Using sensors to study the social dynamics of outdoor play.

Jenny Louise Gibson

Centre for research on Play in Education, Development and Learning (PEDAL)

Faculty of Education, University of Cambridge, jlg53@cam.ac.uk

<https://orcid.org/0000-0002-6172-6265>

Stephen Hailes

Computer Science, Faculty of Engineering, University College London,

s.hailes@cs.ucl.ac.uk

<https://orcid.org/0000-0001-7375-3642>

Bezhad Heravi,

Computer Science, Faculty of Engineering, University College London,

b.heravi@ucl.ac.uk

<https://orcid.org/0000-0002-5577-8464>

David Skuse

Behavioural Sciences Unit, Institute of Child Health, University College London,

d.skuse@ucl.ac.uk

<https://orcid.org/0000-0002-7891-5732>

Disclosure: Authors declare no conflicts of interest.

Funding: Economic and Social Research Council: ES/N006577/1

Acknowledgements: Thanks to Richard Barry, Learning through Landscapes, Children's Scrapstore, Community Playthings, Play England and Touchwood for donations of materials, time, and excellent advice about play. Thanks to Rachel England, Anna Vidos, Sam Hailes, and other student volunteers. Thanks to the children and teachers.

Abstract

This paper reports an exploratory case-study introducing a new method to quantify children's social interactions during unstructured outdoor play. Movements of 18 children were tracked using wearable sensors over 20 sessions of outdoor play at school. Sessions were divided between two play conditions: *Baseline*; the usual play environment and *Intervention*; in which a playground intervention was implemented. Sensor data were used to build a network representing the social interactions that took place each day. Questionnaire-based measures of social and communication skills were completed by teachers, and peer nomination was used as a child-based measure of social skills.

Social connectedness measured during outdoor play correlated positively with peer preference measures but not with teacher reported social skills. Social connectedness averaged over the 10 days of each play condition was not sensitive to between-condition differences. Findings are discussed qualitatively with reflections on measurement issues, implementation and ethics.

Background

Understanding the processes and mechanisms at work during play and exactly how these contribute to social development has long been a subject of interest to developmental psychologists. Unstructured, outdoor play is thought to develop children's social and emotional capabilities as it encourages independence from adults and facilitates peer collaboration (Jarvis, Newman, & Swiniarski, 2014; Ren & Langhout, 2010). Social skills developed in this type of play may include co-operating with others, building friendships, regulating stress, and, managing competition and conflict (Gibson, Hussain, Holsgrove, Adams, & Green, 2011; Ladd, Price, & Hart, 1988). These competencies have important implications; social connectedness is a significant determiner of physical health, mental health and quality of life (Eisenberger & Cole, 2012; van Harmelen et al., 2016). Amid concerns that children's opportunities to participate in unstructured outdoor play with peers are decreasing with urbanisation and attitudinal change (Gray, 2011; Jarvis et al., 2014), school playtime is increasingly recognised as an important context for children to engage in group play that forges social connections and a sense of belonging (McNamara, Colley, & Franklin, 2017).

The very freedom and unpredictability that is considered to have an affordance for social development also makes outdoor group play difficult to study in a quantifiable and replicable way (Gibson, Cornell, & Gill, 2017). The typical way in which psychologists address this challenge is via systematic observation, which has a long tradition in the quest for an understanding of the links between play and social development (Gibson et al., 2011; Pellegrini, 2001; Pellegrini, Symmons, & Hoch, 2004). In the 1930s, Parten developed a method of observing free play that involved an observer attending a preschool every day over several months and observing the daily 1-hour free play session (Parten, 1932). During this hour, each child was observed in turn for a period of 1 minute; their behaviour during the period was categorised into one of several pre-defined 'play states' and the number of playmates was counted. For a subset of observations, additional observers took records independently and their convergence was later evaluated using percentage agreement across the rating categories.

1 These pioneering methods informed early theories of the development of social play and remain
2 influential today.

3 The advent of easily portable video recording and specialist software for analysis means
4 that, presently, observers can be less obtrusive than in earlier work (Hart, 1993); moreover it is
5 easier to vary sampling rates, and it is now possible to use temporal information in analyses
6 (e.g. sequence and duration of play states). Nevertheless, the core methodology is essentially
7 similar to the methods developed by Parten and, although valuable insights are still made with
8 these techniques (Bundy et al., 2016; Engelen et al., 2018; Kuh, Ponte, & Chau, 2013; Mahony,
9 Hyndman, Nutton, Smith, & Te Ava, 2017), there are a number of limitations.

10 Firstly, video/*in vivo* observation techniques are resource intensive. They require a high
11 level of human resource to yield a small amount of data. Often psychologists must make an
12 unsatisfactory trade-off between precision, output and resources. For example, using video data
13 makes more fine-grained approaches possible but at the cost of considerable increase in
14 researcher time.

15 It is also extremely difficult to study group behaviour using typical observational
16 methods. Relational social structures are just as relevant as individual differences between
17 children when it comes to understanding social competence (Howes, Rubin, Ross, & French,
18 1988; Kindermann, 2007). Many studies have demonstrated that children who are reported to
19 have fewer reciprocal friendships, or who are relatively disliked, rejected or ignored by peers
20 are at risk of later mental health difficulties, low educational achievement and other adverse
21 outcomes (Brendgen, Vitaro, Bukowski, Doyle, & Markiewicz, 2001; Henry, 2006). Such studies
22 tend to be based on self- or peer-report and very little work has been done that addresses how
23 exactly group-level rejection or acceptance processes manifest during an unfolding play
24 interaction.

25 An exception is a study conducted by Baines and Blatchford (Baines & Blatchford, 2009)
26 involving four classes of 7-8 year olds. Observations were conducted *in vivo* each playtime for

1 several months, with researchers observing each child in turn for 20 s while using a voice
2 recorder to note with whom the child was interacting and the nature of their play. This
3 information was used to construct 'play networks' that mapped clusters of playmates. Most
4 clusters were sex segregated. Boys were found to play in larger groups than girls, and this was
5 associated with boys playing more often in team games. Girls participated in a greater number
6 of smaller play networks. Another interesting finding was that specific game types appeared to
7 be linked to specific social groups [p.256]. This research is a great example of the insights that
8 careful observations of play at the group level can bring but also demonstrates the enormous
9 amount of work involved: at least 43.9 hours of observation time went into this study.

10 Faced with the challenges described above, it is unsurprising that psychologists,
11 ethologists and others with an interest in the precise and efficient characterisation of complex
12 social behaviours have turned to computer science for technical solutions. For example,
13 Talarowski and collaborators at non-profit organisation Studio Ludo have used Bluetooth Low
14 Energy sensors to track users of an outdoor playground to inform better playground design
15 (<http://www.studioludo.org/smarterplay>). In the psychology literature, Veiga and colleagues
16 (2017) conducted an innovative study of preschool children's behaviour at playtime using a
17 combination of video coding and data gathered from Radio Frequency Identity (RFID) sensors.
18 The RFID sensors were worn by each child during outdoor play and detected whether a child
19 was within 1.5 m of other children with a sampling rate of 4Hz. Researchers then calculated the
20 amount of time each child spent in solitary or socially engaged play and the average duration of
21 solitary episodes. This enabled investigation of the links between emotional development and
22 solitary behaviour during outdoor play. RFID tags have also been used to study sex segregation
23 in children's interactions (Stehlé, Charbonnier, Picard, Cattuto, & Barrat, 2013), and even the
24 social behaviour of mice (Weissbrod et al., 2013)!

25 Inspired by these innovations, the Hopscotch Project, a collaboration between
26 researchers with backgrounds in computer science, playwork, psychiatry and psychology,

1 aimed to develop a method for automated tracking of movement during outdoor playtime as a
2 way of gaining insight into children's social behaviour and development.

3 To enable the study of collective as well as individual behaviour we needed a system
4 with high resolution, sufficient range to capture the whole outdoor play space, data on the
5 relative orientation of the children and synchronisation of measurement across all players. RFID
6 sensors cannot capture all of this information; therefore, we developed a new method using
7 Global Navigation Satellite System (GNSS) receivers, Inertial Measurement Unit sensors and
8 Bluetooth. For brevity we refer to the information collected by this system as 'sensor data.' We
9 have reported on the technical development and set-up elsewhere (Heravi, Gibson, Hailes, &
10 Skuse, 2018). The current study focuses on developing ways of exploring the social and
11 psychological inferences that can be made based on movement data gathered during outdoor
12 play. Our research questions are as follows:

13 *RQ1: How are individual differences in social development related to individual measures of social*
14 *connectedness based on sensor data collected during outdoor play interactions?*

15 *RQ2: How can we understand group dynamics based on sensor data collected during outdoor play*
16 *interactions?*

17 *RQ3: Can we observe changes associated with an outdoor play intervention based on sensor data*
18 *collected during outdoor play interactions?*

Methods

Study design

Given the pioneering nature of this research we opted for a case-study design, with one class of children forming the 'case'. This allowed us to take an in-depth and exploratory approach to understanding how the social dynamics of outdoor play can be studied using sensor data. We collected social and psychological information about the class alongside 45 minutes of sensor data, over 27 sessions of outdoor play and analysed it descriptively (see below for details). This approach was designed to be a 'proof-of-concept' to help determine if the method is likely to be useful and to identify possible issues for implementation at a larger scale.

To explore the potential of the sensor method for use in understanding responses to changes in the outdoor play environment we introduced a playground intervention into our case-study. Observational studies have shown promising results from introducing changes to outdoor play environments that impact on physical and social engagement in play (Engelen et al., 2013, 2018; Gibson et al., 2017; Hyndman, Benson, Ullah, & Telford, 2014). To deliver this, we partnered with Learning through Landscapes, a UK children's charity dedicated to creating stimulating outdoor learning and play experiences for children. The usual outdoor play offer at the school was a 24m×35m hard-surfaced playground painted with colourful lines. To create an affordable yet meaningful change, LtL introduced loose materials (e.g. large wooden blocks, tarpaulins, rope, tyres) into the playground alongside free-standing den building structures (Fig. 1). Two playworkers provided specialist support to facilitate the play sessions.

Figure 1 here.

Ethics statement

The research protocol was reviewed and approved by the Institutional Research Ethics Board.

Participants were minors therefore informed, opt-in consent was obtained from adults who had parental responsibility. Parents/guardians were informed about the study via a

written information leaflet and invited to contact a member of the research team if they had further questions.

The aims and method of the study were explained to the children in a class group discussion. Children assented to the study by indicating verbally if they wished to participate in each play session. Alternative outdoor play opportunities were available for children not wishing to participate.

Participants

The case-study consists of 18 participants (9 female) drawn from a single class in an urban, U.K., primary school. The total class size was 19, however, one child's parents did not consent to her/his participation. Children were aged 7-8 years old at the start of the study.

Measures

Social and psychological measures were collected by teacher and peer-report.

Teacher measures:

Strengths and Difficulties Questionnaire, SDQ (Goodman, 1997)

The SDQ is a 25-item rating scale of child behaviour. Respondents are asked to mark a child as belonging to one of 3 categories with respect to statements such as "is generally obedient" or "gets upset easily." The categories are "Not at all true", "Somewhat true" and "Certainly true." Scores for the category "Somewhat true" are always 1, while the other 2 categories will be scored as either 0 or 2, depending on whether the item is positively or negatively worded. SDQ is an internationally used, well validated instrument. The following subscales were used due to their direct relevance to peer social relations:

Prosocial scale – scores can range from 0-10: higher scores indicate greater competence.

Peer problems scale - scores can range from 0-10: higher scores indicate more difficulty.

Children's Communication Checklist-2, CCC-2 (Bishop, 2003)

1 The CCC-2 is a 70-item questionnaire where respondents rate different aspects of a
2 child's communication skills. The respondent rates the frequency of certain communicative
3 behaviours, (e.g. "gets mixed up between he and she") as follows; 0 = less than once a week (or
4 never); 1 = at least once a week; 2 = once or twice a day; 3 =several times a day (or always). In
5 the current study we use The General Communication Competence scale (GCC), which is a
6 summary score indicating general communicative ability across different domains. The CCC-2 is
7 an internationally used well validated instrument.

8 *Child measure:*

9 *Sociometric Nomination Network* (Coie, Coppotelli, & Dodge, 1982)

10 Children were interviewed on a 1:1 basis and were assured of the confidentiality of their
11 responses. They were asked to indicate their 3 most preferred playmates from an array of
12 photographs showing their classmates who were participating in the study. Photo recognition
13 and understanding of the concept of preference were checked before proceeding with the task.
14 Responses were used to create a network based on the nomination adjacency matrix, weighted
15 according to preference.

16 Peer nomination is a well-known and validated method for quantifying peer
17 relationships and has been used to explore the relative popularity of children in a class-group as
18 well as the relationships between friendship pairs and groups (Bukowski, Laursen, & Rubin,
19 2018).

20 *Tracking movement on the playground* (Heravi et al. 2018)

21 Authors BH and SH developed and built a sensor that could detect and store positional
22 data from the Global Satellite Navigation System (GNSS). Sensors were then made wearable by
23 attaching them to baseball caps. Children wore the wearable sensors for the duration of each
24 playtime in the study.

Data collection

Questionnaires were completed by the class teacher at the start of the project. A trained research assistant conducted the sociometric interviews on a 1:1 basis in a quiet room in the school.

We took sensor data during three types of play session:

1) *Piloting/habituation*: We carried out 7 pilot sensor data collection sessions before beginning data collection. This was intended familiarise children with the wearables and to attenuate any ‘observer’ effects. We also used this period to refine our equipment and implementation protocols, solving such problems as getting the correct sensor on the correct child and ensuring a good supply of charged batteries.

2) *Baseline*: We tracked children’s movements during at least 45 minutes of unstructured play in their usual school playground over 10 sessions held on 10 different days.

3) *Intervention*: Following completion of the *Baseline* data collection, LtL introduced the outdoor play intervention. Again, we tracked children’s movements during at least 45 minutes of unstructured play over 10 sessions held on 10 different days.

Data preparation

We used the sensor data to build a network representing class social relationships and used its properties to give insights into the ways in which social relations are enacted during outdoor play. To create a class network based on sensor data we needed to choose a similarity metric to define a ‘link’ (edge) between pairs of children, to choose a threshold at which such a link should be considered socially important and to decide whether to compute the network based on data from each day individually or to average across all days of data collection. We report our decisions explicitly here to inform the decision-making process for future research.

1 *Defining edges.* As reported in our technical paper (Heravi et al., 2018), we trialled 3
2 methods for defining and weighting links between children on the playground. These are based
3 on the pairwise similarity between trajectories for all the children in the playground over the
4 course of the playtime.

5 In this paper we report data from networks based on the Warping Fréchet Distance¹
6 (WFD) as this was the metric found to be more robust across different types of social play.
7 Having used WFD to quantify trajectory similarity between each pair of children, we then
8 applied different thresholds for considering whether each pair of children's movements were
9 sufficiently similar to warrant establishment of a link in the network.

10 As spatio-temporal information has not previously been used in this way in the study of
11 outdoor social play, the effect of different thresholds is an open question. Clearly, neither a
12 completely saturated nor a very sparse network would be informative. We therefore
13 investigated the impact of different thresholds between these extremes and report results for
14 the most (5) and least (1) permissive values trialled. Networks were computed for each play
15 session individually and aggregated networks were also computed based on averages across the
16 10 play sessions for each condition: *baseline* or *intervention*.

17 **Planned analyses**

18 Our research aims to explore the ways in which using sensors could inform the study of how
19 environmental factors, together with children's individual differences in social development,
20 relate to their engagement in group-based outdoor play. We planned the following analyses to
21 address our research questions:

22 *Individual child analysis (RQ1)*

23 To create a measure of playground social connectedness we computed degree centrality
24 metrics for each individual node¹ (i.e. child) in the sensor networks for each day of play and for

¹ Number of connections a child has divided by the largest number of connections in the group.

the aggregated network. We identified the number of times each child ranked as the first or second most connected in the group using this measure.

We used the Spearman rank correlator to quantify associations between these playground social connectedness measures, the degree centrality scores from the sociometric network and the questionnaire measures. Baseline data were used because the intervention condition was intended to ‘disrupt’ typical social interactions and promote collaboration. In contrast, the baseline data was considered closer to ‘business as usual’ for the outdoor play of this group.

Group analysis (RQ2)

The sensor method used in this study was developed due to its potential to facilitate automated quantification of group interactions during outdoor play. We investigated the global and relational properties of the sensor network, as well the node-level analysis mentioned above. We computed the average *network* centrality (average of node centralities) across each of the 10 days of the *baseline* period to allow assessment of daily variability (scores were scaled by dividing by the largest value). To illustrate the variability of the group interactions as captured by this method we plot and discuss networks from a day with sparse connections compared to a day with dense connections.

Intervention associated change (RQ3)

To explore the influence of the outdoor play intervention we compared the baseline and intervention mean degree measures both quantitatively and qualitatively.

Reflections on using the sensors and interpretation of these analyses are included in the discussion section of the paper.

Results

Descriptive statistics for child characteristics and teacher questionnaire measures are shown in Table 1. The network of classroom relationships as ascertained from the sociometric nomination procedure is shown in Figure 2.

Table 1. here.

Figure 2. here.

Individual differences

As described in the analysis plan, the sensor data were combined across the 10 days of baseline data collection and represented as a network, see Figure 3. This was then used to identify the children with the highest number of connections.

Figure 3 here.

Figure 4 shows the frequency with which individual children were ranked as either the first or second best-connected child over the 10 days of data collection. Most children appear more than once, although two of the girls do not appear at all. There is some correspondence between the more frequently better-connected children in the sensor network and the most popular children identified by the nomination method although clearly there is not a 1:1 mapping between the two.

Figure 4 here.

To investigate further, we correlated children's degree centrality scores from the sensor network with the degree centrality scores from the nomination network and with the behavioural questionnaire scores. These correlations are reported in Table 2, alongside the same analysis run for girls and boys separately. Correlations between in-degree from the nomination network and degree from the sensor networks were positive and ranged between $\rho=0.46$ and $\rho=0.63$ in magnitude.

Table 2 here.

Group measures

Alongside investigation of individual differences, we examined the properties of the group as this is one of the most promising applications for using sensor data to study outdoor play. Figure 5 shows the average weighted degree for the class sensor networks for each of the 10 days in the *Baseline* condition. Scores have been scaled by dividing by the largest value to facilitate comparison across days and conditions. The number and strength of connections varies from day to day. It can be inferred from this plot that the threshold adopted does not make a serious impact as scaling is consistent across days.

Figure 5 here.

Figure 6. shows the average weighted degree for the class sensor networks for each of the 10 days in the *Intervention* condition.

Figure 6 here.

As for the baseline data, the group average connectedness is variable across the 10 days of the intervention. The degree is similar across baseline and intervention conditions when averaged across the 10 days. However, qualitatively it appears this measure is stabilising to the maximum in the final 3 days, following a period of lower connectedness.

Finally, Figure 7 illustrates the group connections for 2 days of the intervention condition. The days have been selected to illustrate sessions with sparse (left) and high (right) connectedness. The network diagram and heatmap are different methods of representing the same adjacency matrix. In the heatmaps (lower boxes) each child on the playground on that day is represented as a row and as a column. The strength of association between pairs of children is shown by the colour map – stronger connections are shown in darker colours. The network diagrams show the same information (edges are weighted by connection strength) but the layout used makes it easier to visualise the clusters and overall connections of the group. Qualitative interpretation of these diagrams is discussed in the reflections section. The diagrams

illustrate the different extremes of connectivity patterns that may be seen within the same group of children playing on different days.

Figure 7 here.

Discussion and reflection

The findings from this study show that sensor methods for tracking the play behaviour of a group of children simultaneously are a promising new research tool in the study of outdoor play. Positive correlations between the centrality measures from the sensor data and the nomination data support the idea that outdoor play is a context in which the social relationships and hierarchies of childhood are enacted. This result is consistent with other studies using proximity sensing devices that have found links between direct measures of child social competence and their playground behaviour (Veiga et al., 2015, 2017). However, we believe this is the first sensor-based study of outdoor play to demonstrate such effects taking into account data from peers.

It is noteworthy that the teacher ratings of prosociality and communication skills have correlations with the sensor measure of social connectedness that are small in magnitude (-0.06 to 0.17). When the sample is split by sex there is evidence of a positive relationship between teacher-rated prosociality and sensor network centrality for girls but not for boys. Indeed, for boys, teacher-rated peer *difficulties* are positively associated with being nominated as a preferred playmate. To the best of our knowledge the current study is the first to report a finding of this nature based on outdoor play data; however, it is consonant with research showing that a 'child's-eye view' of social success, and of play, can often be at odds with adults' perspectives (Factor, 2004; Fink, Browne, Hughes, & Gibson, 2018). Observation using sensors may present a useful way of understanding the child's social world while overcoming some of the challenges of self-, adult-, or peer-reported measurements.

Our findings also show considerable variability in the sensor derived metrics across the 10-day baseline and intervention sessions; both for individual children and for the group as a

whole. A closer look at Figure 7 illustrates this point; it shows day 5 as an example of a ‘sparsely connected’ day and day 9 as an example of a ‘densely connected’ day from the *Intervention* sessions. On day 5, connections are more localised, e.g. there is strong connection between child F-5 and child F-6 and a tightly-connected cluster between F-11, M-16, M-7, M-8 and M-9. These connections are similar to those seen in the nomination network: F5-F6 were reciprocal most-preferred friends and M-16, M-7, M-8 and M-9 were all in the same cluster. However, there is a different picture for day 9 where, except for child F-1, the whole group is more cohesive. Thus we can conclude that although individual socio-communicative profiles and existing social relations impact connectedness during outdoor play, it is also subject to other influences.

Referring to the findings of studies using more traditional observational methods, such as Engelen et al (2018), it seems likely that such influences stem from the type of games and activities in which the children are engaged. Gibson and colleagues (2011) have previously shown that children with social difficulties (e.g. autism, ADHD) display differences in outdoor play regardless of activity type; however, when considering group-level metrics activity type may become more significant. For example, imagine a small group engaged in a football game while others hang around and watch from the edges, compared to a collaborative effort involving the whole class in building and defending a fort made of milk crates. Individual degree centrality scores based on the method used in the present study would be different across scenarios as they are based on comparison to the movement of every other member of the class.

An important next step for research involving this type of sensor data is therefore comparison and validation against play types observed using traditional methods. In our previous work with these data we identified ‘hang out play’, ‘focal play’ and ‘pursuit play’ as movement-based cues to play types and we plan to investigate whether these play types can be automatically detected in the data (Heravi, et al. 2018). The ability to classify more abstract concepts such as fantasy play, competitive play and games with rules would be useful future additions to enable a deep understanding of how play activities link to social development.

1 Our final research question asked whether the sensor data might have utility in
2 detecting change associated with an intervention designed to enhance the play environment.
3 We predicted that there would be a higher mean degree in the intervention condition, compared
4 to the baseline, reflecting greater engagement in collaborative play.

5 Contrary to our prediction, no difference was found between the baseline and the
6 intervention connectedness scores and, as mentioned above, there was considerable day-to-day
7 variability in the structure of the networks. We therefore conclude that the degree centrality
8 scores averaged over 10 days is not a sensitive way to detect changes in group behaviour
9 following an outdoor play intervention. Difficulties in quantifying intervention effects for social
10 emotional benefits of outdoor play interventions are notoriously common in the field (see
11 Gibson, Cornell & Gill, 2017 for a review), although a recent observational study by Engelen and
12 colleagues (2018) has had some success by combining observer scanning techniques usually
13 associated with assessing physical activity outcomes (Saint-Maurice et al., 2011). An interesting
14 avenue for future research could be to combine the scanning and sensor-based approaches.

15 Although the overall mean connectedness was not different, qualitative comparison of
16 the daily mean centrality scores over the 10 days for baseline and for intervention shows an
17 interesting pattern. While the change in baseline mean centrality varies from one day to the
18 next, there appears to be a different structure in the patterns of variation for the intervention
19 period; an initial mid-connectedness period, followed by a low connectedness period and finally
20 3 days of almost maximum connectedness. This tallies with the advice that the experienced
21 playworkers gave us before the study. They explained that the introduction of more
22 adventurous and varied play opportunities can initially require adult support to introduce
23 activities, followed by a period of exploration and uncertainty before children finally immerse
24 themselves in the new play environment. This interpretation is speculative at this point (we
25 have no independent corroboration) but future studies could be designed to validate daily
26 connectivity patterns from sensor data against observer field notes or behavioural coding.

Before drawing conclusions, we wish to reflect on the strengths and limitations of this particular study and also for the use of sensor technology to study outdoor play in general.

Firstly, the nature of this case study means we have an unprecedented amount of data concerning the play of a relatively small number of children. The small sample size is appropriate given that this is the first study to use GNSS/IMU data in this way and it was not clear whether implementation at scale would be a good use of resources. However, the corollary of a small sample size (for inferential purposes) is a lack of power to detect small effects and limited generalisability to wider populations. The correlational results presented in Table 2 should therefore be considered indicative rather than conclusive.

A second issue is that there are many arbitrary decisions to be made when it comes to collection and analysis of this type of data. In the current study this applied to the threshold for defining interactions. This is also applicable to studies using RFID methods – a cut-off of 1.5 m has been used in some studies not because it is socially meaningful but because that is the range of the sensing equipment. In studies such as those by Veiga and colleagues, this has been addressed by standardising scores within the group, but it is important that researchers do not unwittingly codify the limits of the sensing equipment into standard practices. It is conceivable that these decisions could introduce hidden systematic error (bias) into research, making it difficult to make sense of findings across settings and studies. Furthermore, given the well-documented publication bias for ‘positive’ findings in social psychology, analytical choices that support a given hypotheses might be ‘cherry-picked’ over those with less impressive outcomes.

Perhaps the best way to address such pitfalls in this inchoate field would be for future research to investigate issues of measurement error and validity systematically, and for protocols for experimental research using these methods to be published in advance of data collection. In the current study we have attempted to address this through documentation and justification of the decision-making process. Anonymised data and scripts are available from author JG on request.

1 Lastly, we reflect on the ethical challenges of using sensor data. In the present study
2 ethical issues were discussed in a sustained conversation involving children, parents, teachers,
3 third-sector organisations and other researchers. Privacy of personal data, informed consent
4 and provision of alternative play opportunities for non-participating children were the main
5 concerns discussed. Privacy was ensured by only tracking children in the playground during
6 designated study sessions and by ensuring positional data was not linked to personally
7 identifying data. Some parents commented that the tracking methodology preserved anonymity
8 more reliably than video data, which is currently more commonly used in the study of outdoor
9 play. The high-level of engagement and uptake for this study demonstrates that a collaborative
10 approach is important when addressing ethical considerations.

11 **Conclusions**

12 In conclusion, this case-study demonstrates the considerable potential that sensor-
13 based methods bring to the study of outdoor play. Gathering sensor data that, for the first time,
14 permits study of the social play dynamics of a whole group simultaneously is a significant
15 development in the field. Our findings suggest that one useful application will be to study how
16 children's classroom relationships and individual differences are enacted and developed during
17 outdoor play. Importantly, we have also shown that this methodology is ethically acceptable and
18 implementable in a school context. The case-study also shines a light on the complex and
19 variable nature of the social dynamics that unfold during group-based outdoor play. This not
20 only raises challenges for analysis and interpretation but also opens up new and exciting lines of
21 enquiry in play research.

References

- Baines, E., & Blatchford, P. (2009). Sex differences in the structure and stability of children's playground social networks and their overlap with friendship relations. *British Journal of Developmental Psychology*, 27, 743–760. <https://doi.org/10.1348/026151008X371114>
- Bishop, D. V. M. (2003). *The children's communication checklist: CCC-2 manual*. London: Harcourt Assessment.
- Brendgen, M., Vitaro, F., Bukowski, W. M., Doyle, a B., & Markiewicz, D. (2001). Developmental profiles of peer social preference over the course of elementary school: associations with trajectories of externalizing and internalizing behavior. *Developmental Psychology*, 37(3), 308–320. <https://doi.org/10.1037/0012-1649.37.3.308>
- Bukowski, W. M., Laursen, B. P., & Rubin, K. H. (2018). Handbook of peer interactions, relationships, and groups. In *Handbook of peer interactions, relationships, and groups* (2nd ed.). Retrieved from <https://www.guilford.com/books/Handbook-of-Peer-Interactions-Relationships-and-Groups/Bukowski-Laursen-Rubin/9781462525010>
- Bundy, A., Lockett, T., Tranter, P., Naughton, G., Wyver, S., Ragen, J., & Spies, G. (2016). The Sydney playground project: Results from a cluster randomized controlled trial of a school playground-based intervention to increase children's physical activity, play and social skills.
- Coie, J. D., Coppotelli, H., & Dodge, K. a. (1982). Dimensions and types of social status: A cross-age perspective. *Developmental Psychology*, 18(4), 557–570. <https://doi.org/10.1037//0012-1649.18.4.557>
- Eisenberger, N. I., & Cole, S. W. (2012). Social neuroscience and health: Neurophysiological mechanisms linking social ties with physical health. *Nature Neuroscience*. <https://doi.org/10.1038/nn.3086>
- Engelen, L., Bundy, A., Naughton, G., Simpson, J. M., Bauman, A., Ragen, J., ... van der Ploeg, H. P.

- (2013). Increasing physical activity in young primary school children it's child's play: A cluster randomised controlled trial. *Preventive Medicine*, 56(5), 319–325.
<https://doi.org/10.1016/j.ypmed.2013.02.007>
- Engelen, L., Wyver, S., Perry, G., Bundy, A., Chan, T. K. Y., Ragen, J., ... Naughton, G. (2018). Spying on children during a school playground intervention using a novel method for direct observation of activities during outdoor play. *Journal of Adventure Education and Outdoor Learning*, 18(1), 86–95. <https://doi.org/10.1080/14729679.2017.1347048>
- Factor, J. (2004). Tree stumps, manhole covers and rubbish tins the invisible play-lines of a primary school playground. *Childhood*, 11(2), 142–154.
- Fink, E., Browne, W., Hughes, C., & Gibson, J. (2018). Using a 'child's-eye view' of social success to understand the importance of school readiness at the transition to formal schooling. *Social Development*. <https://doi.org/10.1111/SODE.12323>
- Gibson, J. L., Adams, C., Lockton, E., & Green, J. (2013). Social communication disorder outside autism? A diagnostic classification approach to delineating pragmatic language impairment, high functioning autism and specific language impairment. *Journal of Child Psychology and Psychiatry*, 54, 1186–1197. <https://doi.org/10.1111/jcpp.12079>
- Gibson, J. L., Cornell, M., & Gill, T. (2017). A Systematic Review of Research into the Impact of Loose Parts Play on Children's Cognitive, Social and Emotional Development. *School Mental Health*. <https://doi.org/10.1007/s12310-017-9220-9>
- Gibson, J. L., Hussain, J., Holsgrove, S., Adams, C., & Green, J. (2011). Quantifying peer interactions for research and clinical use: The Manchester Inventory for Playground Observation. *Research in Developmental Disabilities*, 32(6), 2458–2466.
- Goodman, R. (1997). The Strengths and Difficulties Questionnaire: A Research Note. *Journal of Child Psychology and Psychiatry*, 38, 581–586.
- Gray, P. (2011). The Decline of Play and the Rise of Psychopathology in Children and

- Adolescents. *American Journal of Play*.
- Hart, C. H. (1993). *Children on Playgrounds: Research Perspectives and Applications*. New York, NY, USA: SUNY Press.
- Henry, D. B. (2006). Associations between peer nominations, teacher ratings, self-reports, and observations of malicious and disruptive behavior. *Assessment*, 13, 241–252.
- Heravi, B., Gibson, J. L., Hailes, S., & Skuse, D. (2018). *Playground Social Interaction Analysis using Bespoke Wearable Sensors for Tracking and Motion Capture*.
- Howes, C., Rubin, K. H., Ross, H. S., & French, D. S. (1988). Peer interaction of young children. *Monographs of the Society for Research in Child Development*, 53(1), 1–92.
- <http://www.studioludo.org/smarterplay>. (n.d.). Retrieved July 28, 2018, from <http://www.studioludo.org/smarterplay>
- Hyndman, B., Benson, A., Ullah, S., & Telford, A. (2014). Evaluating the effects of the Lunchtime Enjoyment Activity and Play (LEAP) school playground intervention on children's quality of life, enjoyment and participation in physical activity. *Bmc Public Health*, 14, 164. <https://doi.org/10.1186/1471-2458-14-164>
- Jarvis, P., Newman, S., & Swiniarski, L. (2014). On 'becoming social': the importance of collaborative free play in childhood. *International Journal of Play*, 3(1), 53–68. <https://doi.org/10.1080/21594937.2013.863440>
- Kindermann, T. (2007). Effects of naturally existing peer groups on changes in academic engagement in a cohort of sixth graders. *Child Development*. Retrieved from <http://onlinelibrary.wiley.com/doi/10.1111/j.1467-8624.2007.01060.x/full>
- Kindermann, T., & Gest, S. (2009). Assessment of the peer group: Identifying naturally occurring social networks and capturing their effects. *Interactions, Relationships, and Groups*. Retrieved from https://www.researchgate.net/profile/Thomas_Kindermann/publication/237816613_Assessment_of_the_peer_group:_Identifying_naturally_occurring_social_networks_and_capturing_their_effects/fulltext.html

essment_of_the_Peer_Group_Identifying_Naturally_Occurring_Social_Networks_and_Captur
ing_their_Eff_ects/links/5564aea008ae06101abdfa79.pdf

Kuh, L. P., Ponte, I., & Chau, C. (2013). The Impact of a Natural Playscape Installation on Young
Children's Play Behaviors. *Children Youth and Environments*, 23(2), 49–77.

Ladd, G. W., Price, J. M., & Hart, C. H. (1988). Predicting Preschoolers' Peer Status from Their
Playground Behaviors. *Child Development*, 59(4), 986–992.

<https://doi.org/10.1111/j.1467-8624.1988.tb03251.x>

Mahony, L., Hyndman, B., Nutton, G., Smith, S., & Te Ava, A. (2017). Monkey bars, noodles and
hay bales: a comparative analysis of social interaction in two school ground contexts.

International Journal of Play, 6(2), 166–176.

<https://doi.org/10.1080/21594937.2017.1348319>

McNamara, L., Colley, P., & Franklin, N. (2017). School recess, social connectedness and health: A
Canadian perspective. *Health Promotion International*.

<https://doi.org/10.1093/heapro/dav102>

Parten, M. B. (1932). Social Participation among Pre-School Children. *Journal of Abnormal
Psychology*, 27, 243–269.

Pellegrini, A. D. (2001). Practitioner review: The role of direct observation in the assessment of
young children. *Journal of Child Psychology and Psychiatry*, 42, 861–869.

Pellegrini, A. D., Symmons, F. J., & Hoch, J. (2004). *Observing children in their natural worlds: A
methodological primer*. London: Lawrence Erlbaum Associates.

Ren, J. Y., & Langhout, R. D. (2010). A recess evaluation with the players: Taking steps toward
participatory action research. *American Journal of Community Psychology*, 46(1–2), 124–
138. <https://doi.org/10.1007/s10464-010-9320-2>

Saint-Maurice, P. F., Welk, G. J., Silva, P., Siahpush, M., Huberty, J., Saint-Maurice F., P., ... Huberty,
J. (2011). Assessing children's physical activity behaviors at recess: a multi-method

approach. *Pediatric Exercise Science*. <https://doi.org/10.1123/pes.23.4.585>

Stehlé, J., Charbonnier, F., Picard, T., Cattuto, C., & Barrat, A. (2013). Gender homophily from spatial behavior in a primary school: A sociometric study. *Social Networks*, 35(4), 604–613. <https://doi.org/10.1016/J.SOCNET.2013.08.003>

van Harmelen, A.-L., Gibson, J. L., St Clair, M. C., Owens, M., Brodbeck, J., Dunn, V., ... Goodyer, I. M. (2016). Friendships and Family Support Reduce Subsequent Depressive Symptoms in At-Risk Adolescents. *PLOS ONE*, 11(5), e0153715. <https://doi.org/10.1371/journal.pone.0153715>

Veiga, G., de Leng, W., Cachucho, R., Ketelaar, L., Kok, J. N., Knobbe, A., ... Rieffe, C. (2015). Social Competence at the Playground: Preschoolers During Recess. *Infant and Child Development*. <https://doi.org/10.1002/icd.1957>

Veiga, G., Ketelaar, L., De Leng, W., Cachucho, R., Kok, J. N., Knobbe, A., ... Rieffe, C. (2017). Alone at the playground. *European Journal of Developmental Psychology*, 14(1), 44–61. <https://doi.org/10.1080/17405629.2016.1145111>
doi.org/10.1080/17405629.2016.1145111

Weissbrod, A., Shapiro, A., Vasserman, G., Edry, L., Dayan, M., Yitzhaky, A., ... Kimchi, T. (2013). Automated long-term tracking and social behavioural phenotyping of animal colonies within a semi-natural environment. *Nature Communications*, 4(May), 2018. Retrieved from <http://www.ncbi.nlm.nih.gov/pubmed/23771126>

1 **Table Captions**

2 Table 1. *Participant characteristics (mean (s.d.), min, max) by sex*

3 Table 2. *Bivariate correlations (Spearman rank correlator) between psychometric, sociometric*
4 *and sensor measures of play.*

5
6 **Figure Captions**

7
8 Figure 1. *A den building structure similar to the one used in the Hopscotch study.*

9
10 Figure 2. *Network representation of the peer nomination matrix.*

11 Figure 3. *Network representation of social relationships collected during outdoor play, averaged*
12 *over 10 days. Each node (Nx) represents a child with a unique ID number; the lines represent*
13 *connections between them.*

14 Figure 4. *Frequency of 1st or 2nd place rankings for social connectedness in the aggregated baseline*
15 *network. Stars represent the most popular children as identified in the sociometric nomination*
16 *network.*

17
18 Figure 5. *Mean weighted degree (scaled) per day and threshold Baseline*

19 Figure 6. *Mean weighted degree (scaled) per day and threshold Intervention*

20 Figure 7. *Comparison of sparsely vs densely-connected days in the intervention condition*

1 Table 1.

	<i>Age yrs.</i>	<i>SDQ-Peer</i>	<i>SDQ-PrS</i>	<i>GCC</i>
<i>Female</i>	8.4 (0.2)	0.7 (0.8)	8.6 (1.1)	73 (18.5)
<i>(n=9)</i>	8.1, 8.6	0, 2	7, 10	43, 98
<i>Male</i>	8.3 (0.5)	0.2 (0.4)	5.8 (1.6)	64.9 (16.8)
<i>(n=9)</i>	7.8, 9.2	0, 1	4, 8	44, 62
<i>All</i>	8.4 (0.4)	0.5 (0.7)	7 (2.1)	68.9 (17.6)
	7.8, 9.2	0, 2	4, 10	43, 98

2 *SDQ-Peer/PrS, Strengths and Difficulties Peer Problems/Prosocial Scale; GCC, General Communication*
 3 *Composite.*

4

1 Table 2.

Total sample	1	2	3	4	5	6	7	8
1. SDQ Prosocial	—							
2. SDQ Peer	0.21	—						
3. GCC	0.21	-0.31	—					
4. Nom. in-degree	-0.06	0.37	0.17	—				
5. Av. deg. thr1	-0.03	-0.21	0.19	0.46	—			
6. Av. w deg. thr1	0.04	-0.18	0.39	0.55*	0.94*	—		
7. Av. deg. thr5	-0.07	-0.18	0.31	0.63*	0.79*	0.75*	—	
8. Av. w deg. thr5	0.17	-0.18	0.35	0.49*	0.90*	0.90*	0.90*	—
Separate by sex	1	2	3	4	5	6	7	8
1. SDQ Prosocial		-0.32	-0.29	-0.29	-0.03	0.10	0.08	0.00
2. SDQ Peer	-0.04		-0.72*	0.75*	0.21	0.10	0.10	0.10
3. GCC	-0.03	-0.28		-0.64	-0.13	0.02	0.07	0.13
4. Nom. in-degree	0.06	0.14	0.77*		0.55	0.36	0.60	0.48
5. Av. deg. thr1	0.42	-0.5	0.61	0.40		0.95*	0.62	0.92*
6. Av. w deg. thr1	0.32	-0.35	0.68*	0.60	0.95*		0.43	0.85*
7. Av. deg. thr5	0.26	-0.30	0.69*	0.65	0.85*	0.96*		0.77*
8. Av. w deg. thr5	0.52	-0.39	0.62	0.55	0.90*	0.93*	0.92*	

2 * $p < .05$. Females lower diagonal; SDQ-Prosocial/Peer==Strengths and Difficulties Prosocial Scale /Peer
3 Problems; GCC==General Communication Composite; Nom. In-degree==sociometric nomination score; Av.
4 (w) deg. Thr x ==Average (weighted) degree at threshold x . from the sensor networks (average computed over
5 the 10 baseline days).
6
7

Figure 1.

Figure 2.

Figure 3.

Figure 4.

1

2 Figure 5.

1

2 Figure 6.

3

Figure 7.