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ORIGINAL ARTICLE

Social networks in parkrun: a comparative analysis of an urban and a rural event

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Abstract

Aim Sustainable initiatives which can multi-solve physical inactivity and social isolation are valuable approaches for improving population health. "parkrun" is a mass-participation free, weekly, timed 5 km walk or run operating in 23 countries. Our study aims to test and extend previous qualitative research which claims that social connection is facilitated in parkrun, using a prospective social network analysis.

Subject and methods We conducted a time dynamic analysis at two new Australian parkrun sites (one rural, one urban) across three waves over 12 months using (1) social connections from a social network survey and (2) demographic, participation and performance metrics from parkrun administrative data.

Results Network members (urban $n=354$, rural $n=145$) became more interconnected over time, especially at the rural parkrun. The network structure at both parkruns comprised a distinct socially connected core persisting over time despite turnover in members, alongside a less densely connected periphery. The core contained those with higher participation (walking, running, or volunteering) rather than those with faster parkrun finish times or better fitness scores. Women were disproportionately represented in the core at both parkruns, and a trend away from the core was observed for young adults over time.

Conclusion Our findings suggest that more intense engagement with parkrun promotes social connection, regardless of location. However, the core–periphery social structure offers recurrent opportunity for connection while not requiring it. Attracting greater participation and volunteering among men and young adults would improve their social connectivity and the sustainability of parkrun.

Keywords Physical activity · Social networks · Maintenance · Health behavior · Mass participation

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Introduction

Social factors have long been understood to have an impact on health status and should be considered when developing effective public health interventions (McNeill et al. 2006). Along with social inequality and neighbourhood or community characteristics, interpersonal relationships, namely social support and social networks, can significantly impact health outcomes by promoting or discouraging healthy behaviours. Common mechanisms by which interpersonal relationships exert their influence on health behaviours include social norms, person-to-person interaction, provision of encouragement and modelling, as well as access to resources (Latkin and Knowlton 2015; Smith and Christakis 2008). However, recent evidence shows that social isolation is increasing (Meehan et al. 2023), restricting the opportunities for social interactions that support health. Initiatives

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which foster both social connection and enhanced physical health offer a promising avenue for improving population well-being.

Physical activity (PA) is one health behaviour where social aspects have been shown to be important in shaping participation. For example, social support can encourage and motivate initiation and maintenance of PA levels (Scarapicchia et al. 2017), while practical or instrumental support are also necessary to assist with PA adherence (Golaszewski and Bartholomew 2019; Graupensperger et al. 2019). At the collective level, group-based exercise has been found to promote participation and enhance PA adherence among teenagers (King et al. 2008), adults (Scarapicchia et al. 2017) and older adults (aged 65 and older) (Beauchamp et al. 2015, 2018). In terms of mechanisms, one study found that participants reported higher exertion and greater enjoyment when there was a stronger sense of "groupness" (the perception that a collective constitutes a group) while exercising (Graupensperger et al. 2019). Hence, the social dimensions of PA, whether derived from independent individuals or a group, can affect the engagement with and experience of this health-enhancing behaviour.

Importantly, not only do social relationships affect people's behaviour, but people's behaviours affect the establishment and proliferation of relationships. Social network analysis (SNA) investigates this complexity, capturing on what basis individuals make connections and are influenced by others given their own and their peers' personal characteristics and health behaviours (Liu et al. 2018; Mercken et al. 2009; Sawka et al. 2013; Snijders et al. 2010). SNA studies can identify key individuals in networks who facilitate behaviour spread (Steglich et al. 2010; Zhang et al. 2013) as well as analysing whether groups form around common behaviours or characteristics to reveal overall network cohesion and segmentation (Flatt et al. 2012; Goodreau et al. 2009; Marquez et al. 2018). In contrast with traditional statistical analyses, SNA emphasizes the relational aspects between network members to account for outcomes rather than characteristics of the individual (Zhang 2010).

Most SNA studies of PA have focused on small, community-based settings or specific groups to identify similarities (or differences) between personal characteristics among individuals and their networks (Mötteli and Dohle 2020; Prochnow and Patterson 2022; Wäsche et al. 2017). A recent review of SNA studies of adults showed that in most cases, people with similar PA levels, whether inactive or highly active, are more likely to be connected to each other and mutually influence those they are socially connected with (Prochnow and Patterson 2022). Factors associated with increased PA include social network size, closer relationships within a personal network and greater network exposure to regular exercisers (Prochnow and Patterson 2022). However, limitations of this research include the fact that the majority use cross-sectional study designs, precluding time-dynamic observations, PA is mostly self-reported (Prochnow and Patterson 2022), and studies of health and social networks including PA seldom consider the implications for initiative implementation and sustainability, which are critical for population impact (Shelton et al. 2019; Valente et al. 2015). Moreover, little attention has been paid to the interaction of location and social connection in SNA studies of PA, despite being a key correlate of PA (Bauman et al. 2012), and one longitudinal study showing that PA-conducive environments only increase PA in those who are social connected (Josey and Moore 2018).

Few studies have examined the role of entire social networks (as opposed to connections of each individual separately) in health in general (Shelton et al. 2019) and in PA specifically (Prochnow and Patterson 2022). Those that have, typically leveraged online data virtual support such as social media, SMS text messages, or other social apps (Aral and Nicolaides 2017; Franken et al. 2023; Huang et al. 2022). For example, across 1.1 million individuals who shared running information via a digital platform, one study found that less-active runners influenced more-active runners in likelihood to run in the following days, but the influence decreased over time, peaking within a day of a run being posted (Aral and Nicolaides 2017). Although new digital technologies are recording and promoting socialisation through shared health behaviours, analyses of these data may not be generalisable to the broader population, especially groups less likely to use such systems (older adults and low socioeconomic groups). Moreover, peer effects may not operate in the same way virtually as they do in person, and online data capture only one part of human interactions. Therefore, there is a need to examine overall network structure and correlates of social connectivity in PA initiatives in place and answer the call to inform intervention implementation and sustainability (Shelton et al. 2019).

Current study

The current study examines social network formation and influence in the global phenomenon known as parkrun, an at-scale PA initiative operating in 23 countries with over 9 million registrants and 2661 weekly parkrun events as of December 2024 (parkrun Global 2024). It was launched in Australia in April 2011 and currently has over 500 locations (parkrun Global Limited 2025). A parkrun is a free, weekly, community-based walk or run on a set 5 km course where people can also volunteer or spectate. Social aspects include exercising with others, volunteering and post-parkrun coffee (Stevens et al. 2019; Wiltshire and Stevinson 2018). Previous qualitative research has suggested that these characteristics promote individual PA maintenance (Dunne et al. 2024) and broader parkrun dissemination by drawing on established networks and facilitating new social connections (Stevens et al. 2019; Stevinson and Hickson 2014; Wiltshire and Stevinson 2018). However, the nature of social networks in parkrun has yet to be systematically investigated.

Our study aims to test and extend previous qualitative parkrun research findings and SNA in PA research by conducting an exploratory whole-network analysis of participants at two new Australian parkrun locations (one urban, one rural) over a 12-month period. Our selection of two contrasting geographical locations provides insights into how social networks adapt and function within diverse community contexts under real-world, in-person conditions. The specific analytic objectives for the study are as follows:

- Generate and descriptively compare social network metrics in two locations, assessing whether these characteristics remain consistent over time.
- Assess the patterns of network members' connections.
- Characterise the demographic and parkrun participation attributes of identified subgroups within the networks.

Methods

The study was approved by the University of Technology Sydney Human Research Ethics Committee, approval number ETH22-7533, 10 October 2022, and by the parkrun Research Board.

Site selection

Two new Australian parkrun sites were purposively selected from those launching at the beginning of the study period (December 2022). Selection was in consultation with parkrun Australia and based on contrasting location according to the Accessibility/Remoteness Index of Australia [ARIA] (Australian Bureau of Statistics 2018a), level of socioeconomic disadvantage (parkrun postcode matched to Socio-Economic Indexes for Areas [SEIFA]; Australian Bureau of Statistics 2018b) and proximity to other parkruns. Site 1 is in an urban area of a major city (Australian Bureau of Statistics 2023a) with almost 160,000 residents (Australian Bureau of Statistics 2021) and a relatively high SEIFA index score (ranked in the eighth decile of the Index of Relative Socioeconomic Advantage and Disadvantage [IRSAD]; Australian Bureau of Statistics 2023b). The course terrain is a trail, and 11 other parkruns are located between 5 and 20 km away. Site 2 is in an inner regional area (Australian Bureau of Statistics 2023a) with less than 10,000 residents and relatively low SEIFA index score (ranked in the second decile of IRSAD; Australian Bureau of Statistics 2023b). The next nearest parkrun event is approximately 70 km away, and the course terrain is grass and gravel. Most residents of both local government areas were born in Australia (urban 74%; rural 82%) and speak only English at home (urban 89%; rural 86%) (Australian Bureau of Statistics 2021). Both parkruns are more challenging than average; average finish time at site 1 is 38 min 18 s and at site 2 is 41 min 11 s (national average, 33 min 25 s; parkrun Global Limited 2025). Further contextual details are provided in the Supplementary material (Appendix A).

Data collection

We used two main sources of data: a survey of who respondents knew at the selected parkrun, and participation and performance data drawn from the publicly available parkrun results tables. We also used contextual data from field notes taken during survey visits and qualitative interviews with the event directors (a volunteer who oversees and coordinates the operation of a parkrun event) of the two parkruns conducted for a separate study for interpretation of some findings.

Social network survey

Permission was sought from the event director from each site. Survey participants were recruited from parkrun participants (walkers/runners or volunteers) either in person at the weekly (Saturday) parkrun event or through the parkrun event's Facebook page in the week coinciding with the in-person event. Individuals aged ≥ 18 years with sufficient English language proficiency to meaningfully consent to participation and who had attended the selected parkrun site at least once since launch were eligible for the study. Survey participants were excluded if they identified as a visitor to the area and were unlikely to return in the next 12 months, or did not consent for their survey data to be linked with their (publicly available) parkrun participation data.

Surveys were conducted at baseline (8 weeks post-launch) and 6-month (post-baseline) and 12-month (post-baseline) follow-ups. Exact survey dates were timed to avoid atypical attendance associated with the launch of a new parkrun, and school and public holidays. Data were collected and managed using REDCap electronic data capture tools hosted at the University of Technology Sydney (Harris et al. 2019, 2009). The survey was primarily administered in person by trained interviewers using iPads. Paper surveys were also available. Participants could, alternatively, self-complete the survey online up to 1 week after the in-person event. For the 6- and 12-month follow-up surveys, unique links were sent to previously participating survey respondents via email or SMS, with up to three reminder emails for non-responders. People who had not participated in the survey previously but met the inclusion criteria could also enter the study at the 6- and 12-month follow-ups. Survey participants were offered entry into a prize draw for the chance to win one of ten $AUD 50 vouchers for groceries or to be spent in the parkrun shop as an incentive.

Surveys took approximately 5 minutes to complete (Supplementary material: Appendix B). Following eligibility screening questions and providing consent, survey participants were asked three social network questions to identify parkrun participants they knew by name, the level of interaction they had with that person (5-point scale from “I talk with this person but only at parkrun” to “This person is my partner/spouse or family member”) and whether they knew them prior to joining the selected parkrun. A cumulative list of parkrun participants’ names, age groups and average running time (since launch) was generated from publicly available parkrun results data in the week preceding the in-person data collection to assist data entry and accurate identification. If a survey participant named someone not on the list, they were recorded manually and later checked for eligibility.

Survey participants were also asked to estimate their PA participation over the past 7 days using a validated single-item measure (Milton et al. 2013) and how often they joined other parkrunners for a beverage or breakfast after parkrun. Lastly, survey participants supplied their unique parkrun identifier (barcode), or their name and age group, for linking their survey responses with publicly available parkrun participation data. Name and contact details were taken separately for entry into the prize drawing.

Parkrun participation and performance data

We extracted publicly available parkrun participation data using the unique parkrun barcode number for survey respondents and those who were named by a survey respondent (who may or may not have completed a survey themselves). Informed consent was not obtained for non-survey participants’ data, as the use of anonymised data for research purposes is covered by the parkrun privacy policy (parkrun Global Limited 2024). We first confirmed study eligibility and then extracted age group, gender, events attended, finish times, age-graded scores (parkrun support 2024), group/club membership status (member or not) (parkrun Australia 2024) and group/club name.

Network boundary

The network boundary defines who is eligible to be included in each analysis. The network for each parkrun included only adults who walked, ran or volunteered at the selected parkrun, with connections comprising individuals they knew before or after joining that specific parkrun, who had also attended the same event on or before each survey date. Therefore, network members include individuals who were either surveyed themselves or named by another survey participant. There were three analysis periods (waves) for each parkrun. Wave 1 extended from the selected parkrun’s launch up to the baseline survey date, the second from the baseline survey to the 6-month survey, and the third from the 6-month survey to the 12-month survey. Network members had to have recorded participation in parkrun either as a walker/runner or volunteer during these periods to be eligible for the SNA for that wave, consistent with the assumption that social relationships change with exposure.

Data treatment

For this analysis, age group and gender were treated as constant values as recorded at first participation at the selected parkrun. Age was operationalised as the midpoint of the age range provided in the parkrun database. For the three study waves, the group/club membership status, number of events attended, average age-graded scores and average finish times were calculated for the period covered by the wave. If a network member completed a survey or was named in more than one wave, they had a record for each of those waves.

Analysis

Our analysis spanned two levels. First, network features such as the total number of connections were calculated over individuals for each parkrun for each wave (for a total of six analyses), providing a macro-level view of the network’s sparsity or connectivity among members, and compared descriptively over time to understand the stability of the network structure. Second, for an intermediate-level view (Liu et al. 2023), network members were clustered into subgroups by identifying where the connections within a group were more dense than that between groups (Fortunato 2010). The subgroups were then compared over demographic and performance characteristics. Further details are given below.

Network features

In this analysis, the term “node” refers to a single network member, and “link” refers to the direct connection between two network members. Nodes are survey respondents (people who completed the survey at a wave) and nominees (individuals identified by survey respondents). A nominee may or may not also be a survey respondent. We mapped the social relationships (i.e. who named whom and who was named by whom) at an individual level in each parkrun for each wave.

First, means and standard deviations were calculated across individuals for a global summary and are reported by wave for each parkrun. The following specific indicators were calculated:

- Out-degree: the total number of links (people the respondent named) originating from a survey respondent. Calculated on survey respondents only.
- Diameter: the maximum of the shortest distances between all pairs of nodes. The diameter is typically expressed as the number of links required to cross the connected component in a network. Usually, a smaller diameter reflects a more interconnected network. In networks where not all nodes are connected, as in our case, the diameter is determined on the largest connected component of the network (the largest subset of nodes connected by uninterrupted pathways). Calculated over all nodes within the largest connected component.
- Shortest distance: the shortest path needed to connect any two nodes within the network; reported as the minimum number of links needed to reach another node in the network. A shorter distance reflects high connectivity, making the network more likely to remain stable, even if some links are lost or nodes are removed. Calculated on survey respondents within the largest connected component.
- Transitivity coefficient: the probability that a survey respondent's nominees are also acquainted with each other; a unitless quantity that ranges from 0 to 1 reflecting network density. Calculated on survey respondents only.

Note that out-degree, shortest distance and transitivity are calculated only on survey respondents in our analysis because we only have outgoing links reported from survey respondents rather the complete network (as would occur in an analysis of social media networks, for example). Diameter and shortest distance are determined only within the largest connected component, because distance cannot be measured if two nodes are not connected.

Network structure

Second, after determining the optimal subgroup arrangement, we classified nodes into these subgroups based on the density of links within and between subgroups within the largest connected component. Density is the total number of existing links divided by the total number of possible links among the subgroups. Although different approaches are available for identification and classification of network structures (Borgatti and Everett 2000; Fortunato 2010; Liu et al. 2023), we used the degree-corrected stochastic block model (DC-SBM) because it removes bias by not having starting assumptions about the structure (see Supplementary material: Appendix C). We predefined the number of subgroups for all networks because all networks were small, but allowed the size of the subgroups themselves to be driven by the data. Finally, we regrouped the unconnected nodes outside of the largest connected component into a third subgroup. The same approach was applied across all networks to facilitate comparisons over location and time. We then summarised and calculated 95% confidence intervals around the estimates for the demographic, parkrun participation and performance data for each subgroup.

Analytic software and commands

The software used for analysis was R software version R 4.3.2 (R Core Team 2024). The specific packages used for the substantive analyses were as follows: *_network* version 1.13.0.1 (for handling network objects) (Butts 2015); *_sna* (for social network analysis algorithms); *igraph* (for network graph and visualisation); and *_Lattice* (for visualisation and multi-panel graphics conditioning on variables).

Results

Data were collected from the parkruns at 8 weeks post-launch, 25 weeks post-baseline (24 weeks for the rural parkrun) and 25 weeks post-wave 2. Note that the rural parkrun only held 20 events within wave 2, as four were cancelled for a range of reasons (work on the course, insufficient volunteers, coincidence with a fun run, festival in park).

Sample description

From the urban parkrun, 132 participants completed a total of 224 surveys across the three waves. For the rural parkrun, 57 participants completed 91 surveys over three waves. After eligibility checks, six individuals were excluded (urban $n=3$, rural $n=3$): five completed an online survey but had not walked/run or volunteered at the selected parkrun for the duration of the study or had participated but not during the relevant period for that survey (see "Network boundary" section). One in-person survey respondent provided a valid barcode but had not walked/run or volunteered at the site on the day of the interview or before (likely a spectator). Therefore 129 survey respondents from the urban parkrun and 54 from the rural parkrun were included in the analysis. Further details are available in the Supplementary Materials, Appendix D.

The demographic and participation characteristics for survey respondents and all network members averaged over the 12-month study period (except for age and gender) are shown in Table 1. Descriptively, survey respondents were similar to the broader network membership at both parkruns in terms of gender and age distribution and fitness levels (age-graded score), and in group/club membership at the urban parkrun (network members higher at the rural parkrun). However, survey respondents had higher rates

Table 1 Demographic, parkrun participation and performance characteristics of survey respondents and network members for the urban and rural parkruns

Characteristic	Urban parkrun[g]		Rural parkrun[g]	
	Survey respondents ($n=129$)	Network members[a] ($n=354$)	Survey respondents ($n=54$)	Network members[a] ($n=145$)
Proportion female, n (%)	71 (55.0%)	189 (53.4%)	35 (64.81%)	96 (66.21%)
Age group (years), n (%)				
18–29	7 (5.4%)	17 (4.8%)	4 (7.4%)	17 (11.7%)
30–49	62 (48.0%)	159 (44.9%)	31 (57.4%)	68 (46.9%)
50–69	57 (44.2%)	167 (47.2%)	16 (29.6%)	53 (36.6%)
70+	2 (1.6%)	10 (2.8%)	2 (3.7%)	6 (4.1%)
Age, mean (SD)	48.1 (11.1)	49.2 (11.0)	46.6 (13.3)	46.7 (13.6)
Age-graded score[b] (mean, SD)	46.5 (11.3)	45.5 (11.7)	39.6 (8.3)	38.9 (8.6)
Proportion who are group/club members[b] (n, %)	71 (55.0%)	194 (54.8%)	5 (9.3%)	31 (21.4%)
Proportion who had volunteered[c] (n, %)	63 (48.8%)	120 (33.9%)	34 (63.0%)	60 (41.4%)
Total events attended as volunteer[d] (mean, SD)	2.9 (5.7)	1.6 (4.0)	5.7 (10.2)	2.4 (6.8)
Total events attended (mean, SD)	11.1 (12.8)	7.4 (10)	15.0 (14.1)	7.9 (10.7)
Events attended prior to this specific parkrun[e] (median, interquartile range)	135 (32, 259)	159.5 (53, 285)	0 (0, 2)	0 (0, 5)
Post-parkrun coffee[f] (n, %)				
Never or almost never	52 (40.3%)	Not available	21 (38.9%)	Not available
Occasionally when I attend parkrun	18 (14.0%)		13 (24.1%)	
At least half the time I attend parkrun	17 (13.2%)		11 (20.4%)	
Always or almost always when I attend parkrun	41 (31.8%)		9 (16.7%)	

Notes:

[a] Network members include all survey respondents and people they named

[b] Calculated over all occasions on which an individual ran or walked during the 12-month study period

[c] Volunteered at least once at the parkrun during the 12-month study period

[d] Calculated over the 12-month study period

[e] All occasions a person walked/ran or volunteered in their state before joining selected parkrun

[f] Average self-reported frequency of attending post-parkrun coffee (survey respondents only)

[g] For both parkruns, some items do not add to the total number due to missing values for one respondent in each parkrun on gender, age, and running club membership. One survey respondent is missing data for post-parkrun coffee at the urban parkrun

of volunteering and attendance at both parkruns but lower median prior parkrun experience at the urban parkrun.

Comparing the two parkruns, women dominated both survey respondents and network members (together called "participants" hereafter) for both parkruns, although proportions at the rural parkrun were higher. Urban participants were slightly older than their rural counterparts and had higher age-graded fitness scores, but rural participants had slightly higher total attendance across the study period. Urban participants had well over double the proportion who were group/club members compared with rural, but a lower proportion who had volunteered over the 12-month study period. Prior parkrun experience (anywhere in their state) was almost ubiquitous (96.6%) among urban parkrunners; network members had accumulated a median of 159.5 walks/runs before joining the selected parkrun. Rural parkrun network members by contrast had a median of 0 previous parkruns, with less than half (40.7%) having participated in the past. Among survey respondents, almost one-third from the urban parkrun attended post-parkrun coffee always or almost always, compared with approximately 17% from the rural parkrun (Table 1).

Network features at macro level (global level)

The overall network structure for the three waves is presented in Figs. 1 and 2 for the urban and rural parkuns, respectively.

Network metrics are supplied in the Supplementary Materials (Appendix E). The average number of people named by survey respondents at the urban parkrun decreased from 6.5 people at baseline to 5 people at 12 months (Table 4,

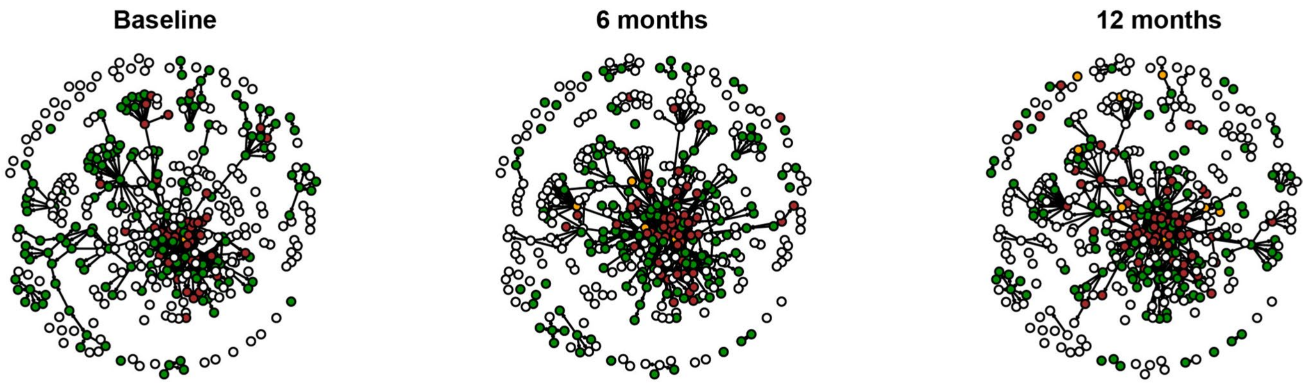

Fig. 1 Overall network structure ($n=354$) across waves at the urban parkrun. Each circle represents a network member as follows: green—those who only walked or ran; brown—those who both walked/ran and volunteered; orange—those who only volunteered. The white circles represent individuals who were surveyed or named in at least one wave but did not participate in this specific parkrun during the wave depicted. Lines between circles indicate links between network members

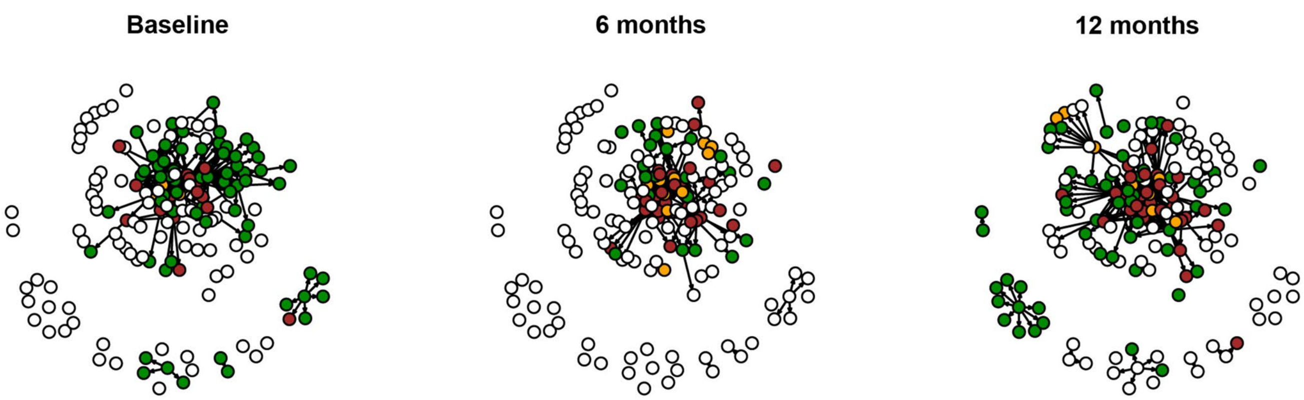

Fig. 2 Overall network structure ($n=145$) across waves at the rural parkrun. Each circle represents a network member as follows: green—those who only walked or ran; brown—those who both walked/ran and volunteered; orange—those who only volunteered. The white circles represent individuals who were surveyed or named in at least one wave but did not participate in this specific parkrun during the wave depicted. Lines between circles indicate links between network members

Appendix E, Supplementary Materials). The network in the urban parkrun was stable in diameter, implying that the shortest path between the most distant network members within the largest connected component remained consistent despite possible changes in participant connections. The probability that the respondent's nominees were also acquainted with each other also remained stable across the three study waves, as shown by the transitivity coefficient. The average shortest distance between surveyed network members within the largest connected component decreased slightly over time (from 2.5 links at baseline to 2.3 links at 12 months), suggesting that the networks of the interconnected part became somewhat more compact.

In contrast, the average number of people named by rural parkrun survey respondents increased from 6 at baseline to almost 9 at 12 months, and the network had a smaller diameter (i.e. they became more interconnected) (Table 5, Appendix E, Supplementary Materials). Moreover, the rural survey respondents moved closer to each other in terms of connections through intermediaries (average shortest distance, 2.7 links at baseline to 1.9 links at 12 months) despite being only slightly further apart at baseline (2.7 links) compared with the urban parkrun (2.5 links). The probability that the participants' nominees were also acquainted with each other (transitivity) increased from 30% to 38% to 42% in waves 1, 2 and 3, respectively, while the urban parkrun stayed relatively stable. Together, the results show that the network members at the rural parkrun became more socially connected over time compared with the urban parkrun.

Network structure at intermediate level (subgroup level)

Subgroups within the network

We identified two consistent social network patterns in the largest connected component for both parkruns (Figs. 3 and 4, Appendix C, Supplementary Materials). First, the network was best described as a "core–periphery" structure. The core subgroup was densely interconnected, while the periphery subgroup had far fewer or, in some cases, no connections to other periphery members. Second, the connections between the core and periphery were sparse, especially relative to within the core. Outside of the largest connected component, there was also a third group which comprised the outer periphery who were not connected to either the core or the periphery, or very connected with each other.

Across the three waves, urban parkrun core subgroup members had an approximately 19–24% chance of being acquainted with each other, whereas between the core and periphery, individuals had an approximately 2.1–4.0% chance. For the rural parkrun, the corresponding figures varied between 26% and 38% for the three core subgroups and between 12.1% and 13.0 % for the core and periphery subgroups. The comparison shows that the urban parkrun members are more loosely connected than the rural parkrun. For both parkruns, members within the periphery subgroup have only up to a 1% chance of being directly acquainted with each other. Thus, people in the periphery were more likely to be connected with someone in the core than they were with someone in the periphery. Post hoc analyses showed that among those in the core at either wave, 43% were in the core in both waves 1 and 2 and 65% were in the core in both waves 2 and 3 at the urban parkrun, demonstrating that a core was maintained despite varying constitutive members. The corresponding proportions were similar for the rural parkrun (W1–W2 39%, W2–W3 66%).

Correlates of subgroup membership

The characteristics across the three subgroups separately for each wave and parkrun are shown in Tables 2 and 3.

Correlates of subgroup membership in common between the two parkruns showed a positive gradient between degree of connection and parkrun participation. Core subgroup members attended the highest number of events (as walkers/runners or volunteers), followed by periphery subgroup members, with the lowest number among the outer periphery members. A similar gradient was observed for the proportion volunteering over a wave, with only one exception in the rural parkrun (wave 2 at 6 months) where the outer periphery exceeded the periphery subgroup (79% vs 41% volunteered). The proportion of women was consistently much higher in the core group for both parkruns across all three waves, except wave 3 at 12 months in the rural parkrun, when the subgroups were comparable. There was a tendency for the outer periphery in both parkruns to comprise younger people over time, whereas the other two groups tended to become older post baseline.

Differences included a high group/club membership rate at the urban parkrun across all three subgroups, ranging from 38% to 64%, but in the rural network, only the outer periphery group showed high group/club membership ($\geq 50\%$ at baseline and 12 months vs $< 10\%$ for the other groups at all waves). Moreover, one running group/club dominated the urban core and periphery subgroups (group/club "R"), whereas in the rural parkrun the dominant running group/club varied by subgroup and wave; only the core group showed any consistency in this respect. There was no consistent pattern across core/periphery/outer periphery for finish times or age-graded score, although the latter was notably higher overall for the urban parkrun for all three waves.

Discussion

Our exploratory study offers new insights into how patterns of social relationships manifest over time in a real-world PA initiative, parkrun, in contrasting locations. The rural parkrun became more interconnected over time, while the degree of connectedness of network members remained relatively stable in the urban parkrun. Both exhibited a "core–periphery" structure including a distinct socially connected core that prevailed over time, irrespective of changes in its individual members. When the two different locations were compared, the attributes of core, periphery and outer periphery subgroup members differed, showing that while more intense engagement with parkrun fuels social network formation, the composition of the network subgroups in the network may depend on place. The implications of our analysis for practice and future research are explored below.

Our findings contribute further evidence of the positive relationship between social connection and PA (Prochnow and Patterson 2022; Smith et al. 2023), specifically in parkrun (Cleland et al. 2019; Stevinson et al. 2015), including volunteering (Haake et al. 2022). Both parkruns displayed some level of increasing density in social connection within the largest connected component with time, as the number of links required to connect one person with any other decreased. Rural parkrunners showed a more accelerated and pronounced network condensation, perhaps reflecting its smaller size overall (average weekly walkers/runners at the 12-month survey was 31.2 vs 101.9 for the urban parkrun). Previous qualitative research shows that some parkrun participants feel that as their local parkrun grows, it becomes "more anonymous", signaling that social

Table 2 Characteristics of subgroup members at the urban parkrun at baseline (8 weeks exposure), 6 months post-baseline (25 weeks exposure) and 12 months post-baseline (25 weeks exposure)

	Wave	Core *n* (95% CI)	Periphery *n* (95% CI)	Outer periphery *n* (95% CI)	Total *n* (95% CI)
Members	Baseline	*n* = 43	*n* = 87	*n* = 69	*n* = 199
	6 months	*n* = 50	*n* = 97	*n* = 67	*n* = 214
	12 months	*n* = 36	*n* = 69	*n* = 96	*n* = 201
Women	Baseline	65% (49%, 79%)	47% (36%, 58%)	54% (41%, 66%)	53% (46%, 60%)
	6 months	68% (53%, 80%)	52% (41%, 62%)	55% (43%, 67%)	57% (50%, 63%)
	12 months	67% (49%, 81%)	60% (48%, 72%)	48% (38%, 58%)	56% (48%, 62%)
Age (years)	Baseline	49 (46, 52)	50 (48, 52)	49 (46, 52)	49 (48, 51)
	6 months	51 (48, 53)	51 (49, 53)	48 (45, 51)	50 (49, 51)
	12 months	51 (48, 54)	53 (51, 55)	47 (45, 49)	50 (48, 51)
Finish time (minutes)	Baseline	39 (35, 42)	38 (36, 41)	37 (35, 40)	38 (36, 40)
	6 months	40 (36, 44)	40 (38, 42)	38 (35, 41)	39 (38, 41)
	12 months	38 (35, 42)	41 (38, 43)	37 (35, 40)	39 (37, 40)
Age-graded score (%)	Baseline	45 (42, 49)	46 (43, 48)	47 (44, 51)	46 (44, 48)
	6 months	45 (42, 48)	44 (41, 46)	46 (43, 48)	45 (43, 46)
	12 months	46 (43, 50)	45 (42, 48)	45 (43, 48)	46 (44, 47)
Group/club membership	Baseline	63% (47%, 77%)	56% (45%, 67%)	51% (39%, 63%)	56% (49%, 63%)
	6 months	58% (43%, 72%)	57% (46%, 67%)	55% (43%, 67%)	57% (50%, 63%)
	12 months	58% (41%, 74%)	64% (51%, 75%)	38% (28%, 48%)	50% (43%, 57%)
Predominant club	Baseline	47%—R	18%—R	10%—M	19%—R
	6 months	44%—R	16%—R	9%—R	21%—R
	12 months	47%—R	20%—R	8%—B	18%—R
Volunteered	Baseline	44% (29%, 60%)	28% (19%, 38%)	4.3% (1%, 13%)	23% (18%, 30%)
	6 months	60% (45%, 73%)	26% (18%, 36%)	13% (7%, 24%)	30% (24%, 37%)
	12 months	64% (46%, 79%)	43% (32%, 56%)	20% (13%, 29%)	36% (29%, 43%)
Run/walk/volunteer (events)	Baseline	3.9 (3.0, 4.7)	2.5 (2.1, 2.9)	1.5 (1.3, 1.6)	2.4 (2.1, 2.7)
	6 months	9.2 (7.3, 11.0)	3.8 (3.0, 4.5)	2.3 (1.8, 2.8)	4.6 (3.9, 5.2)
	12 months	10.6 (8.0, 13.0)	4.1 (3.1, 5.1)	2.7 (2.1, 3.3)	4.6 (3.9, 5.3)

connection may be easier in smaller events (Bowness et al. 2021). Moreover, the rural parkrun in our study was the only one within 70 km, whereas the urban parkrun had 11 others within 20 km, perhaps translating to less network exposure at the selected parkrun by having greater choice. Operationally, our results indicate that larger parkruns may need additional mechanisms to support sociality. Future research could examine parkruns of different sizes to see whether network parameters vary consistently with size and/or remoteness from other parkruns, and whether there are thresholds beyond which the structure becomes more fragmented than the core–periphery organization we observed.

Members of the socially connected core in our parkrun events are characterised by greater walk/run participation and volunteering, compared to the less densely connected periphery and outer periphery. Low participation rates in the outer periphery likely reflect the presence of new participants in combination with persistent lower attendance among existing participants. However, it was beyond the scope of this exploratory, whole-network analysis to determine whether the lower engagement was an outcome of fewer social ties or a cause. The positive relationships between the number of social ties, parkrun attendance and volunteering are likely mutually reinforcing. Greater attendance increases the opportunities for social interaction due to the social nature of parkrun events (Stevinson et al. 2015; Wiltshire and Stevinson 2018), particularly when volunteering (Hindley 2022; Mitchell (Sarah-Louise 2023)). At the same time, those with more social connections at a parkrun may be more likely to walk/run or volunteer, as social support can facilitate PA via companionship and encouragement (Prochnow and Patterson 2022), and social ties are known predictors and outcomes of volunteering (Tucker and Gearhart 2022). Our results therefore provide quantitative evidence supporting previous qualitative research positing the role of social networks in parkrun engagement (Wiltshire and Stevinson 2018). In terms of mechanisms, core group members may identify more strongly with their

Table 3 Characteristics of subgroup members at the rural parkrun at baseline (8 weeks exposure), 6 months post-baseline (20 weeks exposure[a]) and 12 months post-baseline (25 weeks exposure[b])

	Wave	Core *n* (95% CI)	Periphery *n* (95% CI)	Outer periphery *n* (95% CI)	Total *n* (95% CI)
Members	Baseline	$n=20$	$n=48$	$n=13$	$n=81$
	6 months	$n=16$	$n=29$	$n=14$	$n=59$
	12 months	$n=23$	$n=41$	$n=28$	$n=92$
Women	Baseline	80% (56%, 93%)	75% (60%, 86%)	54% (26%, 80%)	73% (62%, 82%)
	6 months	88% (60%, 98%)	62% (42%, 79%)	86% (56%, 97%)	75% (61%, 85%)
	12 months	61% (39%, 80%)	59% (42%, 73%)	61% (41%, 78%)	60% (49%, 70%)
Age (years)	Baseline	44 (39, 48)	43 (39, 46)	57 (52, 62)	45 (42, 48)
	6 months	43 (36, 50)	46 (42, 50)	48 (40, 56)	46 (42, 49)
	12 months	50 (44, 55)	46 (41, 50)	43 (38, 49)	46 (43, 49)
Finish time (min)	Baseline	42 (38, 47)	45 (42, 48)	43 (37, 49)	44 (42, 46)
	6 months	45 (40, 50)	43 (38, 48)	45 (38, 52)	44 (41, 47)
	12 months	44 (40, 49)	42 (39, 46)	41 (37, 45)	42 (40, 44)
Age-graded score(%)	Baseline	39 (35, 43)	37 (34, 39)	41 (36, 47)	38 (36, 40)
	6 months	35 (31, 39)	40 (36, 44)	38 (34, 42)	38 (36, 41)
	12 months	44 (40, 49)	42 (39, 46)	41 (37, 45)	42 (40, 44)
Group/club membership	Baseline	5% (0.3%, 27%)	6% (2%, 18%)	54% (26%, 80%)	14% (7%, 23%)
	6 months	6% (0.3%, 32%)	7% (1%, 24%)	0% (0.0%,0.0%)	5% (1%, 15%)
	12 months	9% (2%, 30%)	9% (3%, 24%)	50% (33%, 67%)	22% (14%, 32%)
Predominant club	Baseline	5%—F	4%—RM	More than one	2%—RM
	6 months	6%—F	More than one	NA	3%—F
	12 months	More than 1	More than 1	36%—I	11%—I
Volunteered	Baseline	35% (16%, 59%)	21% (11%, 35%)	8% (0.4%, 38%)	22% (14%, 33%)
	6 months	88% (60%, 98%)	41% (24%, 61%)	79% (49%, 94%)	63% (49%, 75%)
	12 months	74% (51%, 89%)	41% (27%, 58%)	11% (3%, 29%)	40% (30%, 51%)
Run/walk/volunteer (events)	Baseline	4.2 (3.0, 5.4)	3.1 (2.5, 3.6)	1.1 (0.9, 1.2)	3.0 (2.6, 3.5)
	6 months	8.8 (5.5, 12.0)	3.8 (2.2, 5.4)	2.1 (0.9, 3.2)	4.7 (3.4, 6.1)
	12 months	12.0 (8.9, 16.0)	6.0 (4.3, 8.2)	1.0 (1.0, 1.4)	6.0 (4.8, 7.7)

Notes to table:

[a] No events took place on 4 weeks within the study period

[b] No events took place on 1 week within the study period

local parkrun collective, as previous parkrun studies indicate that higher rates of parkrun attendance are associated with stronger identification with the group (Cranney et al. 2025; Stevens et al. 2019) and more volunteering (Grunseit et al. 2024). Group identification can foster amongst members more "conformative" behaviours toward the collective (Ashforth 2016), meaning that identification may promote more parkrun identity-affirming practices such as regular participation or volunteering (Wiltshire et al. 2018). Given the interaction between network position (i.e. core or periphery) and degree of subgroup identification (Ashforth 2016), future parkrun research could explore the interplay between social ties and group identification and how these intersect with participation and volunteering.

The core, periphery and outer periphery structure raises the potential for "cliques" to form, and these social partitions may reinforce marginalisation of some participants. With identification comes the possibility of negative in- and out-group dynamics (Ashforth 2016); social cliques may undermine parkrunners' sense of belonging, as observed in qualitative parkrun research (Bowness et al. 2021; Fullagar et al. 2020). However, our data support other findings that this may occur only to a limited extent (Hallett et al. 2020), as we saw individuals move in and out of the socially connected core over time, demonstrating resilience as it remained densely connected but compositionally fluid. Recent qualitative research among middle-aged male parkrunners in Ireland whilst flagging the existence of "in" and "out" groups did not find strong evidence of a negative effect (Dunne et al. 2024). The predominant atmosphere described was one of inclusivity, where participants could choose their level of sociability (ranging from none, to “just at parkrun” to deep connection) (Dunne et al. 2024) from week to week or routinely. It seems that the continued and shared experience of participation always raises opportunities for social connection but does not require it. Therefore, there may always exist an outer periphery for whom parkrun has attractions other than social interaction and/or comprises participants who are yet to connect but for whom greater connection is possible if desired. Our findings therefore reinforce the value to parkrun and other PA initiatives of fostering the kind of casual sociability that supports non-demanding social connection (Cattell et al. 2008; Hindley 2022).

We also identified characteristics which distinguish subgroups with varying social connectedness. First, the presence of women in the core subgroup for both parkruns beyond their representation in the network member sample, for example, is consistent with studies noting the greater seeking and use of social ties among women (Bedrov and Gable 2023; Renfree and West 2024). Recent Australian research shows that men have 78% higher odds of experiencing chronic social isolation than women (Lim et al. 2023) and previous parkrun research demonstrated that men parkrunners’ global well-being scores increased significantly with the perceived benefit of community connection of parkrun (Grunseit et al. 2018). Given the centrality of volunteering to social connection in our study, and the fact that 47% of women in the rural and 40% in the urban parkrun had volunteered during the study compared with 29% and 27% of the men, respectively (data not shown), there is the potential to draw more men into volunteering for both event sustainability (Cranney et al. 2025) and greater social connection for men, irrespective of location. Similarly, the trend for younger people away from the core may reflect the role of volunteering in subgroup composition, as others have found that exclusive volunteers were more likely to be older (Haake et al. 2022). In an era where social isolation among young adults is increasing (Kannan and Veazie 2023), there is unrealised potential for parkrun in connecting them to others.

Second, with considerable overlap in the confidence intervals of the subgroups for both parkruns for performance measures (finish time and age-graded score) and no consistent patterns over time and location, there was no evidence that the closely connected core was dominated by faster or fitter participants. The consistent messaging by parkrun that all levels of fitness are welcomed and encouraged (Fullagar et al. 2020; Hindley 2022; parkrun Global 2023) is therefore somewhat reflected in the social structure, with participants of a range of performance profiles present in all segments. If any trend was observed, it was that the outer periphery comprised more fast and fit members, challenging qualitative data suggesting such participants comprised the “in” group (Fullagar et al. 2020). Either way, parkrun’s focus on welcoming those who are less active seems to find support in our findings.

Our analysis has also yielded evidence on the role of location in shaping the interaction between social networks and PA initiatives. For example, unlike the urban setting, in the rural parkrun, a substantial number of members in the outer periphery group had volunteered at least once during the study period but were still not connected to the social core. It is possible that parkrun participants with few or no social connections may be more inclined to volunteer in smaller events than larger events, as they might be more exposed to in-person volunteer recruitment efforts or perceive greater responsibility because of smaller resources for volunteering. Recent quantitative research supports this hypothesis (Grunseit et al. 2023), showing greater diversity in the volunteer workforce in rapidly growing parkruns more common to major city areas, compared with more steady-growth parkruns more common to regional and remote areas. Volunteering in sport settings can foster social capital through increased social connections, but is context-specific (Wiltshire and Stevinson 2018). To better inform implementation, systematic analysis across diverse sites would assist in disentangling the relative impact of parkrun size, location, social ties and parkrun volunteering.

Local context also interacted with pre-existing or external social connections. In our urban parkrun, almost half of the core group members belonged to a particular running group/club (group/club “R”), but less than 10% of network members in the rural parkrun belonged to any group/club. Moreover, the number of parkrun events attended by the urban parkrunners prior to joining the selected parkrun was high, as there were several nearby parkrun events (which many survey participants mentioned having engaged with previously when being interviewed). The rural parkrun had no nearby parkrun events resonating with the low proportion who had completed another parkrun prior to joining the selected parkrun. Our contextual information suggested that the rural event instead drew on existing running and school networks of attendees’ children. Further longitudinal analysis of parkrun social network data that characterises the interpersonal relationships between core group members would enhance our understanding of the extent to which parkrun events both rely on existing local social networks and previous parkrun networks and enable new or deeper social connections over time.

Strengths and limitations

Our study leverages unique prospective network data and is the first to quantitatively examine the nature of social networks in parkrun. Formally investigating causal links between social networks and participation, however, was beyond the scope of the current study. Comparing differently sized networks can be problematic, especially when there is high population turnover, many isolated individuals and difficulty reaching and retaining respondents, as we had. Network metrics are sensitive to missing data, especially when the most connected nodes are missing from the sample. However, we likely captured the most connected nodes, as the known core members in each parkrun were frequently present and likely to participate or at least be nominated by others. We have less information about those who are not connected to the parkrun social fabric, but this would not significantly bias findings regarding the structure of the main connected component.

The urban parkrun grew notably larger than the rural parkrun, which can (a) complicate some network metric comparisons and (b) allow for the aggregate statistics in the smaller parkrun to be more influenced by a small number of individuals, limiting generalisability. We partially mitigated this effect (a) by using metrics less sensitive to network size (e.g. number of links per person rather than the commonly used proportion of connected pairs of individuals to measure network density). Regarding (b), examining more parkruns in less densely populated areas would strengthen our understanding of PA in social networks across remote locations. Finally, small cell sizes and complex data structure (varying study entry dates, incomplete longitudinal data) precluded formal adjusted analyses comparing the subgroups on demographic and performance characteristics, especially in the rural parkrun. However, we provided confidence intervals to indicate the precision of our estimates and degree of overlap across subgroups at least at the bivariate level. Moreover, the focus in this exploratory analysis was on whole-of-network characteristics rather than the influence of personal networks on individual outcomes or hypothesis testing.

Conclusion

The social environment for parkrun, rather than being external to the PA, is co-created with it through opportunities for regular participation and volunteering. Men and young adults at parkrun might require more encouragement, however, to engage in these practices to yield the social dividend. Our analysis suggests that the social networks through which an initiative disseminates are somewhat context-dependent, but models such as parkrun may have greater potential to disseminate widely across different contexts, as they both harness and generate positive interpersonal interaction shaped to local conditions. Irrespective of location, our observation of a coherent core which is both persistent and permeable may simultaneously afford the comfort of familiarity and the potential for new membership conducive to sustainable parkrun engagement over the long term.

Code availability

Not applicable.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s10389-026-02704-4.

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Authors' contributions Conceptualization: Anne Grunseit, Petr Matous, Karina Arias-Calluari. Methodology: Petr Matous, Karina Arias-Calluari. Data collection: Leonie Cranney, Anne Grunseit, Petr Matous, Karina Arias-Calluari. Formal analysis and investigation: Karina Arias-Calluari. Writing—original draft preparation: Karina Arias-Calluari, Anne Grunseit, Leonie Cranney. Writing—review and editing: Anne Grunseit, Petr Matous, Karina Arias-Calluari, Leonie Cranney. Project administration: Leonie Cranney. All authors approved the final version.

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Data availability The data underlying this analysis are not available because they contain information that can identify participants and would be in breach of consent conditions and ethics approval.

Declarations

Ethics approval The study was approved by the University of Technology Sydney Human Research Ethics Committee, approval number ETH22-7533, 10 October 2022, and by the parkrun Research Board.

Consent to participate After the potential participants were informed about the purpose and method of the study, their consent was obtained and recorded electronically. Informed consent was not obtained for non-survey participants' parkrun data, as use of anonymised data for research purposes is covered by the parkrun privacy policy.

Consent for publication Not applicable.

Disclaimer The views, thoughts, and opinions expressed in the manuscript belong solely to the authors, and do not necessarily reflect the position of parkrun or the parkrun Research Board.

Conflict of interest The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Anne Grunseit reports financial support provided by the National Health & Medical Research Council. Anne Grunseit is an unpaid member of the Global parkrun Research Board. Anne Grunseit, Karina Arias-Calluari, Leonie Cranney and Petr Matous are registered parkrunners.

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