the feeds of your followers and your club (see Fig. 1). Strava has introduced competition through various gamifying elements, such as virtual leaderboards, segments (portions of routes where athletes can compare times), monthly challenges, and trophies or badges to earn. Moreover, users can interact with each other via their recorded activities by giving kudos and posting comments.

Communication, sharing of activities, and kudos form a central part of being a Strava user (Smith and Treem, 2017). Using the survey dataset *ABS* (Franken et al., 2020), we explored Dutch runners' reasons for using Strava. Here, Strava runners' ($n = 290$) prime motive for using the app was to *log activities* (83 % expressed this reason) and *track progression* (expressed by 78 %), followed by *comparison* with peers (31 %), *interaction* with (online) friends (23 %) and *receiving support* (21 %) (categories were non-exclusive).

A potential problem with Strava is that it only allows data to be sampled based on user activities, yielding the risk of data being biased towards highly active users (Almquist et al., 2019). To circumvent this, we used Strava *clubs* as our sampling unit. Clubs are easily accessible communities in Strava (like Facebook groups), which enable individuals to form connections, join up and work out together, while interacting with one another and competing on the club's virtual leaderboard. Strava clubs vary in size and whereas most clubs exist only online, fewer function as virtual extensions of offline groups or athletic clubs. We used data from Strava clubs that functioned as a virtual extension of a formalized running club in the Netherlands. The use of such virtual communities is appealing as they have large overlap with their offline

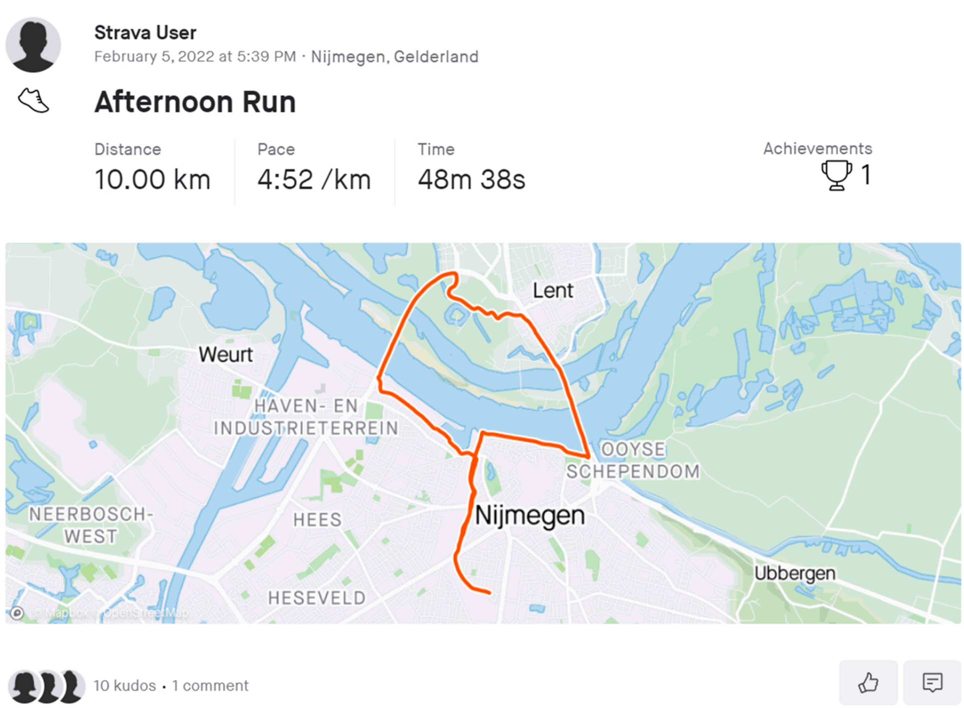

Fig. 1. Example of the type of activity post that Strava displays in the feeds of the user, their followers, and their club.

counterparts (Subrahmanyam et al., 2008) and therefore give a quantitative representation of the offline relationships in the clubs. Moreover, a focus on 'real-life' clubs allowed us to select cases that differed from each other on multiple relevant features and thus to mimic a most-different design. Last, an advantage of focusing on club networks, rather than ego-centered networks of individual Strava users, is that they represent complete networks, which are required input for SAOMs to model selection and influence effects simultaneously, hence controlling one effect for the other.

In this study, we focus on the network made up of the kudos relationships between the members of a Strava club. Kudos are defined as "praise given for achievement" or "fame and renown resulting from an act or achievement" (Merriam-Webster, n.d.). In the context of Strava, kudos are a lighthearted, one-click feedback action that serves as a social cue of affect, support, or admiration. Kudos can be given by simply tapping the thumbs-up button below an activity post (see Fig. 1). There is currently no way to remove kudos once they have been given. While giving kudos may be understood as a momentary event, the kudos ties we defined strongly resemble social states, because the networks arising from them proved to be quite stable over time (see results section).

In line with qualitative studies of Strava, we understand kudos as a form of social affirmation, a popular way of supporting (online) connections in the pursuit of their fitness goals, and an easy cue to scan for appreciation among peers (Spotswood et al., 2020). Kudos are argued to make running a social phenomenon, rather than a solitary activity, and it may shift the emphasis from the hardship of a running workout to the social rewards that an activity post on Strava may attract (Couture, 2021). Substantial research exists on practices of social support in online fitness communities (e.g., Hamari and Koivisto, 2015; Stragier, Mechant et al., 2018) and related work in the gamification literature suggests that digital social support functions such as kudos can motivate sustainable exercise habits (Chen and Pu, 2014). Kudos may elevate self-esteem, intrinsic motivation, and collective efficacy for increasing everyone's activity level.

While kudos may serve to support (online) friends, kudos can also be a token of *admiration* (Couture, 2021). The specific recorded activities a club member gives 'praise' to might serve as goals for their own running. The running frequency and volume of kudos-friends might provide a benchmark for an individual's own running ambitions. Especially those kudos-friends who run more and more often may set the bar.

Expectations

Given the above – if we combine the general ideas from sports literature and the empirical context of Strava – we are able to formulate the following hypotheses:

- Runners who are member of a Strava club will increase their running activity when receiving kudos from more fellow Strava club members, both with respect to running frequency and running volume (*social support expectation*, hypothesis 1).
- Runners who are member of a Strava club will come to resemble their fellow Strava club members who they give kudos to (i.e., kudos-friends), both with respect to running frequency and volume (*social comparison expectation*, hypothesis 2).
- Runners who are member of a Strava club will especially try to mimic the running behavior of kudos-friends who run more (i.e., volume) and more often (i.e., frequency) than they themselves (*upward comparison expectation*, hypothesis 3).

Our unique longitudinal social network data within five different Strava clubs allows us to test the motivational power of (online) social networks, to disentangle influence from selection effects (i.e., to account for the possible tendency of runners to especially award kudos to athletes they admire) and to distinguish between traditional peer influence effects (hypothesis 2) versus peer influence depending on whether alters are more or less active in running than ego (hypothesis 3).

Materials and methods

Sample

At the time of writing (2022), Strava counted more than 700 Dutch Strava running clubs. Most are very small and only exist online; relatively few function as virtual extensions of formal groups or athletic clubs that exist offline. We used convenience sampling to select a set of Dutch running clubs with a Strava club extension. We tried to mimic a most-different design and aimed to select clubs of varying size (largest $n = 159$; smallest $n = 9$), geographical location, organizational setting, and characteristics of members (e.g., amateurs, more experienced runners, seniors). Using this sampling strategy, we hoped to account for potential issues of selectivity and unobserved exogenous influences at the club level. Based on our extensive knowledge of the Dutch running landscape, and keeping in mind the feasibility with respect to data scraping and model exploration, we selected a set of five Strava clubs. A qualitative description of these clubs can be found in appendix A.

Procedure

A web scraping tool was used to collect kudos and activity data from the clubs. We collected club-related information (the members of the clubs), information on the club members (gender, number of activity posts) and information about their activities (workout duration, kudos received, the month the activity took place). Before saving the data, Strava user IDs were replaced with mock IDs. Moreover, we aggregated activity data for each user into one-month intervals before saving. We collected data for January to December 2019. We informed Strava that we were collecting the data. To ensure the correct ethics procedure, we applied the decision tree of the Ethics Committee Social Science of the Radboud University. Our study did not require ethical approval, given that we only collected data from public profiles; our data cannot be traced back to unique activities or users; we did not harvest health data (e.g., heart rate data or power data); and our data was used for scientific purposes only. Replication of this study (using the constructed dataset) is possible with our online replication package, available at https://robfranken.github.io/Strava/.

Sports behavior measures

In sports literature, exercise is quantified using the training variables frequency, volume and intensity (Noakes, 2003). In our study, we were interested in the frequency that actors ran each month, and the total monthly volume of their running activity. Mapping activity intensity would have required collecting heart rate data, which we did not want to do for ethical reasons described above. We collected longitudinal (monthly) information on the frequency that running activities were posted to the Strava club. We used this as an indication of the number of running sessions per month. *Running frequency* was converted to times per week. We chose eight categories, from 0 times per week to 7 (or more) times per week. We aggregated the total volume of running activities per month, and converted *running volume* to hours per week, again, in eight categories, from 0 to 7 (or more) hours per week. In club 5, the category 7 + hours was highly populated, so we added 2 extra categories (so, 0–9 + hours per week), resulting in a rather smooth right-skewed distribution of running volume values for this club.

Social networks measures

In the Strava clubs, network boundaries equal club boundaries. This is arguably realistic, given that our clubs in real life were not in close geographic proximity to one another. We gathered data on who gave who kudos, which we call the 'kudos network' (Fig. 2). We assumed

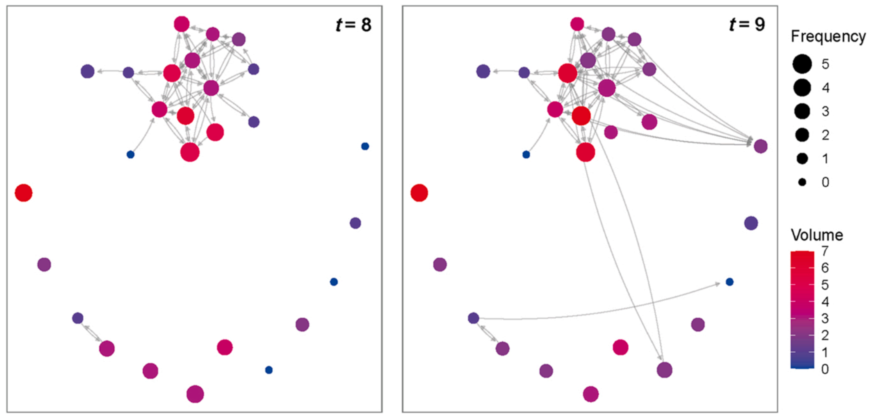

Fig. 2. Snapshots of the kudos network and weekly running activity of members of Strava club 1 ($n = 27$) at $t8$ and $t9$. Note: Circles are nodes, and arrows are kudos ties. Node size is based on running frequency (times per week); color is based on running volume (hours per week). The node-set was stable in this period.

dichotomous network relations and a constant node-set $\{1, \ldots, N\}$ over time. Hence, the sequence of kudos networks at observation moments t_1, …, t_{12} can be represented by a sequence of binary matrices $X^{(1)}, \ldots, X^{(12)} \in 0, 1^{N \times N}$, with $X_{ij}^{(h)} = 1$ if actor i awarded kudos to actor j *at least once* in observation h, and $X_{ij}^{(h)} = 0$ otherwise. We assumed directed networks without self-ties such that $X_{ij}^{(h)} \neq X_{ji}^{(h)}$ is possible and $X_{ii}^{(h)} = 0$ for all actors i at each time point. We defined tie change as the presence of ties regardless of whether they were newly created or maintained (i.e., we used the 'evaluation' function to model network evolution).

The node-set was determined at t_{12}. Data was scraped retrospectively. We assumed the first observation moment, from t_1 onward, that actors either posted an activity or gave another club member kudos, to be the event of them joining the club. We assumed no leavers. Resulting changes to the composition of the networks were modeled as exogenous events at specified time points (see Huisman and Snijders, 2003). Turnover data are summarized in appendix B. Some members did neither post activities nor send kudos in our window of observation (<5 %). We excluded these inactive actors from our analyses. Analyses with the full node-set ($n = 347$) returned similar results.

In our operationalization of the kudos network, for a tie $X_{ij}^{(h)}$ to exist, actor i was required to give kudos to at least one activity of j in observation h. Actor i might give kudos to more than one activity of j in h – the average number of kudos sent from i to j among kudos dyads, meaned over time, ranged from 3.55 (*SD*=0.48) in club 3–8.12 (*SD*=0.61) in club 2. However, a cut-off value of 1 kudos has the advantage that the number of kudos received does not depend on the number of recorded activities of i and that the kudos indegree equals the number of different alters actor i received kudos from.

Additional controls

To accurately identify social influence, we controlled for other characteristics that may be correlated with running activity attributes and may affect who gives who kudos. We included *gender* as a constant covariate, both as an ego/alter covariate (men vs. women and others) and as a dyadic feature (same gender vs. different gender). We expected men to run more and more often than women, and gender similarity to breed kudos ties. Moreover, in our models explaining the dynamics of running frequency, we included the frequency of *other sports activities* (i.e., cycling and swimming) as a time-varying covariate; in our models explaining the dynamics of running volume, we included the volume of other activities. These covariates were constructed similarly to running activity: 0–7 + times/hours per week. We expected higher activity levels in other sports to reduce the frequency of running and the total time spent running, as time and effort devoted to running must be traded off against time required for other sports.

We also explored additional effects on behavior change. We included *winter* (months) as a time-varying dummy variable, as running activity may fluctuate due to seasonal effects. *Years active* on Strava was taken as a constant covariate, as training may be structured differently in experienced athletes compared to novices in running. However, score-type tests (see Schweinberger, 2012) indicated these effects to be negligible.

Stochastic actor-oriented model

We used stochastic actor-oriented models (SAOMs) implemented in R as RSiena. SAOMs represent how changes in network and behavior unfold in the course of sequential decisions taken interdependently by the actors of the network. Expressing these individual decisions as *micro-steps*, the model provides a tool for inferring various micro-level mechanisms underlying the (co)evolution of observed networks (here, kudos ties) and behavior (here, running frequency and volume), taking into account the bounded choice set of actors in the network and controlling for concurrent mechanisms. SAOMs assume that observed networks and behaviors are snapshots (as in Fig. 2) of an underlying dynamic process, which can be modeled as a continuous-time Markov chain, and that network and behavior micro-steps are performed by randomly chosen actors based on myopic decisions. Model parameters were estimated using a method of moments procedure and tested for significance based on a *t*-ratio.

SAOMs are appealing in that they allow for the simultaneous estimation of selection and influence effects. SAOMs are, however, still subject to limitations concerning environmental confounding. We hoped to partially solve this problem by studying a diverse set of clubs. What is more, SAOMs rely on a series of strong modeling assumptions (Snijders et al., 2010). SAOMs assume networks of states with a tendency to endure over time, rather than brief events. While kudos reflect event data, the networks defined by aggregated kudos events proved to be quite stable over time, and therefore resemble networks of states instead of momentary events.[1] Moreover, SAOMs assume that actors have full information on their local networks, based on which they make decisions regarding their ties or behaviors. While this may not be realistic

[1] Dynamic Network Actor Models (DyNAMs) have been developed to take into account the different nature of relational events compared to social network relationships (Stadtfeld and Block, 2017). However, while sports activities (posts) are time-stamped in Strava, kudos are not. Besides, using our data in its unaggregated form would pose a difficult question of ethics. Last, DyNAMs do, currently, not allow for the simultaneous modeling of interpersonal events and behavioral actions, which is the main focus of the present study.

in conventional self-monitoring networks (e.g., when ego cannot recall his alters and their behaviors correctly due to cognitive constraints), this assumption is realistic in the context of our Strava clubs. On the platform, club members can observe the full node-set, what gender other members have (based on their profile name and picture), and how often and long they run (based on their activity posts and position on the club leaderboard). Members can also see the list of Strava users who gave kudos to their own and others' activities. The actor-based framework decomposes the evolution of networks and behaviors into the smallest possible components, an assumption that fundamentally excludes relational dynamics of coordination. For Strava, this is a reasonable assumption, as kudos cannot be coordinated. Besides that, the assumption that behavior changes are by one unit in a single time makes sense intuitively. Running habits naturally tend to evolve incrementally. Runners may consider increasing their training load over time by gradually increasing either their (weekly) running frequency or volume.

Last, an important potential issue with web platform data is the algorithm that shapes users' interactions. Social media platforms like Strava typically work through algorithms that expose users to a selection of contents based on their own socio-demographic attributes (or previously demonstrated preferences/interactions). SAOMs assume that changes in an actor's ties are dependent on a set of exogenous (i.e., covariate-related) and endogenous (i.e., network structure-related) aspects of the local network configuration, but fare independently from exogenous mechanisms driven by (unobserved) algorithmic opportunities and constraints. Such selection algorithms may result in biased estimates for selection and influence effects. A big plus of our data is that, at the time of data collection, such algorithmic selection mechanisms were not in play on Strava's Clubs feed (Strava, 2022; personal user experience of second and third author). Users would navigate to their dashboard, select their club (or their own or their followees' activities), and the activity posts of club members would simply be presented in chronological order. Strava did not rank activities based on characteristics of the activity or the club member (i.e., alter).

SAOM specification

We estimated separate models for both running attributes as the behavior variable. Given the high degree of collinearity between running variables, we did not specify cross-effects. While estimating the dynamics of both running attributes simultaneously was possible, this led to convergence issues and difficulties in model comparison across clubs. Guided by recommendations on model selection by Snijders and colleagues (2010), we combined forward steps (adding effects) with backward steps (deleting effects) based on theoretical considerations and statistical criteria. We tested effects by including them and fixing them at the value 0, corresponding to the null hypothesis, and testing this null value using the score-type test (Schweinberger, 2012). Two equations were specified: (1) the *kudos tie formation function*, which models the process of tie creation (selection); and (2) the *running activity function*, which models the dynamics of running frequency and volume respectively (influence). Estimating both functions simultaneously resulted in credible estimates of our presumed influence mechanisms net of the potential confounding effects of selection. Below we describe the effects we used to define these functions, adopting the effect terminology from the RSiena manual (Ripley et al., 2022).

Kudos tie formation function

We controlled for the simultaneous occurrence of three structural effects: *outdegree*, *reciprocity* and *transitivity*. For transitivity, we used the geometrically weighted edgewise shared partners (*GWESP*) effect. We also controlled for the interaction between reciprocity and transitivity (Block, 2015) and the *out-isolate* effect (leading to not giving any kudos). On top of these structural effects, we included degree-related endogenous effects: *indegree popularity* and *outdegree activity*. We included the square root variant of these effects. Last, we controlled for *reciprocal degree-related activity* and *outdegree-related popularity*.

In addition, we included selection effects with respect to running behavior. First, we included *ego/alter* effects, which reflect how kudos-ties are affected by the behavior attribute of the sender (ego) and the receiver (alter). Second, we included similarity and higher effects, which assess whether kudos-ties are more likely between actors with a certain combination of characteristics. The behavior *similarity* effect represents the degree to which closeness of actors on the behavior scale affects the probability of kudos-ties. The *higher* effect reflects ego's tendency to give kudos to alters who score lower on the behavior attribute. A negative parameter estimate for this effect implies a tendency of actors to give kudos to others who are more active in running than themselves, interpreted here as aspirational kudos.

Running activity function

We included *linear* and *quadratic shape* effects to model general behavioral tendencies and potential self-reinforcing or self-correcting mechanisms. To test the social support expectation (hypothesis 1), we included the *indegree* effect, which expresses the tendency of actors with higher kudos indegree to increase their running activity attribute. If the estimated effect parameter is positive and makes a meaningful contribution to the running activity function, this indicates that receiving kudos indeed spurs activity in running.

We expected actors to try to mimic the running activity of their kudos-friends (social comparison expectation; hypothesis 2). With hypothesis 3, we formulated the expectation that, rather than mimic the running behavior of all network partners, athletes aspire to become (more) similar to alters who outperform themselves. To capture with our models the possibility that ego is differently influenced by alters that score higher and lower on the behavior scale than himself, we designed two new RSiena influence effects: *average attraction towards higher* and *average attraction towards lower*. In appendix C, the new influence effects are discussed in more detail.

Analytical strategy

We stratified all analyses by club, resulting in different parameter estimates for each club. We performed 5000 permutations per model. Models were identical across clubs but, based on score-type tests, we decided to fix the values of parameters of specific effects in some clubs to 0. For each parameter separately, the results of the five clubs were combined in a meta-analysis. Five clubs is too low a sample size to provide adequate information about a population of clubs. Therefore, a Fisher combination procedure was used. This method provides results from combinations of left-sided and right-sided tests of the null hypothesis that in all of the five clubs the parameter is zero. These combinations are based on Fisher's combination of *p*-values, each using a one-sided significance level of $\alpha = .025$, which yields an overall combined test at significance level of $\alpha = .05$ (Hedges and Olkin, 2014). The test statistic in the Fisher procedure is $-2\sum_k ln(p_k)$, for groups $k = 1,\ldots,K$, that have been given the *p*-values p_k, with under the combined null hypothesis a chi-squared distribution with $df = 2K$. In addition, we ran a random-effects multivariate meta-analysis using the R-package 'metafor' (Viechtbauer, 2010) to provide more numerical information about the average effect pattern represented by the five clubs. This method averages coefficients of individual clubs by inverse-variance weighting them by their standard errors. Standard errors of these estimates reflect the standard errors within the studies of the respective clubs, in combination with the uncertainty caused by between-club heterogeneity. Given our small *N* at the club-level, standard errors cannot be used for testing, but are presented to roughly indicate the uncertainty about the average effect estimates. This multivariate meta-analysis approach also accounts for the interdependence of estimated parameters within each club based on their variance-covariance matrix.

We calculated the relative influence of each effect on the probability of change in running attributes (Indlekofer and Brandes, 2013). This allowed us to assess the size of the effects of interest relative to one another. To gain a better understanding of how consequential our effects of interest at the micro-level are for the overall running behavior means in the clubs, we used our estimated SAOMs as empirically calibrated agent-based simulation models.

Goodness of fit

We compared the networks simulated by the SAOM to our observed data based on three auxiliary network statistics: outdegree, indegree, and geodesic distance distribution (see Lospinoso and Snijders, 2019). We also assessed whether our model captured the distribution of actors' running frequency and volume values over time. Moreover, we ensured that model convergence was obtained (t-ratios for deviations from targets < 0.10; overall maximum convergence ratio < 0.24). Overall, our current model specification produced acceptable goodness of fit (GOF).[2] Violin plots of GOF can be found on our GitHub replication website.

Results

Descriptive statistics

Table 1 presents the characteristics of the Strava clubs. In all clubs, men formed the majority. The combination of low network densities, high reciprocity (mutual kudos ties), and transitivity (closure) indicates high levels of clustering within clubs. Moreover, we see that Jaccard coefficients are high, suggesting that the kudos ties we defined are durable online relationships. Club 3 appears to be rather peculiar, in that kudos were given relatively infrequent (average density =.014) and kudos-ties were relatively volatile (average Jaccard index =.500). Low density may have to do with the size of the Strava club. With larger clubs come more fellow club members with whom ego may not be particularly close, and whose activities ego may therefore not give kudos along the way. Besides, this club is the odd one out with respect to its fragmented start locations (see appendix A). High volatility may be due to the club's flexible memberships and training locations. Consequently, unobserved social dynamics among runners may change rather quickly in this club, which may affect turnover in the kudos network.

We described behavioral similarities in the kudos network using Moran's I, a measure of spatial autocorrelation (Moran, 1948). Coefficient values can range from -1–1. Values closer to 0 indicate that connected actors are not more similar with respect to the behavior than would be expected based on random chance, values closer to 1 indicate that connected individuals are more similar (i.e., behavior values are clustered), and values closer to -1 indicate that connected individuals are less similar (i.e., behavior values are dispersed). Coefficient values (see Table 1) indicate that positive spatial autocorrelation (clustering) occurs within kudos networks – although more in some clubs than in others. However, in club 4, we observe negative autocorrelation (dispersion). Thus, overall, kudos-friends tended to have similar running behaviors, with this similarity potentially originating from both selection and influence.

To describe gender segregation in the kudos network, we used Coleman's (1958) homophily index (see Bojanowski and Corten, 2014). This represents individuals' propensity to give kudos to someone of the same gender (i.e., extent of homophily), as opposed to giving kudos randomly. Index values can range from -1 (perfectly avoiding one's own gender) to $+1$ (perfect segregation), with the value 0 representing a situation in which the expected number of same-gender kudos under random choice is exactly equal to the observed number of same-gender kudos. Taken together, index values indicate that in some clubs kudos networks were segregated by gender – though the magnitude of the segregation varied. In one club (club 4) we found a tendency for individuals to give kudos to different-gender clubmates.

We plotted the development of the mean of our running variables over time across clubs, disaggregated by gender (Fig. 3). Running attribute values show considerable heterogeneity, between clubs (means), within clubs (standard errors) and between genders. While running variables differed over time within clubs, no consistent seasonal pattern was observed across clubs.

SAOM results

Kudos tie formation function

Before turning to the influence effects of interest, we briefly discuss the included effects of the kudos tie formation function. Since these were essentially the same across our models with the behavior attributes running frequency (Model 1) and volume (Model 2), for reasons of parsimony we summarize here only the effects of the running frequency model (Table 2). Effects of the running volume model are listed in Table 3.

We observe positive and significant reciprocity (μ_θ=4.153, SE=0.341) and transitivity (μ_θ=1.328, SE=0.187) effects in all clubs, but a negative interaction between the two (μ_θ=−1.170, SE=0.252). The out-isolate effect was generally positive and significant (μ_θ=1.449, SE=0.676). The same holds for the indegree popularity (μ_θ=0.201, SE=0.185) and outdegree activity (μ_θ=0.349, SE=0.196) effects.

We find heterogeneity between clubs in gender effects on kudos tie formation. Women were more popular than men in some clubs [*gender alter*: club 2 (Est.=0.167, SE=0.071); club 5 (Est.=0.159, SE=0.048)], but less popular in another [club 3 (Est.=−0.123, SE=0.062)]. In one club, women seemed less sociable than men with respect to giving kudos [*gender ego*: club 5 (Est.=−0.141, SE=0.049)]. In one club only, we find a tendency to give kudos to same-gender club members [*same gender*: club 2 (Est.=0.194, SE=0.067)].

We found some effects of running behavior on kudos tie formation, but not consistently across clubs. In some clubs, runners who run more (often) received kudos more often [*frequency alter*: club 2 (Est.=0.093, SE=0.032); club 3 (Est.=0.097, SE=0.039)]. Most importantly, we did not find that alters who run more (often) than ego were more attractive. In club 2, we even found the opposite: a tendency to award kudos to those who run less often than yourself [i.e., 'negative aspiration', indicated by a positive *higher* parameter estimate (Est.=0.093, SE=0.032)]. Last, kudos ties between club members who go for a run a more similar number of times per week were more likely in one club [*frequency similarity*: club 3 (Est.=0.380, SE=168)], but less likely in another [club 1 (Est.=−5.160, SE=1.700)].

Running activity function

Next, we turn to the estimated parameters for the running activity function. These are listed in Table 2 (frequency) and Table 3 (volume). We briefly discuss the shape effect estimates. These were essentially the same for both models, so we, again, discuss only the running frequency model. Linear shape effects were close to zero in all clubs (μ_θ=−0.002, SE=0.069), suggesting that increases in running activity over time were not more or less likely than decreases in running activity. The quadratic shape effect was positive in one club [club 5 (Est.=0.062, SE=0.016)], indicating that club members tended to be polarized with either high or low running frequency; and negative in another [club 1 (Est.=−0.071, SE=0.030)], indicating that club members leaned towards the mean running frequency over time, rather than extreme values.

Evidence for the social support effect. The Fisher-type combined test and the multivariate meta-analysis indicated that the indegree effect was positive on running frequency (Table 2; $\mathscr{X}^2$=29.042, $p = .001$;

[2] In club 5, features of the observed data were not accurately reproduced by our model.

Table 1
Descriptive statistics of Strava clubs[a].

	Club 1 (n = 27)	Club 2 (n = 58)	Club 3 (n = 159)	Club 4 (n = 9)	Club 5 (n = 76)
Density	.108 (.014)	.198 (.011)	.014 (.003)	.316 (.030)	.111 (.007)
Average degree	2.642 (0.411)	10.855 (0.895)	1.855 (0.291)	2.000 (0.296)	7.15 (1.007)
Reciprocity index	.804 (.06)	.634 (.036)	.386 (.062)	072 (.129)	.607 (.03)
Transitivity index	.582 (.034)	.544 (.016)	.276 (.076)	.735 (.143)	.526 (.018)
Jaccard index[b]	.840 (.050)	.760 (.030)	.500 (.060)	.810 (.090)	.690 (.020)
Gender segregation[c]	.197 (.116)	.269 (.038)	.098 (0.065)	-.183 (.116)	.018 (.034)
Network autocorrelation – direct neighbors[d]					
Running frequency	.069 (.153)	.133 (.056)	.130 (.072)	-.185 (.164)	.252 (.048)
Running volume	.077 (.162)	.115 (.07)	.156 (.068)	-.209 (.168)	.282 (.062)
Network autocorrelation – distance decay[d]					
Running frequency	.020 (.087)	.050 (.024)	.078 (.048)	-.148 (.145)	.123 (.026)
Running volume	.021 (.090)	.044 (.027)	.085 (.039)	-.159 (.129)	.137 (.027)
Male gender (%)	59.259	72.414	70.440	88.889	67.105

Notes:

[a] Network measures: mean values over time with standard deviations in parentheses.

[b] The Jaccard similarity index measures the extent of tie change between consecutive waves and is defined as $\frac{N_{11}}{N_{01}+N_{10}+N_{11}}$, where N_{11} is the number of ties present at both observations (t1 and t1 + 1), N_{01} is the number of ties newly created, and N_{10} is the number of ties terminated.

[c] The gender segregation measure used is Coleman's homophily index, constructed as $\left\{\begin{array}{ll} \frac{m_{gg1} - m^*_{gg1}}{\sum_{i\in G_g}\eta_i - m^*_{gg1}} & \text{if } m_{gg1} \geq m^*_{gg1}, \\ \frac{m_{gg1} - m^*_{gg1}}{m^*_{gg1}} & \text{if } m_{gg1} < m^*_{gg1}, \end{array}\right\}$ with m_{gg1} denoting the number of ties *within* group G_g (e.g., males), m^*_{gg1} denoting the expected number of ties within the gth group in a random network ($m^*_{gg1} = \sum_{i\in G_g}\eta_i\frac{n_{g-1}}{N-1}$), η_i denoting the out-degree of actor i and the fraction $\pi_g = (n_g - 1)/(N - 1)$ denoting the probability for an actor to choose an actor from the same group (here, gender) if the choice is random.

[d] The network autocorrelation measure used is Moran's I, computed as $\frac{n\sum_{ij}w_{ij}(z_i-\bar{z})(z_j-\bar{z})}{\left(\sum_{ij}w_{ij}\right)\left(\sum_i(z_i-\bar{z})^2\right)}$, where n is the number of actors in the network, w_{ij} is the weight matrix and z is the behavior attribute of interest. We calculated Moran's I based on outgoing kudos ties. To construct the weight matrix, we first measured the geodistance (d) between all club members. In the weight matrix for Moran's I among *direct neighbors*, club members with d= 1 received the value 1 and 0 otherwise. For the second weight matrix we used a negative exponential *distance-decay* function (e^{-d}). We did not row-standardize the weight matrices.

μ_θ=0.020, SE=0.006) and running volume (Table 3; $\mathscr{X}^2$=24.731, p = .006; μ_θ=0.015, SE=0.006). This is in line with the social support expectation (hypothesis 1). In all individual clubs, the parameter estimates for the indegree effect were positive, both in the running frequency and running volume models. However, in the running frequency model, t-ratios were only significant two-sidedly at α = .05 in one club [Table 2; club 5 (Est.=0.025, SE=0.009)], and one-sidedly in another [club 2 (Est.=0.014, SE=0.008)]. In the running volume model, t-ratios reached two-sided significance in one club only [Table 2; club 5 (Est.=0.020, SE=0.009)].

To illustrate this effect, consider two fictive runners, A and B, who are members of a random club drawn from a hypothetical population of Strava clubs. The runners are completely identical except that runner A received kudos from one clubmate more than runner B. In that case, runner A is almost 3 % ($e^{\mu_\theta} = e^{0.020} \approx 1.028$) more likely than runner B to increase their running by one session per week. Considering that the average standard deviation of the mean kudos indegree, pooled over clubs and weighted by their size, is 4.94, a 1-SD increase in kudos-indegree is estimated to drive up the probability of a one-unit increase in running frequency by 10 % ($e^{0.020*4.94} \approx 1.10$), ceteris paribus.

Evidence of peer influence on running activity. The Fisher-type combined test and the multivariate meta-analysis indicated that the *average attraction towards lower* effect was positive on running frequency (Table 2; $\mathscr{X}^2$=31.072, p < .001; μ_θ=5.139, SE=1.478) and running volume (Table 3; $\mathscr{X}^2$=21.701, p = .006; μ_θ=3.500, SE=1.307). In the running frequency model, t-ratios were significant two-sidedly in two clubs [Table 2; club 1 (Est.=4.776, SE=2.430); club 5 (Est.=9.015, SE=2.642). In the running volume model, t-ratios were significant two-sidedly in one club [Table 3; club 5 (Est.=8.800, SE=3.411)]. On the other hand, the combined test indicated that the *average attraction towards higher* effect was not significant for both running frequency (Table 2; $\mathscr{X}^2$=8.162, p = .418; μ_θ=0.359, SE=0.962) and running volume (Table 3; $\mathscr{X}^2$=11.360, p = .182; μ_θ=1.269, SE=1.014).

Thus, we find that actors are influenced by the behavior of their kudos-friends, in line with our social comparison expectation (hypothesis 2). Contrary to our upward comparison expectation (hypothesis 3), we did not find greater attraction towards higher effects compared to lower effects. If anything, the reverse was true: athletes were more likely to come to resemble the running behavior of kudos-friends who ran less and less often than they themselves.

To illustrate this, we use ego-alter influence plots (Fig. 4). The y-axis represents the 'desirability' of different potential values of ego's own running behavior (on the x-axis). Columns show different alter (kudos-friends) scenarios for ego. We calculated the evaluation score under the assumption that changes in running behavior were driven by the average estimates of the linear and quadratic shape effects and attraction towards higher and lower effects. Ego's behavioral scores move in the direction of higher evaluation scores on the running activity function. The plots demonstrate ego's tendency to move towards the behavior of alters. Alters who score lower than ego, draw ego down more strongly than higher-behavior alters pull ego up: the downward gradient is steeper than the upward gradient.

Robustness checks

Overall, club 5, the most professional club of our sample (see appendix A), displayed the most significant influence effects on running. Following the suggestion of an anonymous reviewer, we checked the robustness of our aggregate findings by excluding this club from our

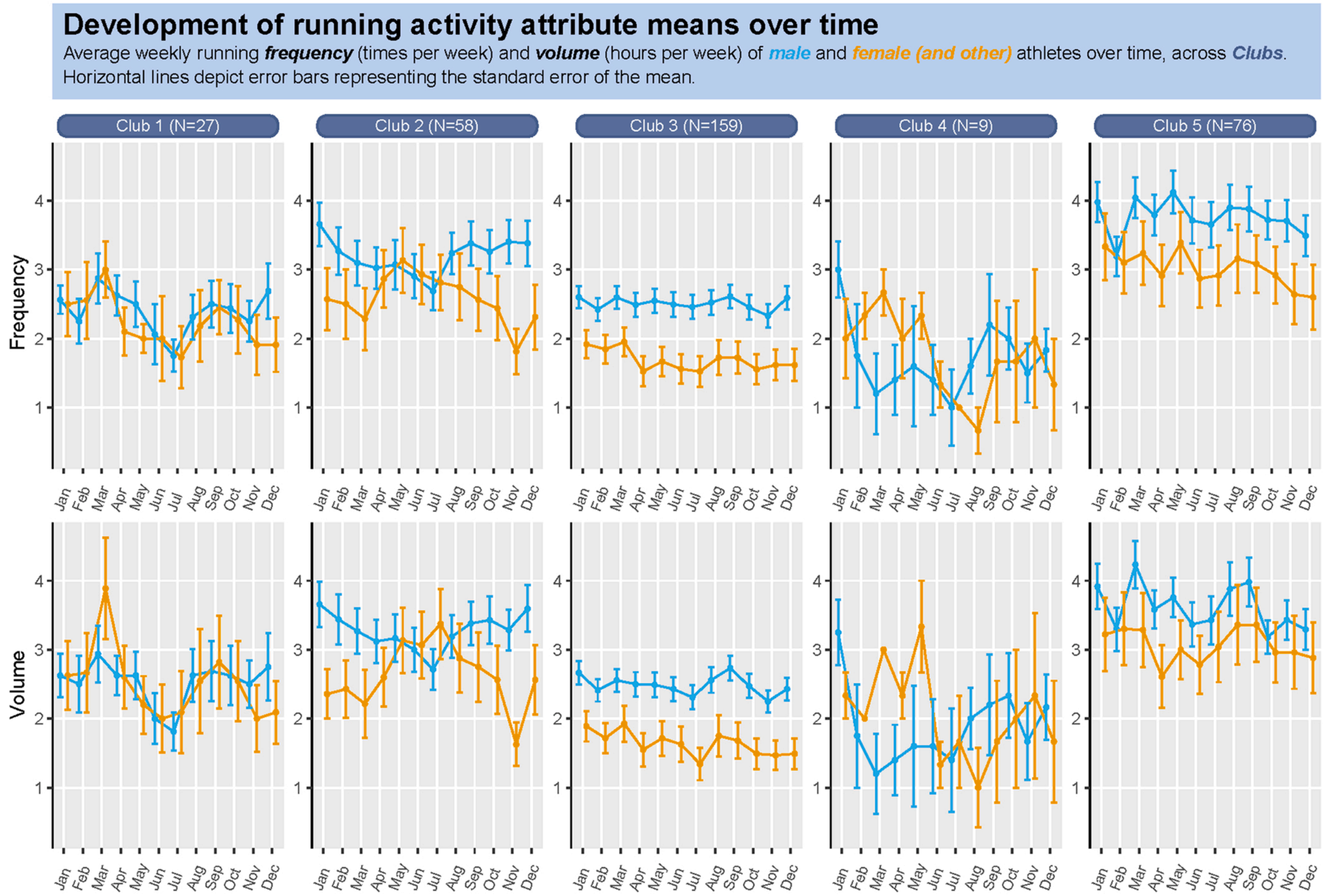

Fig. 3. Development of the mean of running attributes.

summary of estimates (see our replication website). Here, the combined p-values for the indegree ($p = .021$) and average attraction towards lower ($p = .016$) effects were still significant at $\alpha = .025$ in the running frequency model. In the running volume model, the effects were in the expected direction, but no longer significant ($p = .038$ and.065, for the indegree and attraction effects, respectively).

Results of models with the average similarity and average alter effects as alternative specifications for social influence can be found on our replication website. While both effects were significant based on the combined Fisher's test, average similarity was stronger than average alter in terms of statistical certainty and reached two-sided significance at $\alpha = .05$ in three clubs; average alter only reached two-sided significance in club 5.

Importance of influence effects

We calculated the relative importance of our effects of interest, following the procedure described by Indlekofer and Brandes (2013) (see appendix D). We observe that in all clubs, except club 4, peer influence effects were more important than receiving kudos. Moreover, the influence of lower alters was more important than the influence of higher alters.

Next, we investigated how consequential our influence effects are for the overall running behavior in the different clubs. To that end, we utilized our empirically estimated models as agent-based simulation models in RSiena (see e.g., Stadtfeld, 2018) (see appendix E). We concluded that "switching off" the effects of receiving kudos and the activities of lower alters substantially affected the simulated running means. Paradoxically, without influence effects, Strava users would generally run more and more often.

Heterogeneity of influence effects

As a last step, we explored influence heterogeneity between actors within clubs (see appendix F). No evidence was found that social influence differed between athletes depending on their current behavior (cf. Franken et al., 2022). While in some clubs the effects of receiving kudos and the activity level of friends depended on actors' experience with Strava, we did not find a consistent pattern across clubs. Finally, we did not find that receiving kudos and the activities of kudos-friends worked differently for males and females.

Discussion

Harnessing the novel opportunities offered by social media, we pioneered the use of Strava's big data to investigate how (online) social networks impact sports behavior. Our objective was to investigate (online) friends' influence on each other's training habits. We argued that support provided via social ties can improve an individual's sports participation, that social comparison processes stimulate athletes to resemble their co-athletes, and that athletes especially try to mimic the sports behavior of co-athletes who outperform themselves (in this case, by running more and more often).

Our findings showed rather consistently that runners' activity levels were positively influenced by receiving kudos. While the finding that the number of people who give you kudos positively affects your running frequency and volume corroborates previous studies on the significance of social support for sports outcomes (e.g., Sheridan et al., 2014), it contradict the experimental study by Zhang and colleagues (2016). The reason for this discrepancy may be that the motivational power embedded in naturalistic networks – such as networks on Strava – is

Table 2

Meta-analysis of parameter estimates for the kudos tie formation function and running frequency function (Model 1).

	Parameters																										
	Club 1 (n=27)				Club 2 (n=58)				Club 3 (n=159)				Club 4 (n=9)				Club 5 (n=76)				Fisher's combination test					RE-model	
																					Left-sided		Right-sided				
	Est.		SE	p	Est.		SE	p	Est.		SE	p	Est.		SE	p	Est.		SE	p	$\mathscr{X}^2$	p	$\mathscr{X}^2$	P	df	μ_θ	SE
Kudos tie formation dynamics																											
1. Outdegree	**-7.464**	***	1.573	<.001	**-6.962**	***	0.368	<.001	**-4.826**	***	0.181	<.001	3.161		2.745	.249	**-3.900**	***	0.175	<.001	**1,622.091**	<.001	4.163	.940	10	-4.616	1.359
2. Reciprocity	**5.665**	***	0.754	<.001	**4.424**	***	0.256	<.001	**4.388**	***	0.139	<.001	**2.627**	***	0.646	<.001	**3.793**	***	0.176	<.001	0.000	1.000	**1,864.632**	<.001	10	4.153	0.341
3. Transitivity (GWESP)	**1.225**	***	0.342	<.001	**0.871**	***	0.132	<.001	**1.236**	***	0.076	<.001	**2.107**	**	0.619	.001	**1.708**	***	0.095	<.001	0.001	1.000	**684.135**	<.001	10	1.328	0.187
4. Reciprocity * GWESP	0.000				**-0.691**	***	0.166	<.001	**-1.580**	***	0.117	<.001	0.000				**-1.204**	***	0.103	<.001	**356.498**	<.001	0.000	1.000	6	-1.170	0.252
5. Out-isolate	0.000				0.433		0.345	.209	**2.544**	***	0.127	<.001	**3.918**	*	1.900	.039	**0.567**	*	0.227	.013	0.273	1.000	**429.915**	<.001	8	1.449	0.676
6. Indegree pop. (sqrt.)	0.294		0.317	.353	**0.173**	***	0.042	<.001	**0.680**	***	0.059	<.001	-1.183		0.867	.173	**-0.093**	**	0.031	.002	18.802	.043	**163.191**	<.001	10	0.201	0.185
7. Outdegree pop. (sqrt.)	0.000				0.000				**-0.515**	***	0.050	<.001	0.000				0.000				**113.691**	<.001	0.000	1.000	2	-0.515	0.050
8. Outdegree act. (sqrt.)	**0.735**	***	0.187	<.001	**0.771**	***	0.091	<.001	**0.244**	***	0.021	<.001	-1.542		0.842	.067	**0.071**	***	0.019	<.001	6.792	.745	**264.233**	<.001	10	0.349	0.196
9. Reciprocated-degree act.	0.000				**-0.090**	***	0.015	<.001	0.000				0.000				0.000				**42.566**	<.001	0.000	1.000	2	-0.090	0.015
10. Frequency alter	-0.205		0.332	.537	**0.093**	**	0.032	.003	**0.097**	**	0.039	.014	0.216		0.576	.707	-0.016		0.033	.636	5.810	.831	**26.108**	.004	10	0.054	0.037
11. Frequency ego	-0.594		0.389	.127	**-0.099**	**	0.032	.002	0.025		0.040	.532	-0.186		0.547	.734	0.047		0.034	.158	**22.285**	.014	8.769	.554	10	-0.020	0.047
12. Frequency similarity	**-5.160**	*	1.700	.002	-0.077		0.128	.549	**0.380**	*	0.168	.024	-3.453		2.120	.103	0.220		0.125	.077	**22.063**	.015	16.129	.096	10	-0.922	0.900
13. Higher frequency	1.220		1.843	.508	**0.501**	**	0.191	.009	0.252		0.210	.229	-0.182		2.494	.942	-0.328		0.204	.108	8.187	.611	19.362	.036	10	0.159	0.239
14. Gender alter (ref. = male)	0.220		0.356	.536	**0.167**	*	0.071	.018	-0.123	*	0.062	.049	0.000				**0.159**	**	0.048	.001	8.063	.427	**27.650**	.001	8	0.076	0.088
15. Gender ego	-0.456		0.404	.260	0.086		0.070	.222	-0.121		0.065	.061	0.000				**-0.141**	**	0.049	.004	**23.740**	.003	4.740	.785	8	-0.075	0.068
16. Same gender	-0.486		0.317	.124	**0.194**	**	0.067	.004	0.062		0.060	.305	0.000				0.084		0.046	.068	5.957	.652	**23.253**	.003	8	0.097	0.033
Running frequency dynamics																											
17. Linear shape	-0.007		0.100	.948	-0.079		0.310	.798	-0.087		0.078	.265	0.149		0.668	.823	0.243		0.154	.114	8.549	.575	10.092	.432	10	-0.002	0.069
18. Quadratic shape	**-0.071**		0.030	.018	0.041		0.037	.267	-0.009		0.013	.503	-0.203		0.128	.112	**0.062**		0.016	<.001	18.223	.051	**25.183**	.005	10	-0.003	0.030
19. *Indegree*	0.047		0.032	.141	0.014		0.008	.090	0.008		0.028	.773	0.306		0.238	.198	**0.025**	**	0.009	.008	1.432	.999	**29.042**	.001	10	0.020	0.006
20. *Average attraction higher*	-0.034		1.836	.985	1.437		2.406	.550	1.559		2.086	.455	-4.544		5.303	.391	-0.136		1.703	.936	4.094	.849	8.162	.418	10	0.359	0.962
21. *Average attraction lower*	**4.776**	*	2.430	.049	4.440		4.337	.306	2.398		2.286	.294	6.187		5.882	.293	**9.015**	**	2.642	.001	0.701	1.000	**31.072**	<.001	10	5.139	1.478
22. Gender (ref. = male)	-0.184		0.123	.134	0.028		0.093	.762	**-0.192**	**	0.060	.001	0.000				-0.089		0.071	.209	**25.486**	.001	2.289	.971	8	-0.115	0.050
23. Frequency other sports	-0.047		0.051	.358	0.005		0.020	.809	0.007		0.015	.617	-0.026		0.147	.857	0.031	*	0.020	.119	7.030	.723	11.327	.333	10	0.010	0.010

Notes: Est. = estimate; SE = standard error; **Bold** values represent significant results. Significance level was set at α =.025 for Fisher's combination test. μ_θ represents the average effect estimates.
All convergence t-ratios <0.10; overall maximum convergence ratios <0.24. Score-type tests indicated that some effects were not significant for specific clubs; these were fixed to 0.
Model results including rate parameter estimates can be found online.
*Two-sided p <.05; ** Two-sided p <.01; *** Two-sided p <.001.

Table 3
Meta-analysis of parameter estimates for the kudos tie formation function and running volume function (Model 2).

	Parameters																				
	Club 1 (n=27)			Club 2 (n=58)			Club 3 (n=159)			Club 4 (n=9)			Club 5 (n=76)			Fisher's combination test					RE-model	
																Left-sided		Right-sided				
	Est.	SE	P	Est.	SE	p	Est.	SE	p	Est.	SE	p	Est.	SE	p	$\mathscr{X}^2$	p	$\mathscr{X}^2$	p	df	μ_θ	SE
Kudos tie formation dynamics																						
1. Outdegree	**-6.406** ***	1.119	<.001	**-7.109** ***	0.385	<.001	**-4.942** ***	0.185	<.001	1.508	2.949	.609	**-3.863** ***	0.171	<.001	**1,632.035**	<.001	2.378	.993	10	-5.040	0.875
2. Reciprocity	**5.264** ***	0.542	<.001	**4.433** ***	0.263	<.001	**4.441** ***	0.139	<.001	**2.698** ***	0.698	.001	**3.794** ***	0.175	<.001	0.000	1.000	**1,916.450**	<.001	10	4.203	0.294
3. Transitivity (GWESP)	**1.182** ***	0.316	<.001	**0.863** ***	0.131	<.001	**1.255** ***	0.077	<.001	**1.970** **	0.569	.001	**1.718** ***	0.094	<.001	0.001	1.000	**698.218**	<.001	10	1.323	0.185
4. Reciprocity * GWESP	0.000			**-0.656** ***	0.170	<.001	**-1.622** ***	0.117	<.001	0.000			**-1.197** ***	0.102	<.001	**362.801**	<.001	0.000	1.000	6	-1.169	0.274
5. Out-isolate	0.000			0.394	0.350	.261	**2.553** ***	0.125	<.001	3.411 *	1.855	.066	**0.569** *	0.220	.010	0.356	1.000	**445.675**	<.001	8	1.397	0.662
6. Indegree pop. (sqrt.)	0.229	0.281	.416	**0.173** ***	0.042	<.001	**0.684** ***	0.059	<.001	-1.043	0.971	.283	**-0.108** **	0.031	<.001	**21.049**	0.021	**168.333**	<.001	10	0.204	0.181
7. Outdegree pop. (sqrt.)	0.000			0.000			**-0.517** ***	0.049	<.001	0.000			0.000			**119.815**	<.001	0.000	1.000	2	-0.517	0.049
8. Outdegree act. (sqrt.)	**0.643** ***	0.172	<.001	**0.794** ***	0.093	<.001	**0.242** ***	0.020	<.001	-1.436	0.829	.083	**0.073** ***	0.019	<.001	6.363	.784	**264.510**	<.001	10	0.345	0.186
9. Reciprocated-degree act.	0.000			**-0.094** ***	0.015	<.001	0.000			0.000			0.000			44.124	1.000	0.000	1.000	2	-0.094	0.015
10. Volume alter	-0.270	0.251	.284	**0.113** **	0.035	.001	**0.101** **	0.036	.005	0.624	0.65	.337	-0.005	0.028	.844	6.008	.815	**31.652**	<.001	10	0.061	0.039
11. Volume ego	-0.241	0.247	.330	**-0.121** **	0.034	<.001	-0.022	0.036	.550	-0.619	0.58	.286	0.031	0.028	.267	**27.295**	.002	5.342	.867	10	-0.045	0.044
12. Volume similarity	**-2.240** *	1.096	.041	-0.089	0.134	.508	0.186	0.153	.226	-1.593	1.731	.357	**0.311**	0.148	.035	14.239	.162	13.478	.198	10	0.089	0.127
13. Higher volume	0.464	1.419	.744	**0.643** **	0.219	.003	**0.482** *	0.203	.018	2.084	2.752	.449	-0.359	0.185	.052	8.741	.557	**27.304**	.002	10	0.276	0.294
14. Gender alter (ref. = male)	0.293	0.331	.376	**0.168** *	0.072	.019	**-0.143** *	0.062	.022	0.000			**0.152** **	0.049	.002	9.474	.304	**26.681**	.001	8	0.074	0.094
15. Gender ego	-0.399	0.369	.280	0.085	0.072	.236	-0.117	0.066	.074	0.000			**-0.139** **	0.050	.005	**22.666**	.004	4.655	.794	8	-0.074	0.067
16. Same gender	-0.466	0.297	.117	**0.196** **	0.068	.004	0.066	0.061	.282	0.000			0.082	0.046	.076	6.063	.640	**22.923**	.003	8	0.096	0.032
Running volume dynamics																						
17. Linear shape	-0.056	0.099	.572	-0.212	0.298	.476	-0.128	0.078	.099	1.210	2.159	.575	-0.007	0.146	.963	13.531	.195	5.125	.883	10	-0.090	0.055
18. Quadratic shape	-0.033	0.025	.179	0.013	0.033	.688	-0.008	0.013	.513	-0.391	0.459	.394	0.024	0.013	.061	11.697	.306	10.344	.411	10	0.001	0.013
19. *Indegree*	0.041	0.029	.164	0.011	0.007	.114	0.004	0.027	.893	0.753	0.684	.271	**0.020** *	0.009	.030	1.793	.998	**24.731**	.006	10	0.015	0.006
20. *Average attraction higher*	0.275	1.775	.877	1.692	2.201	.442	1.882	2.086	.367	-17.830	21.100	.398	1.869	2.147	.384	2.485	.962	11.360	.182	10	1.269	1.014
21. *Average attraction lower*	3.450	2.108	.102	1.358	4.112	.741	1.768	2.176	.416	16.374	16.305	.315	**8.800** *	3.411	.010	1.507	.993	**21.701**	.006	10	3.500	1.307
22. Gender (ref. = male)	-0.073	0.116	.527	0.031	0.075	.680	**-0.201** **	0.059	.001	0.000			-0.015	0.064	.819	**21.063**	.007	3.822	.873	8	-0.069	0.058
23. Volume other sports	-0.020	0.026	.435	0.002	0.014	.877	0.013	0.013	.327	-0.074	0.102	.467	**0.041** *	0.016	.010	7.479	.680	16.890	.077	10	0.012	0.010

Notes: Est. = estimate; SE = standard error; **Bold** values represent significant results. Significance level was set at α =.025 for Fisher's combination test. μ_θ represents the average effect estimates.
All convergence t-ratios <0.10; overall maximum convergence ratios <0.24. Score-type tests indicated that some effects were not significant for specific clubs; these were fixed to 0.
Model results including rate parameter estimates can be found online.
*Two-sided p <.05; ** Two-sided p <.01; *** Two-sided p <.001.

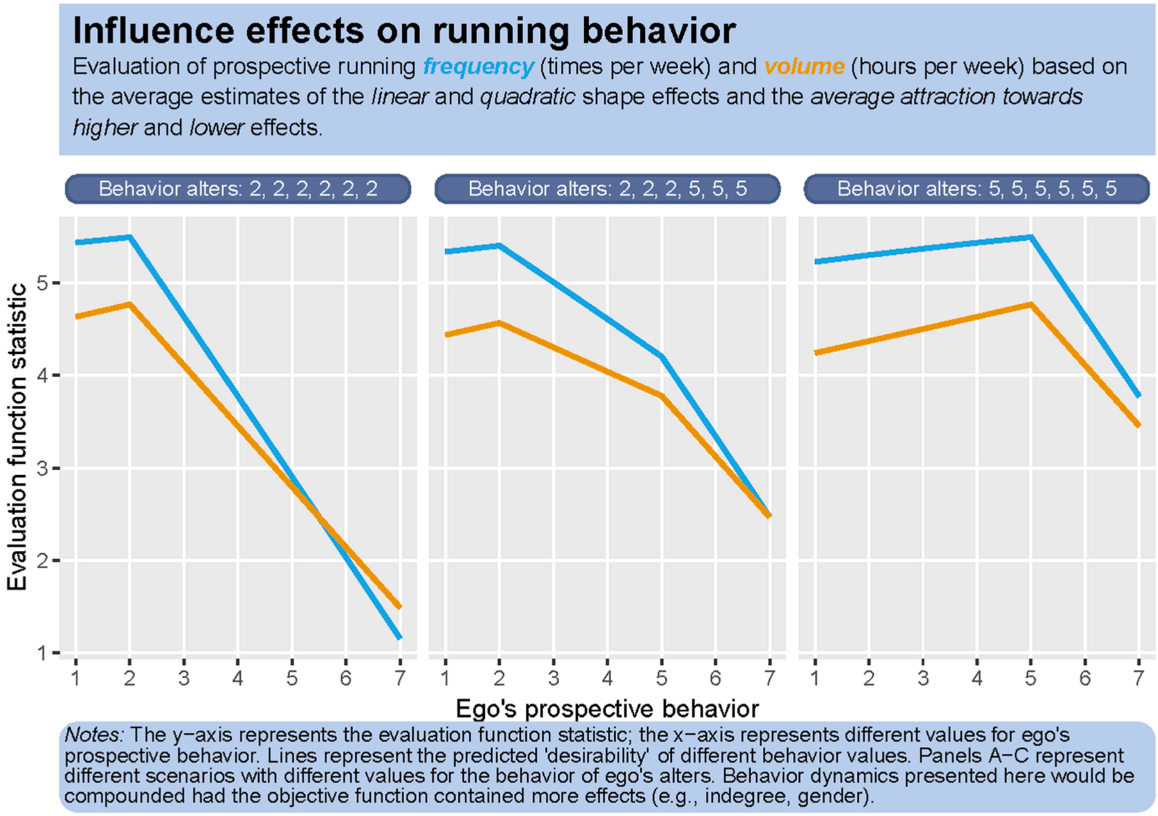

Fig. 4. Ego-alter influence plot.

greater than in artificially constructed anonymous networks. Naturally, a follow-up question would be whether other online networks, both within Strava or outside Strava (e.g., on Zwift, Garmin connect, Final Surge), or offline networks of runners embed even greater positive motivational power.

In accordance with prior SAOM studies in the field of physical activity behaviors, we found that individuals were influenced by the activity levels of their friends over time. However, somewhat surprisingly and in contrast to our expectation, we discovered that athletes on Strava were mainly negatively influenced by the activity levels of alters who ran less and less often than they themselves. Paradoxically, our results also seem to indicate that without influence effects, Strava users would exercise more (often). Being on Strava in itself may fuel running motivation, through the act of self-tracking and various motivational game-elements (e.g., challenges and badges). Once on Strava, the receipt of kudos may motivate us to increase our running, but more importantly, our friends who run less (often) show it is okay to do less and may justify deviation from our goals (Diel et al., 2021b; Karahanoğlu et al., 2021).

Selection and influences processes are closely entwined. In our study, we assumed that Strava users could only be influenced by those who ego gave kudos to. We therefore investigated whether Strava runners have the tendency to especially award kudos to (higher) runners they admire or to runners with similar activity levels. However, we did not find this (cf. Centola and van de Rijt, 2015).

This study points to a promising avenue for future interventions aimed at increasing physical activity, as our findings highlight the potential of online fitness programs and (offline and online) sports communities to facilitate supportive interactions among members. Social support, even just a (virtual) thumbs-up, motivates people to increase their activity level.

Naturally, we need to recognize that the competitive nature of platforms like Strava may also have adverse effects, such as psychological distress and pressure created via constant comparison with others (e.g., Schmidt-Kraepelin et al., 2019).

We theorized that social influence on sports behavior may not be symmetrical. The positive and negative influences of alters who score higher and lower on running attributes may not necessarily cancel each other out. We integrated this idea into our analyses using one-sided versions of the average similarity effect to capture ego's tendency to become more similar to alters who score higher or lower than their own score. Future research might extend our approach to modeling asymmetrical influence effects. Some behaviors may have intrinsic value or signal status. Actors exhibiting those behaviors to a higher degree than ego may be more attractive ties (selection), but more importantly, they may also constitute more important sources of influence compared to alters who engage in those behaviors to a lesser degree than ego. This may hold, for example, for academic functioning (e.g., Rambaran et al., 2017), adolescents' deviant behavior (e.g., Gallupe et al., 2019) and health-related behaviors such as alcohol consumption and smoking (e.g., Ragan, 2020). We invite scholars in these fields to test this proposition.

Naturally, this study presents limitations. First, we used a very specific sample: athletes who were members of a formal club with a virtual extension on Strava. When it comes to Strava, app usership is skewed toward young males (e.g., Janssen et al., 2017). Although running as a sports activity has become popular among diverse participants, it seems that higher educated individuals still are overrepresented among the running population, especially in club-organized running (Scheerder et al., 2015). A Strava club runner may therefore not be your typical runner. They may be particularly committed to running and they may be driven by social motives to a greater degree than are other types of runners. While our findings indicate that influence is no different for highly and lowly active runners within clubs, and while previous research suggests that peer effects on running fare independently from social running motivations (Franken et al., 2022), we should still exercise caution in generalizing findings of our specific sample of Strava club runners to a broader population of runners, let alone athletes in other sports. We specifically assessed influence processes taking place between kudos-friends within virtual clubs on Strava, but the question remains of whether the (relative) importance of the support and comparison mechanisms are similar in different types of online and real-life networks of runners. Strava's big data provide new resources for studying social influence processes among athletes, but they do not eclipse the need for traditional field study approaches and large-scale data collection targeting diverse populations. Our study is complementary.

A second limitation of this study refers to our inability to harvest relevant demographic and socio-psychological characteristics of club members. This would have allowed us to investigate to what extent, for instance, the kudos indegree effect was mediated by variables such as perceived support and intrinsic motivation. Besides, more detailed information on the individual-level characteristics of club members may be relevant to exploring why influence mechanisms vary across clubs. We, therefore, recommend that future research integrates Strava's big data with thick data (e.g., survey data) covering relevant individual-level variables (Stier et al., 2020).

Web-scraping enormous amounts of data of Strava poses serious practical challenges. Since the time of our data collection, Strava has blocked multiple endpoints of their API and updated their robot exclusion protocols. We also observe that at the time of writing (2022), far more athletes have set their activities to private than when we collected our data (2019). Both these factors severely limit ethically sound web-scraping opportunities. We could say, we were just in time in collecting our unique dataset. However, we fully acknowledge that a larger number of clubs would have heightened the generalizability of our findings, while simultaneously allowing for comparison between contexts (e.g., McFarland et al., 2014).

Strava regularly modifies and removes existing features of the platform and adds new ones. For example, multiple features that were free at the time of our data collections, such as leaderboards, are currently paywalled an available only to premium subscribers.[3] Collecting data on a number of new clubs – either via web-scraping or manually – would allow for exploring how changes to the platform are related to observed influence dynamics within clubs. Naturally, multiple other online fitness communities exist next to Strava. Therefore, another extension to heightening the generalizability of our findings would be to compare the motivational power of social networks across different platforms.

Despite these limitations, this study makes several contributions to the literature. It is the first to use Strava's big data to investigate social dynamics in sports. Unlike the majority of SAOM studies in the field of sports and active living, we focused on adult athletes and their objective sports behavior, which we followed for a relatively long period. We conceptualized a novel network of kudos relationships. We tested a new hypothesis, which we called the upward comparison expectation, for which we developed new behavioral effects for RSiena.

A focus on social networks may be a fruitful direction for policies aimed at promoting sports participation, as our study shows that social networks harbor (untapped) motivational power: runners on Strava will increase their running if they receive kudos.

Funding

This work was supported by the Netherlands Organization of Sciences [NWA.1160.18.249]; NWA grant for the project "Transition Into Active Living ", Prof. Dr. B. Steenbergen; and by ZonMW [ZonMw 538001037] Sport Innovator grant for the project Altijd Blijven Sporten!, Prof. Dr. J. Tolsma & Dr. H. Bekhuis.

[3] Although Strava does not keep a public changelog, changes to the platform are normally extensively discussed on the blog of DC Rainmaker (see https://www.dcrainmaker.com, use 'Strava' as keyword search).

Declaration of interest

None.

Data availability

All relevant data and its replication package can be found on GitHub: https://robfranken.github.io/Strava/.

Acknowledgements

Special thanks to Manuel Mínguez Carretero and Miriam Sackers for developing the web crawler for Strava. We thank prof. dr. Tom Snijders for implementing the *attraction towards higher* and *lower* effects in RSiena.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.socnet.2022.10.001.

References

Ajzen, I., 1991. The theory of planned behavior. Organ. Behav. Hum. Decis. Process. 50 (2), 179–211.
Almquist, Z.W., Arya, S., Zeng, L., Spiro, E., 2019. Unbiased sampling of users from (online) activity data. Field Methods 31 (1), 23–38. https://doi.org/10.1177/1525822×18799426.
Bandura, A., 2001. Social cognitive theory: an agentic perspective. Annu. Rev. Psychol. 52 (1), 1–26.
Bernard, H.R., Killworth, P.D., 1977. Informant accuracy in social network data Ii. Hum. Commun. Res. 4 (1), 3–18. https://doi.org/10.1111/j.1468-2958.1977.tb00591.x.
Block, P., 2015. Reciprocity, transitivity, and the mysterious three-cycle. Soc. Netw. 40, 163–173. https://doi.org/10.1016/j.socnet.2014.10.005.
Bojanowski, M., Corten, R., 2014. Measuring segregation in social networks. Soc. Netw. 39, 14–32. https://doi.org/10.1016/j.socnet.2014.04.001.
Centola, D., van de Rijt, A., 2015. Choosing your network: social preferences in an online health community. Soc. Sci. Med. 125, 19–31. https://doi.org/10.1016/j.socscimed.2014.05.019.
Chen, Y., Pu, P., 2014. HealthyTogether: Exploring social incentives for mobile fitness applications. In: Proceedings of the Second International Symposium of Chinese CHI on - Chinese CHI '14, 25–34. https://doi.org/10.1145/2592235.2592240.
Coleman, J.S., 1958. Relational analysis: the study of social organizations with survey methods. Hum. Organ. 17 (4), 28–36.
Couture, J., 2021. Reflections from the 'Strava-sphere': Kudos, community, and (self-)surveillance on a social network for athletes. Qual. Res. Sport, Exerc. Health 13 (1), 184–200. https://doi.org/10.1080/2159676X.2020.1836514.
de la Haye, K., Robins, G., Mohr, P., Wilson, C., 2011. How physical activity shapes, and is shaped by, adolescent friendships. Soc. Sci. Med. 73 (5), 719–728. https://doi.org/10.1016/j.socscimed.2011.06.023.
Diel, K., Broeker, L., Raab, M., Hofmann, W., 2021. Motivational and emotional effects of social comparison in sports. Psychol. Sport Exerc. 57, 102048 https://doi.org/10.1016/j.psychsport.2021.102048.
Diel, K., Grelle, S., Hofmann, W., 2021. A motivational framework of social comparison. J. Personal. Soc. Psychol.
Dyrstad, S.M., Hansen, B.H., Holme, I.M., Anderssen, S.A., 2014. Comparison of self-reported versus accelerometer-measured physical activity. Med. Sci. Sports Exerc. 46 (1), 99–106. https://doi.org/10.1249/MSS.0b013e3182a0595f.
Edelmann, A., Wolff, T., Montagne, D., Bail, C.A., 2020. Computational social science and sociology. Annu. Rev. Sociol. 46 (1), 61–81. https://doi.org/10.1146/annurev-soc-121919-054621.
Festinger, L., 1954. A theory of social comparison processes. Hum. Relat. 7 (2), 117–140. https://doi.org/10.1177/001872675400700202.
Fitzgerald, A., Fitzgerald, N., Aherne, C., 2012. Do peers matter? A review of peer and/or friends' influence on physical activity among American adolescents. J. Adolesc. 35 (4), 941–958. https://doi.org/10.1016/j.adolescence.2012.01.002.
Franken, R., Bekhuis, H., Tolsma, J., 2022. Running together: how sports partners keep you running. Front. Sports Act. Living *4*.
Franken, R., Bekhuis, H., Tolsma, J., 2020. Always Stay Active 2019/2020. https://doi.org/10.17026/DANS-ZD5-BP24.
Fujimoto, K., Snijders, T.A.B., Valente, T.W., 2018. Multivariate dynamics of one-mode and two-mode networks: Explaining similarity in sports participation among friends. Netw. Sci. 6 (3), 370–395. https://doi.org/10.1017/nws.2018.11.
Gallupe, O., McLevey, J., Brown, S., 2019. Selection and influence: a meta-analysis of the association between peer and personal offending. J. Quant. Criminol. 35 (2), 313–335.
Goethals, G.R., Darley, J.M., 1977. Social comparison theory: an attributional approach. Soc. Comp. Process. Theor. Empir. Perspect. 259–278.

Hamari, J., Koivisto, J., 2015. "Working out for likes": an empirical study on social influence in exercise gamification. Comput. Hum. Behav. 50, 333–347.
Heaney, C.A., Israel, B.A., 2008. Social networks and social support. Health Behav. Health Educ. Theory, Res., Pract. 4, 189–210.
Hedges, L.V., Olkin, I., 2014. Statistical Methods for MEta-analysis. Academic Press.
Huisman, M., Snijders, T.A.B., 2003. Statistical analysis of longitudinal network data with changing composition. Sociol. Methods Res. 32 (2), 253–287. https://doi.org/10.1177/0049124103256096.
Hunter, R.F., Haye, K. de la, Murray, J.M., Badham, J., Valente, T.W., Clarke, M., Kee, F., 2019. Social network interventions for health behaviours and outcomes: a systematic review and meta-analysis. PLoS Med. 16 (9), e1002890 https://doi.org/10.1371/journal.pmed.1002890.
Indlekofer, N., Brandes, U., 2013. Relative importance of effects in stochastic actor-oriented models. Netw. Sci. 1 (3), 278–304. https://doi.org/10.1017/nws.2013.21.
Janssen, M., Scheerder, J., Thibaut, E., Brombacher, A., Vos, S., 2017. Who uses running apps and sports watches? Determinants and consumer profiles of event runners' usage of running-related smartphone applications and sports watches. PLoS One 12 (7), e0181167. https://doi.org/10.1371/journal.pone.0181167.
Karahanoğlu, A., Gouveia, R., Reenalda, J., Ludden, G., 2021. How Are sports-trackers used by runners? running-related data, personal goals, and self-tracking in running. Sensors 21 (11), 3687.
Keegan, R., Spray, C., Harwood, C., Lavallee, D., 2011. From 'motivational climate' to 'motivational atmosphere': A review of research examining the social and environmental influences on athlete motivation in sport. Sport Psychol. 1, 1–55. ⟨https://www.novapublishers.com/catalog/product_info.php?products_id=16424&osCsid=05228c9e3971bce63ca9314df2ab94e1⟩.
Keeling, M.J., Eames, K.T.D., 2005. Networks and epidemic models. J. R. Soc. Interface 2 (4), 295–307. https://doi.org/10.1098/rsif.2005.0051.
Koivisto, J., Hamari, J., 2019. The rise of motivational information systems: a review of gamification research. Int. J. Inf. Manag. 45, 191–210.
Lospinoso, J., Snijders, T.A., 2019. Goodness of fit for stochastic actor-oriented models (2059799119884282). Methodol. Innov. 12 (3). https://doi.org/10.1177/2059799119884282.
Lupton, D., 2016. The Quantified Self. John Wiley & Sons.
Marsh, H.W., Trautwein, U., Lüdtke, O., Köller, O., 2008. Social comparison and big-fish-little-pond effects on self-concept and other self-belief constructs: role of generalized and specific others. J. Educ. Psychol. 100 (3), 510–524. https://doi.org/10.1037/0022-0663.100.3.510.
McFarland, D.A., Moody, J., Diehl, D., Smith, J.A., Thomas, R.J., 2014. Network ecology and adolescent social structure. Am. Sociol. Rev. 79 (6), 1088–1121. https://doi.org/10.1177/0003122414554001.
McMillan, C., Felmlee, D., Osgood, D.W., 2018. Peer influence, friend selection, and gender: how network processes shape adolescent smoking, drinking, and delinquency. Soc. Netw. 55, 86–96. https://doi.org/10.1016/j.socnet.2018.05.008.
McPherson, J.M., Smith-Lovin, L., Cook, J.M., 2001. Birds of a feather: homophily in social networks. Annu. Rev. Sociol. 27 (1), 415–444. https://doi.org/10.1146/annurev.soc.27.1.415.
Merriam-Webster. (n.d.). Kudos. In: Merriam-Webster.com Dictionary. ⟨https://www.merriam-webster.com/dictionary/kudos⟩. (Accessed 14 March 2022).
Moran, P.A., 1948. The interpretation of statistical maps. J. R. Stat. Soc. Ser. B (Methodol.) 10 (2), 243–251.
Moreno, M.A., Christakis, D.A., Egan, K.G., Brockman, L.N., Becker, T., 2012. Associations between displayed alcohol references on Facebook and problem drinking among college students. Arch. Pediatr. Adolesc. Med. 166 (2), 157–163.
Murray, J.M., Brennan, S.F., French, D.P., Patterson, C.C., Kee, F., Hunter, R.F., 2017. Effectiveness of physical activity interventions in achieving behaviour change maintenance in young and middle aged adults: a systematic review and meta-analysis. Soc. Sci. Med. 192, 125–133. https://doi.org/10.1016/j.socscimed.2017.09.021.
Noakes, T., 2003. Lore of Running. Human Kinetics.
Pratt, M., Varela, A.R., Salvo, D., Iii, H.W.K., Ding, D., 2020. Attacking the pandemic of physical inactivity: what is holding us back? Br. J. Sports Med. 54 (13), 760–762. https://doi.org/10.1136/bjsports-2019-101392.
Ragan, D.T., 2020. Similarity between deviant peers: developmental trends in influence and selection. Criminology 58 (2), 336–369. https://doi.org/10.1111/1745-9125.12238.
Rambaran, J.A., Hopmeyer, A., Schwartz, D., Steglich, C., Badaly, D., Veenstra, R., 2017. Academic functioning and peer influences: a short-term longitudinal study of network–behavior dynamics in middle adolescence. Child Dev. 88 (2), 523–543. https://doi.org/10.1111/cdev.12611.
Ripley, R.M., Snijders, T.A., Boda, Z., Vörös, A., Preciado, P., 2022. Manual for RSIENA, 1. University of Oxford, Department of Statistics, Nuffield College.
Salathé, M., Vu, D.Q., Khandelwal, S., Hunter, D.R., 2013. The dynamics of health behavior sentiments on a large online social network. EPJ Data Sci. 2 (1), 4. https://doi.org/10.1140/epjds16.
Sauder, M., Lynn, F., Podolny, J.M., 2012. Status: insights from Organizational Sociology. Annu. Rev. Sociol. 38 (1), 267–283. https://doi.org/10.1146/annurev-soc-071811-145503.
Scheerder, J., Breedveld, K., Borgers, J., 2015. Who is doing a run with the running boom? In: Running Across Europe. Springer, pp. 1–27.
Schmidt-Kraepelin, M., Thiebes, S., Stepanovic, S., Mettler, T., Sunyaev, A., 2019. Gamification in health behavior change support systems-a synthesis of unintended side effects. In: Proceedings of the Fourteenth International Conference on Wirtschaftsinformatik, 1032–1046.
Schweinberger, M., 2012. Statistical modelling of network panel data: goodness of fit. Br. J. Math. Stat. Psychol. 65 (2), 263–281. https://doi.org/10.1111/j.2044-8317.2011.02022.x.
Shalizi, C.R., Thomas, A.C., 2011. Homophily and contagion are generically confounded in observational social network studies. Sociol. Methods Res. 40 (2), 211–239.
Sheridan, D., Coffee, P., Lavallee, D., 2014. A systematic review of social support in youth sport. Int. Rev. Sport Exerc. Psychol. 7 (1), 198–228. https://doi.org/10.1080/1750984X.2014.931999.
Shoham, D.A., Tong, L., Lamberson, P.J., Auchincloss, A.H., Zhang, J., Dugas, L., Kaufman, J.S., Cooper, R.S., Luke, A., 2012. An actor-based model of social network influence on adolescent body size, screen time, and playing sports. PLoS One 7 (6), e39795. https://doi.org/10.1371/journal.pone.0039795.
Simpkins, S.D., Schaefer, D.R., Price, C.D., Vest, A.E., 2013. Adolescent friendships, BMI, and physical activity: untangling selection and influence through longitudinal social network analysis. J. Res. Adolesc. 23 (3), 537–549. https://doi.org/10.1111/j.1532-7795.2012.00836.x.
Smith, N.R., Zivich, P.N., Frerichs, L., 2020. Social influences on obesity: current knowledge, emerging methods, and directions for future research and practice. Curr. Nutr. Rep. 9 (1), 31–41. https://doi.org/10.1007/s13668-020-00302-8.
Smith, W.R., Treem, J., 2017. Striving to be king of mobile mountains: communication and organizing through digital fitness technology. Commun. Stud. 68 (2), 135–151. https://doi.org/10.1080/10510974.2016.1269818.
Snijders, T.A.B., van de Bunt, G.G., Steglich, C.E.G., 2010. Introduction to stochastic actor-based models for network dynamics. Soc. Netw. 32 (1), 44–60. https://doi.org/10.1016/j.socnet.2009.02.004.
Spotswood, F., Shankar, A., Piwek, L., 2020. Changing emotional engagement with running through communal self-tracking: the implications of 'teleoaffective shaping' for public health. Sociol. Health Illn. 42 (4), 772–788. https://doi.org/10.1111/1467-9566.13057.
Stadtfeld, C., 2018. The Micro–Macro Link in Social Networks, 1–15. https://doi.org/10.1002/9781118900772.etrds0463.
Stadtfeld, C., Block, P., 2017. Interactions, actors, and time: dynamic network actor models for relational events. Sociol. Sci. 4, 318–352. https://doi.org/10.15195/v4.a14.
Steglich, C., Snijders, T.A., West, P., 2006. Applying SIENA: an illustrative analysis of the coevolution of adolescents' friendship networks, taste in music, and alcohol consumption. Methodol. Eur. J. Res. Methods Behav. Soc. Sci. 2 (1), 48.
Stier, S., Breuer, J., Siegers, P., Thorson, K., 2020. Integrating survey data and digital trace data: key issues in developing an emerging field. Soc. Sci. Comput. Rev. 38 (5), 503–516. https://doi.org/10.1177/0894439319843669.
Stragier, J., Mechant, P., De Marez, L., Cardon, G., 2018. Computer-mediated social support for physical activity: a content analysis. Health Educ. Behav. 45 (1), 124–131. https://doi.org/10.1177/1090198117703055.
Strava , (2022, March 24). Feed Ordering [update]. ⟨https://support.strava.com/hc/en-us/articles/115001183630-Feed-Ordering⟩. (Accessed 3 October 2022).
Subrahmanyam, K., Reich, S.M., Waechter, N., Espinoza, G., 2008. Online and offline social networks: use of social networking sites by emerging adults. J. Appl. Dev. Psychol. 29 (6), 420–433. https://doi.org/10.1016/j.appdev.2008.07.003.
Viechtbauer, W., 2010. Conducting meta-analyses in R with the metafor package. J. Stat. Softw. 36 (3), 1–48. https://doi.org/10.18637/jss.v036.i03.
Walton, C.C., Baranoff, J., Gilbert, P., Kirby, J., 2020. Self-compassion, social rank, and psychological distress in athletes of varying competitive levels. Psychol. Sport Exerc. 50, 101733 https://doi.org/10.1016/j.psychsport.2020.101733.
WHO, 2019. Global Action Plan on Physical Activity 2018-2030: More Active People for a Healthier World. World Health Organization.
Zhang, J., Brackbill, D., Yang, S., Becker, J., Herbert, N., Centola, D., 2016. Support or competition? How online social networks increase physical activity: a randomized controlled trial. Prev. Med. Rep. 4, 453–458. https://doi.org/10.1016/j.pmedr.2016.08.008.
Zhang, J., Brackbill, D., Yang, S., Centola, D., 2015. Efficacy and causal mechanism of an online social media intervention to increase physical activity: results of a randomized controlled trial. Prev. Med. Rep. 2, 651–657.