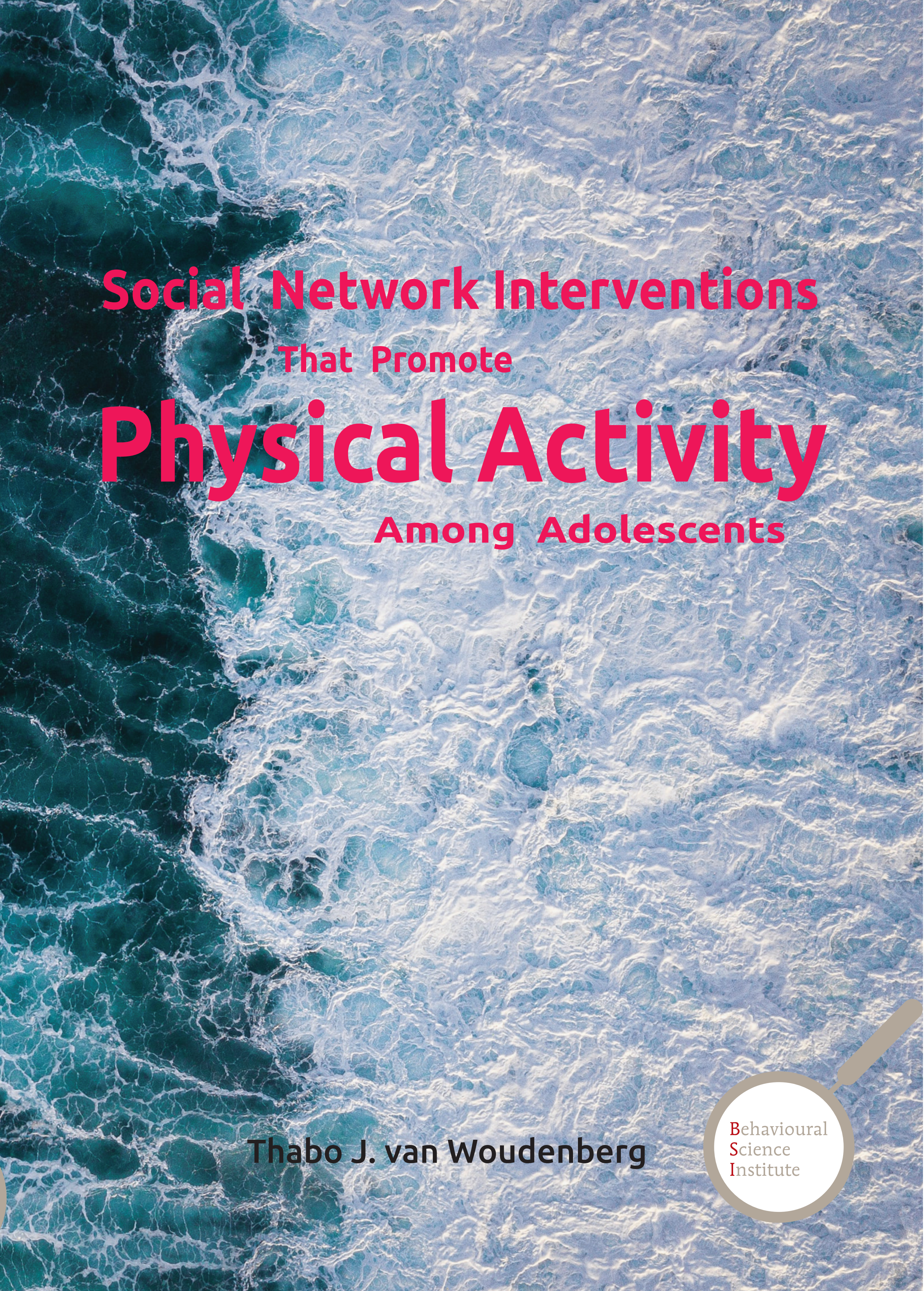

# Social Network Interventions That Promote Physical Activity Among Adolescents

Thabo J. van Woudenberg

Behavioural
Science
Institute

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Thabo Joshua van Woudenberg

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Promotor:

Prof. dr. M. Buijzen

Copromotoren:

Dr. W. J. Burk

Dr. ir. K. E. Bevelander

Manuscriptcommissie:

Prof. dr. B. Steenbergen (voorzitter)

Prof. dr. H. H. J. Das

Dr. C. E. G. Steglich (Rijksuniversiteit Groningen)

# Social Network Interventions That Promote Physical Activity Among Adolescents

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Thabo Joshua van Woudenberg

Born on August 29, 1989

in Leiden, the Netherlands

Supervisor:

Prof. dr. M. Buijzen

Co-supervisors:

Dr. W. J. Burk

Dr. ir. K. E. Bevelander

Doctoral Thesis Committee:

Prof. dr. B. Steenbergen (Chair)

Prof. dr. H. H. J. Das

Dr. C. E. G. Steglich (University of Groningen)

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Chapter 1

# General Introduction

## Background

Adolescents are not physically active enough (Nader, Bradley, Houts, McRitchie, & O'Brien, 2008; Riddoch et al., 2004). Young people tend to become less active as they grow up, and adolescents today are less physically active than adolescents in previous generations (Boreham & Riddoch, 2001; Kohl et al., 2012; Tudor-Locke et al., 2011). According to the World Health Organization (2010), adolescents (12- to 15-year-olds) should accumulate at least 60 minutes of moderate-to-vigorous physical activity (MVPA) every day, which is reflected in approximately 10,000 to 11,700 steps per day. However, the majority (80%) of adolescents worldwide are not meeting these guidelines (Brusseau, Tudor-Locke, & Kulinna, 2013; Butcher, Sallis, Mayer, & Woodruff, 2008; Hallal et al., 2012). For example, 93% of adolescents (12- to 15-year-olds) in the United States and 85% of adolescents in the Netherlands (the country of this dissertation) do not meet the recommended amount of physical activity (Burghard et al., 2016; Katzmarzyk et al., 2016).

These statistics are alarming, because a lack of physical activity is seen as a major risk factor for health-related problems, such as obesity in adolescence (Jiménez-Pavón, Kelly, & Reilly, 2010; Rey-López, Vicente-Rodríguez, Biosca, & Moreno, 2008) and adulthood (Parsons, Power, Logan, & Summerbell, 1999), numerous psychosocial (Biddle & Asare, 2011) and physiological diseases (Ebbeling, Pawlak, & Ludwig, 2002; Ekelund et al., 2012; Janssen & LeBlanc, 2010), and even premature mortality (Füzéki, Engeroff, & Banzer, 2017; Reilly & Kelly, 2011). Having an active lifestyle has a positive effect on youth's physical (Füzéki et al., 2017; Janssen & LeBlanc, 2010) and mental health (Biddle & Asare, 2011; Brooks, Smeeton, Chester, Spencer, & Klemera, 2014), academic performance (Trudeau & Shephard, 2008), and life satisfaction (Brooks et al., 2014).

Therefore, it is important to investigate how physical activity during adolescence could be increased.

## The Role of Peers in Adolescents' Physical Activity

Systematic reviews have shown that peers play an important role in the physical activity of adolescents (Chung, Ersig, & McCarthy, 2017; Fitzgerald, Fitzgerald, & Aherne, 2012; Salvy & Bowker, 2013). For example, the reviews have shown that the amount of physical activity is positively associated with encouragement from friends and with the amount of physical activity undertaken by friends (Maturo & Cunningham, 2013). The importance of the social environment in physical activity is not surprising, given that socio-environmental or contextual effects are emphasized in three of the most dominant theoretical perspectives: the theory of planned behavior (Ajzen, 1991), social cognitive theory (Bandura, 1986), and social learning theory (Bandura & Walters, 1977). In the theory of planned behavior (Ajzen, 1991), subjective norms are one of the three antecedents of behavioral intention, along with attitude and behavioral control. Subjective norms are the belief that important individuals or groups approve or disapprove of one performing a given behavior (Ajzen, 1991), and this has an impact on the intention to be physically active (Hagger, Chatzisarantis, & Biddle, 2002).

In social cognitive theory (Bandura, 1986), the (social) environmental factor is also one of the three determinants that predict behavior (along with cognitive and behavioral factors), and these three determinants jointly predict physical activity. Closely related to this theory is social learning theory (Bandura & Walters, 1977), which postulates that behavior is learned from the environment through the process of observational learning. In other words, individuals observe others in their social environment being physically active and imitate or adjust their behavior accordingly.

What becomes apparent from the different theories is that the social environment plays an important role and can change physical activity in multiple ways. However, these theories are not specific about the underlying mechanisms whereby peers influence adolescents' behaviors. Salvy et al. (Salvy & Bowker, 2013; Salvy, de la Haye, Bowker, & Hermans, 2012) have proposed four interrelated mechanisms that explain the social influence on physical activity in adolescents: social norms, social facilitation, modeling, and impression management.

*Social norms* explain social influence on physical activity by looking at the perceptions of others about what is a normal, and what is a desirable, amount of physical activity. More specifically, in the social norms approach (Perkins & Berkowitz, 1986) subjective norms are divided into two distinct types: descriptive norms and injunctive norms (Cialdini, Reno, & Kallgren, 1990). Descriptive norms are perceptions of how physically active the social environment is. Injunctive norms are perceptions of how physically active the social environment thinks one should be (similar to subjective norms in the theory of planned behavior; Priebe & Spink, 2011). Both types of social norms influence physical activity. If adolescents observe that their peers are more physically active than they are themselves, or perceive that their peers think that they should be more physically active, the adolescents will adjust to the behavior of their peers. For example, previous research in adults has demonstrated that adults who are more physically active reported higher descriptive norms for their peers (Priebe & Spink, 2011) and that social norms consistently predicted adults' physical activity (Ball, Jeffery, Abbott, McNaughton, & Crawford, 2010). In adolescents, social norms (descriptive and injunctive norms) have been shown to predict the intention to be physically active, which in turn predicted the behavior itself (Maddison et al., 2009).

Closely related to social norms is the mechanism of *social facilitation*. Social facilitation explains social influence on physical activity by looking at the consequences of the sheer presence of others on individual's health-related behaviors. That is, peers might serve as spectators of physical activity or might be engaged in the same physical activity (Zajonc, 1965). During adolescence, most physical activities are social activities, typically involving some form of organized or spontaneous active play with one or more partners. For instance, soccer, tag, or dancing (Pellegrini, Blatchford, Kato, & Baines, 2004). There is a small body of work indicating that adolescents are more physically active when others are present (Beets, Vogel, Forlaw, Pitetti, & Cardinal, 2006; Salvy et al., 2007, 2008; Voorhees et al., 2005). For example, one study showed that adolescents biked a greater distance when in the presence of a friend than when alone (Salvy et al., 2008).

The third mechanism is *modeling*. Modeling explains social influence on physical activity by positing peers as role models of health-related behaviors. Through the process of observational learning (Bandura & Walters, 1977), adolescents observe their role models being physically active and the beneficial outcomes that are achieved (e.g., enjoyment or being part of the in-group). As a result, adolescents may copy or imitate this behavior to achieve the same beneficial outcomes. Research on the effect of role models on physical activity is scarce and only one study has shown that young people became more physically active when they were exposed to videos of adolescents who were physically active (Weiss, McCullagh, Smith, & Berlant, 1998).

The last mechanism is *impression management*. Impression management explains social influence on physical activity by looking at how individuals want to control the impressions others form of them (Leary & Kowalski, 1990). Again, most physical activities of adolescents are of a social nature, and participating more in physical activities has been found to result in a higher social status (Evans & Roberts, 1987). For example, a study has shown that physical activity of children in grade 1 predicts social status among peers in grade 4 (Ommundsen, Gundersen, & Mjaavatn, 2010). Also, individuals who are more physically active are more often rated as being sociable and confident, and having more self-control (Martin, Sinden, & Fleming, 2000). Therefore, it might be desirable for adolescents to portray the impression of being an active individual by being physically active when others are around.

These mechanisms all indicate that having peers to observe or interact with can foster an increase in physical activity (Salvy et al., 2012). The involvement of peers in physical activity also implies that physical activity does not occur in social isolation and that the effects of peers depend on which adolescents are part of the peer group. For example, when an adolescent wants to come across as an active person, he or she might become more physically active. At the same time, his or her peers might observe the increase in the social norm and become more physically active themselves. As a result, both the adolescent and peers have been influenced in the amount of their physical activity. In a similar vein, when two adolescents are physically active together, they both enable each other's physical activity simultaneously. As a result, social influences are best understood when the behaviors of the entire social environment are assessed simultaneously in terms of social networks. Social network approaches focus on relationships among social entities (i.e., adolescents) and on the patterns and implications of these relationships (Wasserman, 1994).

## Social Network Theory

Social network theory describes the interrelated connections between actors and is useful for understanding individual or group behavior (Valente, 2015). More specifically, social network theory acknowledges that individuals do not act in social isolation, and that they are embedded in a social context. Therefore, social network theory stresses the importance of relations between individuals for understanding the behavior of individuals within a social group or the collective behavior of the group (Valente, 2015). Social network theory consists of three main propositions: individuals act based on their social environment, an individual's behavior is influenced by his or her position and role in a social network, and the structure of the social network influences the behaviors of the entire group (Valente, 2015). Studying and applying these propositions using traditional models can become complex very quickly. However, there is one analytical approach that is particularly suited to cover all these propositions at once; this is *social network analysis*.

Social network analysis is the collection of concepts and methods for the measurement, representation, and analysis of social structures (Butts, 2008). That is, social network analysis provides a set of tools for describing and modeling behaviors while taking the relational context into account. In social network analysis, social structures are represented in *sociograms* (see Figure 1 for a visual representation). A graph is a relational structure that consists of two components: the actors and the relationship between the actors (Butts, 2008). The actors, called *nodes* or *vertices,* are the social entities that fall within the boundaries of the social network. The nodes have a relationship with other nodes, indicated by *ties* or *edges* between the nodes.

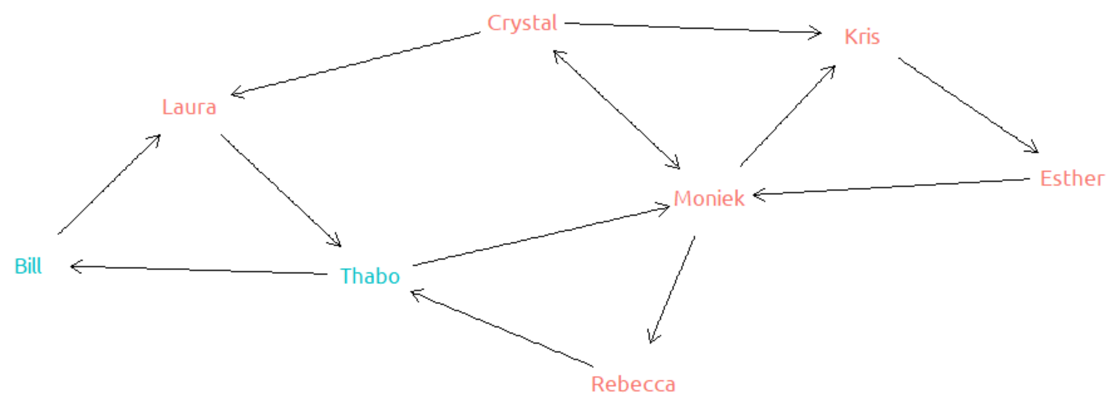


*Figure 1.* Example of a social network graph, based on the *MyMovez* project team.

For example, the nodes in Figure 1 are researchers in the *MyMovez* project team. The researchers have nominated one or more peers to bring a cake to the next project meeting. The member with the most nominations must bake a nice cake. In the graph, each arrow represents a nomination. Thus, in our example network, Kris has nominated Esther. Luckily for Esther, she has received only one nomination and is therefore exempted from baking duties. Who should bring a cake to the next meeting? Moniek has received three nominations, represented by three incoming arrows (referred to as *in-degree*). Therefore, Moniek has to bake the cake for the next meeting. Next to determining which member of a research team should bake a cake, social network analysis has experienced rapid growth in terms of interest and development in various scientific disciplines (Borgatti & Halgin, 2011).

One of the topics that is often studied in social network analysis is the similarity in behavior between peers (Badaly, 2013). In general, similar people interact more with each other than with dissimilar people. Therefore, people who are similar in their behavior or attitude, are more likely to share a connection, than people who are less similar to each other (Brechwald & Prinstein, 2011). This similarity also applies to physical activity in adolescents (Ali, Amialchuk, & Heiland, 2011; Efrat, 2009; Fitzgerald et al., 2012; Macdonald-Wallis, Jago, Page, Brockman, & Thompson, 2011; Sawka, McCormack, Nettel-Aguirre, Hawe, & Doyle-Baker, 2013; Schaefer & Simpkins, 2014; Schofield, Mummery, Schofield, & Hopkins, 2007). For example, adolescents have been found to participate in a similar amount of organized and non-organized physical activities as their friends (de la Haye, Robins, Mohr, & Wilson, 2010), there are associations between the physical activity of male and female best friends (Jago et al., 2011; Schofield et al., 2007; Stearns et al., 2018), and adolescents are clustered in friendship groups characterized by similar amounts of MVPA (Macdonald-Wallis et al., 2011). In short, there is convincing evidence that the physical activity of adolescents is similar to the physical activity of their friends (Badaly, 2013; Sawka et al., 2013). This may have positive and negative consequences for adolescents. Friendships among physically active adolescents could reinforce the physical activity behavior of peers, yet friendships among physically inactive adolescents might reinforce sedentary behaviors (Simpkins, Schaefer, Price, & Vest, 2013).

The observed similarities among the behaviors of adolescents and their friends have generally been attributed to social influence processes (Kandel, 1978). That is, scholars have assumed that the observed similarity is the result of the influence of the social environment on the behavior of the individual. However, the fact is often neglected that similarity in physical activity can plausibly be attributed to two processes that are not mutually exclusive and that could co-occur in the social networks of adolescents (Kandel, 1978). On the one hand, adolescents who are friends with each other, irrespective of their prior similarity, could influence each other's behavior (i.e., *peer influence* or *socialization*). On the other hand, behavioral similarities between friends could be a result of assortative pairing (i.e. *peer selection*), in which two individuals who are more similar are more likely to select each other as friends (de la Haye, Robins, Mohr, & Wilson, 2011). By observing the behavior and the social network longitudinally, these two processes can be disentangled from one another.

Several longitudinal social network studies have investigated both the selection and the influence processes in physical activity in adolescents (de la Haye et al., 2011; Long, Barrett, & Lockhart, 2017; Ommundsen et al., 2010; Shoham et al., 2012; Simpkins et al., 2013). On the one hand, all these studies found clear evidence for the influence effect, by showing that the physical activity of friends predicted changes in the physical activity of adolescents (de la Haye et al., 2011; Long et al., 2017; Shoham et al., 2012; Simpkins et al., 2013). That is, when an adolescent's friends were more physically active, the adolescent became more physically active, and vice versa. On the other hand, less clear evidence for the selection effect in adolescents has been found. Two out of the four longitudinal studies observed a selection effect (de la Haye et al., 2011; Simpkins et al., 2013), one study only observed the selection effect in one of the two studied schools (Shoham et al., 2012) and one study did not observe a selection effect at all (Long et al., 2017). Also, the tendency for adolescents to adopt the behaviors of their friends accounted for a greater proportion of similarity between friends than selection (de la Haye et al., 2011). Therefore, influence effects seem to be a more pervasive explanation of similarity in adolescents' physical activity than selection effects.

To conclude, there is an abundance of theories and studies that show that adolescents' physical activity is related to the physical activity of their peers, and that, without any form of intervention, adolescents influence the amount of physical activity of their peers. Recently, a new line of intervention research has started to capitalize on these social influences in order to increase healthy behaviors, decrease unhealthy behaviors or accelerate the diffusion of innovations (Valente, 2012, 2015); such an intervention is called a *social network intervention*.

## Social Network Interventions

In social network interventions, the most central individuals within a social network are used as the starting point of the intervention and are called *influence agents* (also referred to as *change agents*, *opinion leaders*, or *champions*; Valente, 2012). The influence agents are important in the social network because they hold the most power over the flow of information, in the same way as *opinion leaders* in the theory of the two-step flow of communication (Katz, 1957), and are role models for their peers, like the *innovators* in the theory of the diffusion of innovation (Rogers, 2003). Social network interventions use these influence agents as seeds in the dissemination of the intervention.

Social network interventions are characterized by three distinct stages (Valente, 2012). First, the researchers determine and map the relationships within the social network. There are a wide variety of methods used to identify the social network (e.g., self-selection, teacher rating, or expert identification), and the most commonly used method is peer nominations by all network members (Valente & Pumpuang, 2007). Second, the researchers select a small subgroup of individuals based on a selection criterion. For example, they might select those individuals identifying themselves as opinion leaders or advocates of the targeted health-related behavior. A more valid and reliable means for identifying influence agents is peer nominations: participants nominate peers by answering certain sociometric questions (Valente & Pumpuang, 2007). Individuals who hold the most central places are then selected as influence agents (Freeman, 1978; Valente & Pumpuang, 2007). Centrality has multiple definitions (Borgatti, 2005, 2006), but in practice researchers most often select the individuals who received the most nominations (*in-degree* centrality) from their peers (Valente & Pumpuang, 2007). Third, the influence agents are used as the seeds for spreading the intervention among the social network. Usually, the influence agents are taught how they could promote the targeted behavior within their social network (Valente, 2012).

'A Stop Smoking In Schools Trial' (ASSIST) is one of the most widely known large-scale social network interventions (Campbell et al., 2008; Starkey, Audrey, Holliday, Moore, & Campbell, 2009). In ASSIST, adolescents nominated classmates by answering five questions. The top 17.5% of the nominated males and females in each social network were identified as influence agents and were trained in providing information, communication skills, and personal development. In the 10 weeks that followed, the influence agents were asked to have informal conversations with peers from their school to encourage smoking cessation (Starkey et al., 2009). This intervention proved to be an effective way to reduce the prevalence of smoking in adolescents, both immediately after the intervention and also two years later (Campbell et al., 2008).

Since the first ASSIST study, a few studies have adopted the social network approach to promote physical activity among adolescents (Bell, Audrey, Cooper, Noble, & Campbell, 2014; Brown et al., 2017; Jong et al., 2018; Owen et al., 2018; Sebire, Edwards, Campbell, Jago, Kipping, Banfield, Kadir, et al., 2016; Sebire et al., 2018). Most of the interventions used peer nominations to select the adolescents with the highest in-degree centrality as influence agents (Bell et al., 2014; Brown et al., 2017; Jong et al., 2018; Sebire, Edwards, Campbell, Jago, Kipping, Banfield, Kadir, et al., 2016; Sebire et al., 2018) and held intensive face-to-face training sessions to teach the influence agents how they could promote the behavior within their social network (Bell et al., 2014; Brown et al., 2017; Jong et al., 2018; Owen et al., 2018; Sebire, Edwards, Campbell, Jago, Kipping, Banfield, Kadir, et al., 2016; Sebire et al., 2018). Two of these studies focused on adolescent females only (Owen et al., 2018; Sebire, Edwards, Campbell, Jago, Kipping, Banfield, Kadir, et al., 2016; Sebire et al., 2018). All studies, apart from that by Bell et al. (Bell et al., 2014), successfully increased the average physical activity in the targeted social networks.

## This Dissertation

The aforementioned social network interventions relied heavily on the design decisions of ASSIST (Campbell et al., 2008; Starkey et al., 2009), and used methods that were labor-intensive for all the parties involved (i.e., the participants, the schools, and the researchers). In social network interventions, numerous decisions in the design of the intervention have to be made (e.g., how to determine the social network, how to select the influence agents, and what the influence agents are supposed to do). While defensible choices were made by the ASSIST project members, there is little understanding of the advantages and disadvantages of these decisions in general. For example, are the in-degree central participants in a classroom the most effective in spreading healthy behaviors or are intensive face-to-face training sessions required to teach influence agents how to promote physical activity? Furthermore, there is no existing evidence that a social network intervention is more effective than a more traditional type of intervention (i.e., a mass media intervention in which large target audiences are addressed by standardized messages). In short, there is a gap in the scientific knowledge of how to design effective social network interventions and of whether a social network intervention is more effective than a more traditional mass media intervention.

Therefore, the aim of this dissertation was to understand, test and improve social network interventions that promote physical activity among adolescents. In order to create effective social network interventions and to extend the literature, the three stages of a social network intervention were addressed. For each stage, one specific gap in the scientific literature was investigated. First, we looked at the *mapping* stage by comparing networks identified by peer nomination methods to networks identified using more automated and unobtrusive ways to measure relationships in social networks. Second, we investigated the stage of *selecting* influence agents by comparing the effectiveness of influence agents who were selected based on three measures of network centrality (in-degree, betweenness, and closeness). Third, we explored how to improve the *training* of the influence agents, by implementing online training for them and asking them to create vlogs about physical activity. In addition, we compared the effectiveness of a social network intervention to a mass media intervention. All the performed studies were part of the *MyMovez* project.

## *MyMovez* Project

The *MyMovez* project is a large-scale project that focuses on the social environment of adolescents (aged between 9 and 15 years) and three important health-related behaviors: nutrition, media use, and physical activity (Bevelander et al., 2018). In the project, participants received the *Wearable Lab*: a smartphone with a research application (app) and a wrist-worn accelerometer. On the *MyMovez* app, the participants received daily questionnaires (e.g., questionnaires, peer nominations, or experience sampling questions), were able to create a personalized avatar, could play a puzzle game, and could use the *Social Buzz*. The *Social Buzz* is a social platform in which participants could chat with the researchers, post messages on the class message board and have one-on-one chats with classmates. The research smartphones also served as beacons for other *MyMovez* smartphones. That is, the research smartphones detected other smartphones that were within Bluetooth range (approximately 10 meters) every 15 minutes of the day. This resulted in an unobtrusive measure of peer interactions within the *MyMovez* project, named the *proximity network*.

## Outline of the Chapters

This dissertation reports on four empirical studies that are reflected in the next four chapters (chapters 2-5). The content of the chapters is equivalent to papers that have been published, or are under review for publication, in scientific journals. The four empirical chapters are briefly introduced below, and the aims of each are explained. The chapters are structured based on the three stages of a social network intervention: mapping (chapter 2), selecting (chapter 3), and training (chapters 4 and 5). The last chapter (chapter 6) discusses the results of the empirical studies and provides implications for research and practice.

**Chapter 2: Comparing the Measurement of Different Social Networks: Peer Nominations, Online Communication, and Proximity Data.** Chapter 2 describes a study that investigated the *mapping* stage of social network interventions. The aim of the study was to compare the three types of social networks (nominated, communication, and proximity networks), and validate the proximity and communication networks in reference to the nominated network based on sex segregation and the effect of the physical activity of affiliating peers on the physical activity of adolescents. Generally, social network studies use questionnaires in which participants nominate their peers by answering a number of questions (e.g., “With whom do you spend time during the breaks?”). In the *MyMovez* project, two additional types of social networks were measured: a communication network and a proximity network. The communication network was based on the online messages of the participants on the *Social Buzz* platform. The proximity network was based on Bluetooth connections between the smartphones of the participants.

We created the social networks for two samples: a sample of the first year of the *MyMovez* project (25 classrooms, $N = 444$) and a sample of the third year of the *MyMovez* project (43 classrooms, $N = 774$). The accuracy, stability, and overlap of the different types of social networks were assessed. In addition, the study investigated the effect of physical activity of affiliating peers on the physical activity of adolescents based on the three different networks and compared the predictive value of the networks.

**Chapter 3: Simulated Social Network Interventions That Promote Physical Activity: Who Should be the Influence Agents?** Chapter 3 focuses on the second stage (selecting) of social network interventions. The aim of the study (van Woudenberg et al., 2019) was to test which influence agents are most effective in spreading an intervention message in a social network intervention. The chapter describes a study that investigated different criteria for selecting the influence agents and tested the most effective set of influence agents within simulated social network interventions. The study used the data from 26 classes in the first year of the *MyMovez* project ($N = 460$, 52% male, $M_{age} = 10.81$, $SD_{age} = 1.28$). For each class, simulations were conducted for five different hypothetical interventions that differed in the criterion used to select the influence agents. More specifically, the study had five conditions with influence agents were selected based on their *in-degree centrality*, *betweenness centrality*, *closeness centrality*, *random selection*, or a *control* condition with no influence agents.

**Chapter 4: A Randomized Controlled Trial Testing a Social Network Intervention That Promotes Physical Activity Among Adolescents.** Chapter 4 focuses on the third stage (training) of social network interventions. The aim of the study (van Woudenberg et al., 2018) was to test the effectiveness of a social network intervention in which the influence agents were trained via online training on the research smartphone. The chapter describes a randomized controlled trial that tested the effectiveness of a social network intervention that promoted physical activity. In the study, 11 classes from one secondary school ($N$ = 190, 46% male, $M_{age}$ = 12.17, $SD_{age}$ = 0.50) were randomly allocated to a social network intervention or a control condition. In the social network intervention, participants nominated peers by answering a number of sociometric questions, and the top 15% of the participants were selected as influence agents (based on closeness centrality). Subsequently, the influence agents received training on their research smartphones on how to promote physical activity in their classrooms.

**Chapter 5: Testing a Social Network Intervention using Vlogs That Promotes Physical Activity among Adolescents: a Randomized Controlled Trial.** Chapter 5 again focused on the third stage (training) of social network interventions. The aim of the study was to investigate the additional benefit of adopting a social network approach rather than a mass media intervention. The chapter describes an experiment that compared the effectiveness of a social network intervention to a mass media intervention and no intervention. In the study, 26 primary and secondary school classes ($N$ = 446, 47% male, $M_{age}$ = 11.35, $SD_{age}$ = 1.34) were randomly allocated to one out of three conditions: a social network intervention, a mass media intervention or no intervention. In the social network intervention, 15% of the participants were selected as *influence agents* based on peer nominations. The influence agents created vlogs about physical activity. During the intervention period, participants were able to view the vlogs on a smartphone. In the mass media intervention, participants were exposed to vlogs made by unfamiliar peers (i.e., the vlogs of the social network intervention). The control condition did not receive vlogs about physical activity.

**Chapter 6: General discussion.** The last chapter of this dissertation aims to provide a short overview, to merge the results of the performed studies and to discuss how these results fit within current theories. The general limitations of this dissertation and the *MyMovez* project are then discussed. The dissertation ends by suggesting implications for society and practice.

Chapter 2

# Comparing the Measurement of Different Social Networks: Peer Nominations, Online Communication, and Proximity Data

This chapter is in review as:

Van Woudenberg, T.J., Bevelander, K.E., Burk, W.J., Smit, C.R., Buijs, L., & Buijzen, M. (n.d.). Comparing the Measurement of Different Social Networks: Peer Nominations, Online Communication, and Proximity Data. *Network Science*.

## Abstract

### Background

Technological progress has enabled researchers to use new unobtrusive measures of relationships between actors in social network analysis. However, research on how these unobtrusive measures of peer connections relate to traditional sociometric nominations is scarce. Therefore, the current study compared traditional peer-nominated networks with more unobtrusive measures of peer connections: Communication networks that consist of instant messages in an online social platform, and proximity networks based on smartphones' Bluetooth signals that measure peer proximity. The three social network types were compared in their coverage, stability, overlap, and criterion validity (i.e., sex segregation, peer influence on physical activity).

### Method

Two samples were derived from the *MyMovez* project: a longitudinal sample of 444 adolescents who participated in the first three waves of the first year of the *MyMovez* project (Y1; 51% male; $M_{age}$ = 11.29, $SD_{age}$ = 1.26), and a cross-sectional sample of 774 adolescents that participated in fifth wave in the third year (Y3; 48% male; $M_{age}$ = 10.76, $SD_{age}$ = 1.23). In the project, all participants received a research smartphone and a wrist-worn accelerometer for one or three weeks. On the research smartphone, participants received daily questionnaires such as peer nomination questions (i.e., nominated network). In addition, the smartphone automatically scanned for other smartphones via Bluetooth signal every 15 minutes of the day (i.e., proximity network). In the Y3 sample, the research smartphone also had a social platform in which participants could send messages to each other (i.e., communication network).

## Results

The results show that nominated networks provided data for the most participants compared to the other two networks, but in these networks participants had the lowest number of connections with peers. Nominated networks showed to be more stable over time compared to proximity networks. That is, more connections remained the same in nominated networks than in proximity networks over the three waves of Y1. The overlap between the three networks was rather small, indicating that the networks measured different types of connections. Nominated and communication networks were segregated by sex, whereas this was less the case in proximity networks. However, proximity networks explained the most variance in the effect of the physical activity of peers on adolescents' physical activity.

## Conclusion

The communication and proximity network seem promising unobtrusive measures of peer connections and are less of a burden to the participant compared to a nominated network. However, given the structural differences between the networks and the number of connections per wave, the communication and proximity networks should not be used as direct substitutes for sociometric nominations and researchers should bear in mind what type of connections they wish to assess.

Keywords: social networks, Bluetooth, nominations, communication, proximity, adolescents, physical activity

## Background

In social network analysis, the majority of studies have relied on self-reported nominations by participants (Eagle, Pentland, & Lazer, 2009; Wasserman, 1994). Usually, the nomination process involves asking participants to select or rank peers based on one or multiple questions. For example, “Who are close friends?” (de la Haye et al., 2011) or “Who do you look up to [in your class]?” (Campbell et al., 2008). Participants are either free to nominate as many classmates as they prefer, or are restricted to a limited number. However, asking participants about their relationships with peers has some disadvantages.

First, a common problem is non-response (De Lange, Agneessens, & Waege, 2004). Non-response can be caused by a lack of time or motivation of the participant to provide the answers. In social network analysis non-response is especially problematic because each missing nomination brings about an additional gap in the social network. That is, the missing data do not only relate to the participant that nominates, but also to the participant who would otherwise be nominated (De Lange et al., 2004).

Second, peer-nomination or self-reporting could lead to social desirability and recall biases (Van de Mortel, 2008). For example, participants could underreport relationships with socially undesirable peers or overestimate interactions with participants who have a strong presence in the social network.

Third, participants can have different interpretations of the questioned concept (Marin & Hampton, 2007). For example, adolescents might differ in their interpretation of what a friendship is, as indicated by an often observed finding that not all friendships are reciprocal by default (Hartup, 1996). That is, person A would interpret person B as a friend, but person B does not nominate person A as a friend.

Technological progress has enabled researchers to measure peer relationships without relying on peer nominations. For example, existing data of relationships (e.g., social media messages; Garton, Haythornthwaite, & Wellman, 1997), or unobtrusive measures of interactions (proximity based on location data; Cho, Myers, & Leskovec, 2011; Li & Chen, 2009), could be used to infer relationships between participants. However, it is unknown how these new types of measurement relate to the gold standard of sociometric nominations. Therefore, the current study has investigated three types of social networks: A *peer-nominated network* based on self-reported relationships by adolescents, a *proximity network* that exists of connections between Bluetooth devices, and a *communication network* that exists of connections between senders and receivers of online instant messages. The aim of this study was to compare the three types of social networks and validate the proximity and communication network in reference to the nominated network based on sex segregation in the networks and the role of the social networks in relation to physical activity in adolescents.

### Communication Network

A small line of research has explored methods to gather peer interactions by looking at mediated communication (Garton et al., 1997), such as phone conversations (e.g., Aiello, Chung, & Lu, 2000; Onnela et al., 2007), e-mail (e.g., Ebel, Mielsch, & Bornholdt, 2002; Kossinets, 2006), or online social platforms such as Facebook (e.g., Del Vicario, Zollo, Caldarelli, Scala, & Quattrociocchi, 2017; Wilson, Sala, Puttaswamy, & Zhao, 2012) and Twitter (e.g., González-Bailón, Wang, Rivero, Borge-Holthoefer, & Moreno, 2014; Takhteyev, Gruzd, & Wellman, 2012). Online social networks can be established based on online connections (e.g., friends on Facebook or followers on

Twitter) or online interactions (e.g., messages sent in WhatsApp). Using online communication as a measure of connections for social network analysis involves some challenges. For example, there is a difference between online and offline relationships (Subrahmanyam, Reich, Waechter, & Espinoza, 2008). The quality of online and offline friendships differs (Chan & Cheng, 2004) and the most important peers online are not the most important peers offline by default (Subrahmanyam et al., 2008). In addition, online social networks express different network properties than offline social networks (Wilson et al., 2012). For example, online social networks are less centralized around a few influential individuals who ensure that all peers are more closely connected in a network. As a result, “small-world” properties (the principle that individuals are all linked by short chains of acquaintances) are less present in online social networks than in offline social networks (Wilson et al., 2012). Wilson, Sala, Puttaswamy, and Zhao argue that online interactions (e.g., online conversations) as a more accurate representation of meaningful peer connections on social networks (Wilson et al., 2012). In other words, online interactions with peers (e.g., the number of messages between peers) in a network seem more meaningful than the existence of an online connection (e.g., being a friend on Facebook). An additional benefit of using the interactions is that the network is more specific because it has the ability to disentangle more and less active relationships by looking at the number of interactions between peers. However, it is unknown how these online interactions relate to offline nominations.

### Proximity Network

Another emerging line of social network research has used GPS data to construct location-based social networks (Cho et al., 2011; Li & Chen, 2009). Based on GPS data, researchers can infer whether people are in the same location, and thus are in close proximity of each other. Inspired by this approach, we designed an objective, continuous and easy-to-use measure of social interactions by using Bluetooth technology. By using Bluetooth connections, peer proximity can be measured multiple times per day. Moreover, it allows gathering data without storing sensitive location data that is traceable to the participants. To our knowledge, no previous studies have used Bluetooth assessments as a measure of peer proximity in social network analysis. Therefore, we developed a measure of peer proximity based on beacon technology (a device that sends out Bluetooth signals that are to be detected by smartphones). We extended the beacon concept by using smartphones as mobile beacons to be detected by other smartphones. This way, the proximity network was able to capture a network of smartphones that were within Bluetooth range, irrespective of their physical location. The proximity network was programmed to scan for other devices multiple times per day, resulting in multiple connections per day.

## Approach and Hypotheses

In sum, the current study aimed to compare the three types of social networks (i.e., nominated, communication, and proximity), and validate the communication and proximity network in reference to the nominated network. More specifically, we compared the three types of networks in terms of coverage, stability, and overlap between networks. The coverage was assessed by looking at how many participants provided data for the social network, and how many connections were established between peers. The stability was assessed by looking at the ratio of connections within a network that remained over time. The overlap between networks was assessed by pairwise comparisons, looking at the ratio of connections that were present in both networks compared to the connections that were only present in one of the two networks.

We hypothesized that (H1) the most participants would be included in the proximity network because no additional effort is required of the participants, and the least participants would be included in the communication network because not all participants would make use of the social platform. Second, (H2) we hypothesized that more connections would be measured in the communication and proximity network because these connections could be measured multiple connections per measurement period. Third, we hypothesized that (H3) the nominated network would be a more stable network than the other two network, because it measures a more solid type of relationship that will change less over time, while the communication and proximity network captures interactions that could vary more from week to week. Lastly, we did not have any specific expectations about the overlap between the different networks. Therefore we explored the overlap between the three types of networks as a research question.

In addition, this study tested the criterion validity of the communication and proximity networks in reference to the nominated network by investigating the often observed sex segregation in the networks and by investigating the effect the behaviors of peers on individual's behavior (i.e., physical activity). Previous studies have shown that adolescents' social networks based on nominations are segregated by sex (Camarena, Sarigiani, & Petersen, 1990; McPherson, Smith-Lovin, & Cook, 2001; Mercken, Snijders, Steglich, & de Vries, 2009). That is, males tend to nominate other males and females tend to nominate other females more often. We hypothesized that (H4) the nominated network and the communication network were highly segregated because it is more likely that adolescents spend time, or communicate with others of the same sex. However, we expected that the proximity network would be less sex-segregated because being in close proximity is a less deliberate decision than nominating or talking to peers. Therefore, connections in the proximity network are less bounded by cultural conventions or friendship preferences.

The criterion validity of the communication and the proximity networks in reference to the nominated network was investigated by testing whether the physical activity of affiliating peers in the three networks predicted the physical activity of adolescents. More specifically, the last set of analyses investigated the effect the peers in the three social networks had on adolescents' physical activity. We looked at physical activity of adolescents because previous studies showed pervasive similarity effects in the physical activity of adolescents and peers (Ali et al., 2011; Efrat, 2009; Fitzgerald et al., 2012; Macdonald-Wallis et al., 2011; Sawka et al., 2013; Schaefer & Simpkins, 2014; Schofield et al., 2007). This means that the physical activity of adolescents is predicted by the physical activity of affiliating peers. We expected that this effect would be present in all three networks. But because of the differences in specificity between the networks, we expected that (H5) the peer influence of adolescents' physical activity could be modeled more accurately in the communication the proximity networks than in the nominated network.

## Methods

### Participants

The study used data of the *MyMovez* project (Bevelander et al., 2018), which investigated adolescents' health behaviors (ie., nutrition, media use, and physical activity) and their social networks for three years. The first year (data collection waves 1, 2, 3) and the second year (wave 4) marked the first phase of the project in which the health behaviors of adolescents were monitored without intervening. The third-year (waves 5, 6, 7) marked the second phase of the project in which four different types of interventions were tested to promote either water consumption or physical activity.

In the course of the project, participants and classrooms were allowed to enter and drop out of the sample. As a result of the different phases of the project, the number of included classrooms and participants in the sample varied between the years. In addition, a social platform was added to the research application in the third year. Therefore, the current study used two distinct samples. For both samples, we used the inclusion criterion that at least 60% of the classrooms had to participate in the project to obtain representative samples of the social networks within each classroom (Marks, Babcock, Cillessen, & Crick, 2013).

**Y1 sample**The longitudinal Y1 sample contained the first three waves in the first year of the project. Each wave contained a week of measurement with an eight-week time interval in between February-March 2016 (W1), April-May 2016 (W2), and May-June 2016 (W3). The Y1 sample included 444 participants (51% male, $M_{\text{age}}$ = 11.29 years, $SD_{\text{age}}$ = 1.26) in 25 classes.

**Y3 sample**The cross-sectional Y3 sample contained the data of the fifth wave of the project, which was assessed in the third year (February-March 2018). This year, new classrooms were added to the project because this wave served as the baseline measure for the project's interventions. The Y3 sample included 774 participants (48% male, $M_{age}$ = 10.76 years, $SD_{age}$= 1.23) in 43 classes. Because of the set up the project, 11 classrooms (*n* = 190; 18% of all participants) were part of both the Y1 and Y3 samples. For an overview of the included social networks per sample see Table 1.

## Procedure

Parents/legal guardians of the adolescents in the participating classrooms received information about the project and could enroll their children by providing active consent. For more details see Bevelander et al. (2018).

Table 1
*Overview of the measured social network in the two samples.*

| | Y1 | | | Y3 |
|---|---|---|---|---|
| | Wave 1 | Wave 2 | Wave 3 | Wave 5 |
| Nominated network | Y1 sample | Y1 sample | Y1 sample | Y3 sample |
| Proximity network | Y1 sample | Y1 sample | Y1 sample | Y3 sample |
| Communication network | - | - | - | Y3 sample |

On the first day of the project, participants received instructions on the procedure and the use of the *MyMovez Wearable Lab*: A smartphone with a tailor-made research application and a wrist-worn accelerometer. Before receiving the *Wearable Lab*, participants signed for assent to participate in the project. Subsequently, participants were instructed to wear the accelerometer at all times (it was water-resistant) and take the smartphone with them as much as possible. The smartphone was equipped with a research application by which daily questionnaires were administered (e.g., peer nomination questions). As of wave 5, the app contained a social platform in which the participants could communicate with each other. The smartphone also connected to the accompanying accelerometer and other research smartphones via Bluetooth.

## Measures

***Nominated network.*** Participants received a sociometric question (i.e., “With whom do you hang out during the breaks?”) on a random moment of the day during the measurement week. The app provided a list of all classmates as well as lists of students from the other participating classrooms of that school. In addition, participants could search for names in the provided search field and were required to nominate at least one peer from the same grade (self-nominations were impossible). Each nomination resulted in a connection (*edge*) going from the nominee (*ego*) to the nominated participants (*alter*). In this study, nominations outside of the same classroom were excluded.

***Communication network.*** The communication network was derived from the *Social Buzz*, the social platform that was incorporated in the *MyMovez* application in the third year. In the *Social Buzz*, participants could post messages on the message board of the classroom or send 1-on-1 messages to classmates. The latter type of message was used to create the communication network. For every message that a participant (*ego*) sent to a classmate (*alter*), the communication network would assign an edge from the sender to the receiver. Because multiple messages between participants could be sent during one measurement period, the communication networks could consist of multiple ties between participants. Participants sent between 1 and 221 messages per day ($M$ = 16.53, $SD$ = 28.99). Similar to the nomination network, only edges within the same classroom were included.

*Proximity network.* The smartphones scanned for other research smartphones every 15 minutes between 7:00 AM and 7:30 PM, except school hours (when the participants were forced to be in close proximity). One scan existed of three bursts. For every time that two smartphones were within Bluetooth range (approximately 10 meters or 32 feet) for two or more bursts, the proximity network would assign a connection (*edge*) between the two participants. The edge was assigned from the smartphone of the participant (*ego*) to the peer (*alter*). Due to a small time difference between smartphones, not all edges were registered at the same time point and not all connections were reciprocal by default. In fact, 92% of all edges in Y1 and 100% of all edges in Y3 were reciprocal. Again, multiple edges per day could be assigned between two participants. The first and last days of the measurement were excluded because these days the smartphones were handed out by the researchers or the participants had to hand in the materials. As can be seen in Figure 1, most of the edges were accumulated before and after school hours and during the breaks (around 10:00 and 12:00 am). Again, only nominations within the same classroom were included.

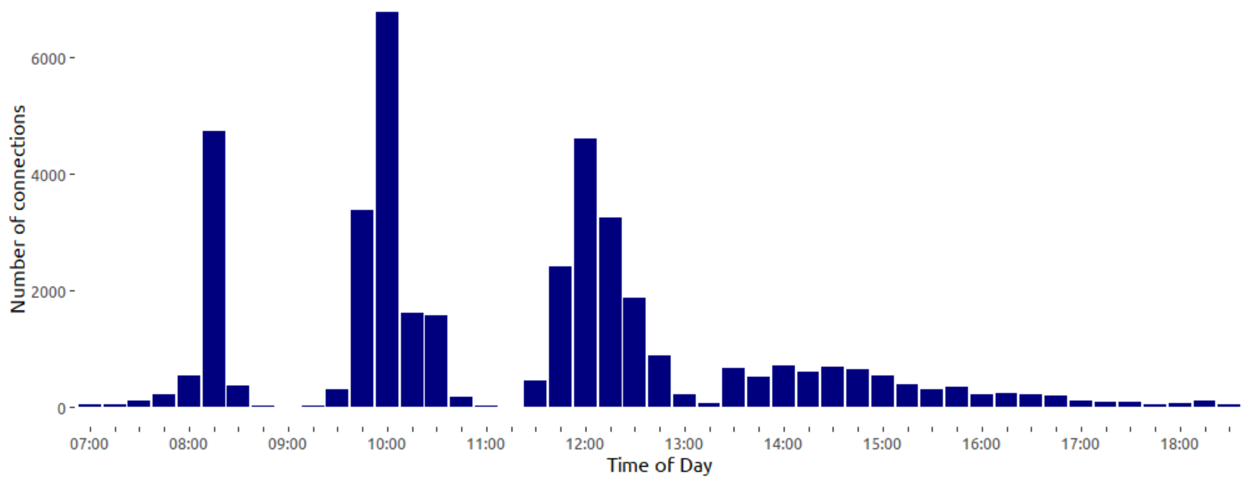


*Figure 1*. The number of Bluetooth connections per 15 minutes of the day.

***Physical activity.*** The wearable accelerometer (Fitbit Flex®) measured the number of steps per day. Incomplete days (<1,000 steps or <1,440 minutes [24 hours]) of measurement were excluded from the analyses, to ensure that only days were included on which the device was worn and the battery was not empty. Also, the first and the last days were excluded from the analyses. When participants had less than three days of observed data but at least one day of data, single multilevel predictive mean matching imputation (Van Buuren, 2011) was used to generate imputed physical activity data (based on 500 iterations). The data points were imputed based on other physical activity data of the participant, class, school, day of the week, sex, age, BMI, weather conditions of that day, and psycho-social measures of the participant (i.e., athletic competence, attitude, enjoyment, intentions, motivation, and subjective norms). When participants had no data for the entire wave, no physical activity data were imputed. On average, participants accumulated 9,642 (*SD* = 3,829) steps per day.

## Strategy of Analysis

Based on the sociometric nominations, communication and Bluetooth data, social network graphs were created by using the Igraph package (Csardi & Nepusz, 2005) in RStudio (2015). For each sample and each type of network, one large graph was created. This resulted in five graphs: a nominated network for the Y1 sample and Y3 sample, a communication network for the Y3 sample, and a proximity network for the Y1 sample and Y3 sample. All analyses were performed on the Y1 and Y3 samples separately. Figure 2 shows an example of three graphs based on the three different network types for one of the classrooms.

First, the coverage was evaluated by looking at the number of participants and the number of nominations for each of the social networks per wave. The differences between the number of included participants and the number of edges were tested by using mixed-effects models (Bates, 2010). Next, the stability of the nominated and the proximity network over the waves in Y1 was assessed by looking at the amount of change in connections between the waves. This was done on the bases of the Jaccard index: the number of edges that were present in one time point and the next time point, divided by the total number of edges in the two time points (Hamers, 1989). Previous research has shown that in adolescents' nominated social networks, between 50% and 65% (Jaccard index between .50 and .65) of the friendship connections are stable over time (Berndt, Hawkins, & Hoyle, 1986; Berndt & Hoyle, 1985). In addition, the Jaccard index was also used to assess the overlap between the different networks in Y1 and Y3.

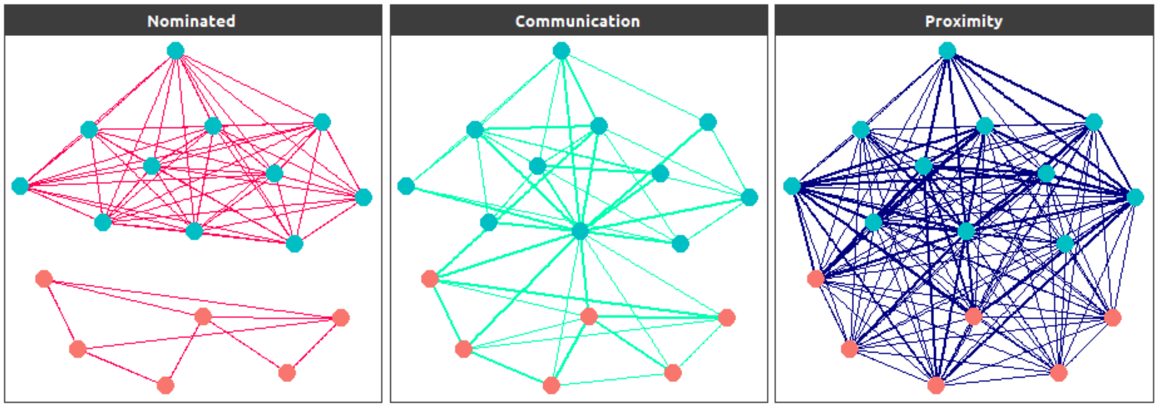


*Figure 2*. Example graph of one classroom for the three networks.
*Note*. The dots represent the adolescents (blue is male, pink is female). The lines represent the connections between adolescents. The thickness of the lines indicates the number of edges per wave.

Lastly, we validated the communication and the proximity networks in reference to the nominated network. First, we investigated sex segregation in the three networks by looking at the ratio of same-sex connections in the networks. The differences between the ratio of same-sex connections were tested by using mixed-effects models (Bates, 2010). Second, we calculated an average of physical activity of the peers, based on the networks. More specifically, the average physical activity of peers that shared a connection with the participants was calculated per wave for the nominated network, and per day for the communication and proximity networks. Mixed-effects models (Bates, 2010) were run with the adolescents' physical activity as the outcome variable, predicted by sex, age and average physical activity of affiliating peers in the three networks. Random intercepts per participant and per wave were added to control for clustering of data. For each network, a separate mixed effect model was run. The last model included all three peer physical activity of the three networks. Based on this model, the partition of variance of the physical activity of affiliating peers variable was determined by using the vegan package (Oksanen et al., 2019).

# Results

## Coverage

The first set of analyses investigated the coverage of the three networks. More specifically, we looked at how many participants and how many connections were included in the social networks in Y1 and Y3.

**Y1 sample.** In total 444 participants, in 25 classes, were included in the longitudinal Y1 sample. Of those participants, 392 (88%) filled out the nomination question in at least one of the three waves. For 370 participants (83%) proximity data were available for at least one of the waves. On average, more participants filled out the nomination question per classroom per wave ($M = 13.6$), than participants providing proximity data per classroom per wave ($M = 10.1$). A mixed-effects model with a random intercept per wave and classroom showed that this difference was statistically significant, $b = 3.49$, $SE = .50$, $p < .001$. For an overview of the coverage per wave per classroom see Appendix A.

The participants in the Y1 sample provided a total of 7,919 edges in the nominated network and 9,585 in the proximity network. Despite fewer participants providing data for the proximity network, the proximity network provided more edges (3,195, range: 1,614 - 4,814) than the nominated network (2,640, range: 2,499 - 2,735) per wave. Looking at the classroom level, participants provided equal amounts of nominated edges ($M = 106$) and proximity edges ($M = 128$) per wave. A mixed-effects model with a random intercept per wave and classroom showed that there was no significant difference between the number of edges in the two networks, $b = 22.21$, $SE = 15.70$, $p = .16$.

**Y3 sample.** In the cross-sectional sample, 774 participants, in 43 classrooms, were included. Of those participants, 723 (93%) filled out the nomination question. For 598 participants (77%) proximity data was available and for 518 participants (67%) communication data was available. A mixed effects model with a random intercept per classroom showed that on average, more participants ($M = 16.74$, $SD = 6.00$) filled out the nomination question per classroom than participants providing proximity data ($M = 13.90$, $SD = 6.66$; $b = 2.84$, $SE = .68$, $p < .001$) and communication data ($M = 12.05$, $SD = 6.40$; $b = 4.70$, $SE = .68$, $p < .001$). For an overview of the coverage per wave per classroom see Appendix B.

The participants in the Y3 sample provided fewer edges in the nominated networks (5,541) than in the proximity networks (16,068) and the communication networks (22,456). A mixed-effects model with a random intercept per classroom showed that per classroom, the participants provided more edges in the communication networks ($M = 522$) than the nominated networks ($M = 129$), $t(126) = 3.33$, $p = .003$, but the number of edges in the proximity networks ($M = 373$) was comparable to the number of edges in the communication networks, $t(126) = -1.28$, $p = .42$, and the number of edges in the nominated networks, $t(126) = 2.07$, $p = .100$.

In short, both samples showed that fewer participants were included in the communication and the proximity networks, than the nominated networks. However, the nominated networks had the lowest number of edges and the communication networks produced the most edges. Only the difference in number of edges between the nominated networks and the communication networks was significant. Therefore, we have found no support for the first hypotheses (H1) that most participants would be included in the proximity network. However, we did find partial support for the second hypothesis (H2) that more connections would be measured in the communication and proximity networks than in the nominated networks.

### Stability

The second analysis investigated the stability of the nominated and the proximity networks over the first three waves. More specifically, we looked at the ratio of connections that was present in two consecutive waves compared to all connections in these two networks. The stability of the social networks could only be assessed in the longitudinal sample (Y1), and therefore the stability of the communication network was not assessed.

In the Y1 sample, some of the classrooms had low coverage of one of the networks in one or multiple waves (see Appendix A). In order to investigate the stability in representative social networks, two subsamples of the longitudinal sample were created. The first subsample included classrooms in which at least 50% of the participants provided data for both networks in wave 1 and 2. The second subsample included classrooms in which at least 50% of the participants provided data for both networks in wave 2 and 3. In both subsamples, classrooms were excluded in which fewer than eight participants provided information for one of the two types of networks. This resulted in subsamples of 16 and 7 classrooms, respectively. The two subsamples were used in the subsequent tests to examine the stability of both types of networks.

To test for the stability of the nominated and proximity networks, the Jaccard index was used to assess the degree of overlap within each network over time. Overall, more than half of the edges in the nominated network were stable from wave 1 to wave

2 (Jaccard index = .56) and from wave 2 to wave 3 (Jaccard index = .59). Around one in four edges in the proximity network was stable from wave 1 to wave 2 (Jaccard index = .26) and from wave 2 to wave 3 (Jaccard index = .28). In addition, the Jaccard indices were calculated per classroom for the two subsamples of the Y1 sample. A mixed-effects model with a random intercept per wave and classroom showed that on average, the Jaccard indices of the nominated network ($M_{W12}$ = .57; $M_{W23}$ = .56) were significantly higher than the Jaccard indices of the proximity network ($M_{W12}$ = .22; $M_{W23}$ = .26), $t(29.15) = 10.00$, $p < .001$ and $t(8.77) = 4.76$, $p = .001$. This means that in both subsamples, the stability of the nominated networks were similar to previous research (Chan & Poulin, 2007) and more stable over time than the proximity networks. In contrast, the stability of the proximity is rather low, indicating more variability in the networks between the waves. Therefore, we found support for the third hypothesis (H3) that the nominated network would be more stable over time than the proximity network.

### Overlap

The third set of analyses investigated the overlap between the three social networks. More specifically, we looked at the ratio of connections that is shared with another network compared to all connections in two networks.

**Y1 sample.** To assess the overlap between the nominated networks and the proximity networks in the Y1 sample, the Jaccard index was used to express the ratio of edges that was present in both networks. Over the three waves, 1,670 edges were only present in the nominated networks, 1,580 edges were only present in the proximity networks, and 2,276 edges were present in both networks (Jaccard index = .41). This means that 41% of all edges were overlapping in both nominated networks and proximity networks. Also, the number of unique edges of the two networks were comparable, indicating that there was not one network oversampling the other.

However, comparing the two networks per wave separately resulted in less overlap between the two networks, see Table 2. Potentially, subsequent waves added more interactions that were not included in both networks in the first wave, complementing the social networks and thus increasing the overlap between the networks.

Table 2
*The number of unique and shared edges per wave for the nominated and the proximity networks.*

| | Nominated only | Proximity only | Both networks | Jaccard index |
|---|---|---|---|---|
| Wave 1 | 1,446 | 1,448 | 1,059 | .27 |
| Wave 2 | 1,866 | 1,040 | 876 | .23 |
| Wave 3 | 2,187 | 507 | 498 | .16 |

**Y3 sample.** The same Jaccard indices were used to express the overlap between the nominated networks, the proximity networks, and the communications network in the Y3 sample. As can be seen in Table 3, the overlap between the different types of networks was comparable, ranging from 26% to 30% of the edges being present in both networks. Also, a slightly higher Jaccard index was found for the overlap between the nominated networks and the proximity networks in the Y3 sample (.30) compared to the average Jaccard index of the Y1sample (.22).

Table 3
*The number of shared and unique edges for the nomination, communication and proximity networks in year 3.*

| Nominated only | Communication only | Proximity only | Both networks | Jaccard index |
|---|---|---|---|---|
| 3,836 | 1,105 | - | 1,705 | .26 |
| 2,610 | - | 4,209 | 2,931 | .30 |

| | | | | |
|---|---|---|---|---|
| - | 646 | 4,976 | 2,164 | .28 |

What stands out is that the nominated networks and the proximity networks had a high number of unique edges. In addition, the communication networks did not add many edges to the proximity networks (11% of unique edges), which suggests that participants did not have many online conversations with individuals that they hang out with during the breaks or are in close proximity to each other during the day.

### Criterion Validity

The last set of analyses investigated the criterion validity of the communication and the proximity networks against the well-established nominated networks by examining to what extent the segregation of sex in adolescents' nominated networks was reflected in the other networks. Also, we investigated whether the proximity and the communication networks had the same ability to predict the often found social influence of adolescents' behaviors in social networks.

**Sex segregation.** The first test of criterion validity inspected the differences in sex segregation in the networks for the Y1 sample and the Y3 sample.

***Y1 sample.*** In the Y1 sample, 70.18% of the connections in the nominated networks was between same-sex participants. In the proximity networks, only 53.49% of the connections was between same-sex participants. A mixed-effects model with a random intercept per classroom and wave showed that this difference was significant, $b = .19$, $SE = .02$, $p < .001$.

***Y3 sample.*** In the Y3 sample, 75.02% of the connections in the nominated networks was between same-sex participants. This percentage was 62.02% in the communication networks and 53.57% in the proximity networks. A mixed-effects model with a random intercept per classroom showed that only the difference between the nominated and the proximity networks was significant, $b = -.20$, $SE = .03$, $p < .001$. This means that sex segregation was less prevalent in the proximity networks than in the nominated networks, which reproduces the finding in the Y1 sample.

**Effect on physical activity.** The second test of the criterion validity looked at the ability of the networks to predict adolescents health-related behavior (i.e., physical activity) based on the behaviors of connecting peers. More specifically, the average physical activity was taken of peers that had a connection in that wave (for nominated networks) or on that day (for proximity and communication networks). The average physical activity of the affiliating peers was used as a predictor of the physical activity of the adolescents.

***Y1 sample.*** In the Y1 sample, two separate models were run for the nominated networks and the proximity networks, which produced comparable results, showing that adolescents' physical activity was predicted by the average physical activity of the peers with which they shared a connection (see Table 4 and 5).

Second, both peer physical activity variables were entered in one model to test whether the proximity networks explained more unique variance than the nominated networks. The analysis of the partition of variance showed that the two networks both contributed to shared variance ($R^2 = .02$), but also produced a part of individual contribution to the explained variance. The physical activity of alters based on the proximity networks had a slightly larger unique individual contribution ($R^2 = .04$) than the physical activity of alters based on the nominated networks ($R^2 = .02$).

***Y3 sample.*** The same analysis was performed on the Y3 sample. First, three separate models were run for the three types of networks (see Table 6, 7 and 8). The same models were used as before with the exclusion of the random intercept per wave.

What stands out from the models is that in this sample, nominated networks produced a non-significant effect of the physical activity of alters in the network. Potentially, having only one assessment of peer relations is not specific enough to predict the physical activity of adolescents per day.

Table 4
*Standardized estimates of the mixed-effects model for nominated networks.*

| | | $s^2$ | *B* | *SE* | *DF* | t-value | *p* |
|---|---|---|---|---|---|---|---|
| Random | Child | .18 | | | | | |
| | Wave | .07 | | | | | |
| | Day | .01 | | | | | |
| Fixed | (Intercept) | | -.05 | .13 | 5.28 | -.41 | .70 |
| | Sex: male vs female | | .27 | .06 | 302.69 | 3.90 | <.001 |
| | Age | | -.04 | .03 | 301.21 | -1.04 | .30 |
| | Mean steps alters | | .11 | .03 | 764.67 | 3.39 | <.001 |

*Note*. $N$ = 349. Pseudo $R^2_M$ = .04, Pseudo $R^2_C$ = .29

Contrary, the finding of the proximity networks in the Y1 sample was reproduced. Based on the proximity networks, adolescents' physical activity is predicted by peers' physical activity. Also, the communication networks model showed that adolescents' physical activity was predicted by the physical activity of peers with whom they communicated online.

Table 5
*Standardized estimates of the mixed effects model for proximity networks.*

| | | $s^2$ | *B* | *SE* | *DF* | t-value | *p* |
|---|---|---|---|---|---|---|---|
| Random | Child | .19 | | | | | |
| | Wave | .04 | | | | | |
| | Day | .00 | | | | | |
| Fixed | (Intercept) | | -.06 | .10 | 4.97 | -.60 | .57 |
| | Sex: male vs female | | .31 | .06 | 309.09 | 4.66 | <.001 |
| | Age | | -.04 | .03 | 302.47 | -1.30 | .19 |
| | Mean steps alters | | .17 | .03 | 1294.12 | 6.14 | <.001 |

*Note.* $N = 346$. Pseudo $R^2_M = .05$, Pseudo $R^2_C = .28$

Next, the three peer physical activity variables were entered in one model to investigate whether one type of network explained more unique variance than the other networks. The analysis of the partition of variance showed that the three networks contributed to shared variance ($R^2 = .01$) and that the proximity networks and the nominated networks produced a part of the individual contribution to the explained variance (both $R^2 = .01$; See Figure 3). Therefore, we found partial support for the fifth hypothesis (H5) that peer influence could be modeled more accurately in the communication and proximity networks compared to the nominated network.

Despite no individual unique contribution of the communication networks, the communication networks had a shared contribution with the proximity networks to the explained variance that was not explained by the nominated networks. Although these are very small effect sizes, these findings support the idea that the different networks partly overlap, but are also partly unique.

Table 6
*Estimates of the mixed effects model for the nominated network*

| | | $s^2$ | *B* | *SE* | *DF* | *t*-value | *P* |
|---|---|---|---|---|---|---|---|
| Random | Child | .37 | | | | | |
| | Day | .02 | | | | | |
| | | | | | | | |
| Fixed | (Intercept) | | -.04 | .07 | 4.94 | -.60 | .58 |
| | Sex: male vs female | | .28 | .05 | 744.31 | 5.76 | <.001 |
| | Age | | -.08 | .02 | 730.88 | -3.24 | .001 |
| | Mean steps alters | | .01 | .01 | 7922.98 | .97 | .33 |

*Note*. $N = 743$. Pseudo $R^2_M = .03$, Pseudo $R^2_C = .40$

Table 7
*Estimates of the mixed effects model for the proximity network*

| | | $s^2$ | *B* | *SE* | *DF* | *t*-value | *p* |
|---|---|---|---|---|---|---|---|
| Random | Child | .34 | | | | | |
| | Day | .00 | | | | | |
| | | | | | | | |
| Fixed | (Intercept) | | .11 | .04 | 8.42 | 2.86 | .02 |
| | Sex: male vs female | | .29 | .06 | 545.92 | 4.94 | <.001 |
| | Age | | -.04 | .03 | 597.44 | -1.57 | .11 |
| | Mean steps alters | | .17 | .02 | 1244.96 | 7.50 | <.001 |

*Note*. $N = 583$. Pseudo $R^2_M = .07$, Pseudo $R^2_C = .39$

Table 8
*Estimates of the mixed effects model for the communication network*

| | | $s^2$ | *B* | *SE* | *DF* | *t*-value | *p* |
|---|---|---|---|---|---|---|---|
| Random | Child | .28 | | | | | |
| | Day | .01 | | | | | |
| | | | | | | | |
| Fixed | (Intercept) | | .05 | .06 | 5.61 | .91 | .40 |
| | Sex: male vs female | | .39 | .06 | 478.80 | 6.18 | <.001 |
| | Age | | -.08 | .03 | 582.75 | -2.73 | .006 |
| | Mean steps alters | | .06 | .02 | 1209.43 | 2.65 | .008 |

*Note*. $N = 509$. Pseudo $R^2_M = .06$, Pseudo $R^2_C = .34$

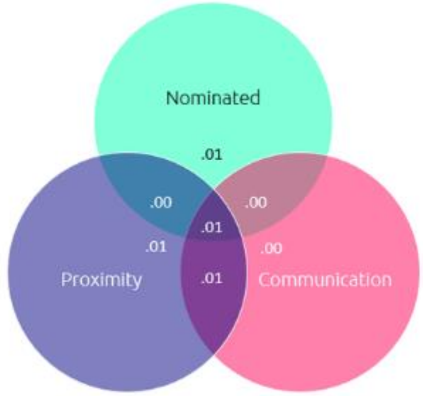


*Figure 3.* Venn diagram of the explained variance of the adolescents' physical activity by the physical activity of affiliating peers based on the three networks.

## Discussion

The current study was the first to compare nominated, communication, and proximity networks. This comparison was made as a first step to investigate the possibilities to use unobtrusive and automatic measures of social relationships, which potentially could be used as substitutes for peer nomination questionnaires. The three networks were compared in the coverage, stability, and overlap of the different types of social networks. In addition, the validity of the communication and the proximity networks in reference to the nominated networks was assessed, by comparing the sex segregation in the networks and how the physical activity of affiliating alters in the social networks predict the physical activity of adolescents. The results showed that the social networks are structurally different from each other. Therefore, neither the communication network, nor the proximity network can be a direct substitute for nominated networks.

More specifically, this study showed that relatively fewer participants provided information for the proximity network compared to the nominated network in both the longitudinal and cross-sectional samples. One explanation is that the participants did not take the smartphone with them all the time and left it in a fixed place where they filled out the questionnaires (e.g., at home). This is supported by our observations in the classrooms when collecting the research materials at the end of each wave. Some participants did not bring the research smartphones to school and told us that their parents did not allow them to take the smartphone outside of their home. Furthermore, the communication network included the lowest number of participants while having the highest number of connections, and the participants who used the online social platform produced more connections than in the other two networks. This means that the social networks based on peer nominations included the most participants, but lacked the specificity of connections per day compared to the social networks based on online communications and Bluetooth connections.

In addition, this study showed that the nominated network was more stable over time than the proximity network. That is, more than half of the connections in the nominated network were present in one wave and in the subsequent wave. Only one in four connections in the proximity network was present in one and in the subsequent wave. This could indicate that the nominated network measured a state of relationship, whereas proximity network measured an event of a relationship. Both types of relationships can be relevant for different types of research questions, making one type of network not more important than the other. The idea that both networks measure different types of relationships is supported by the low overlap between the networks that was observed within the waves. In pairwise comparisons of the networks, on average only one in four connections was present in both the nominated network and the proximity network.

Also, this study investigated the validity of the communication and proximity networks by looking at sex segregation within the networks and the effect of the physical activity of affiliating alters on an individual's physical activity. Our findings showed that in both the longitudinal Y1 sample and the cross-sectional Y3 sample, the proximity network was less sex-segregated than the nominated network. The nominated network and the communication network were similarly sex-segregated. However, looking at the validity of the networks in predicting adolescents' physical activity based on the physical activity of affiliating peers, we observed that the effect was significant in all models, except the nominated network in the cross-sectional Y3 sample. In addition, when multiple networks were put into the same model, the networks shared a portion of the variance with the other networks but also had a portion of the unique explained variance. Overall, the unique explained variance was greatest for the proximity network, which is likely the result of having a more specific (i.e., day-to-day) measure of the peer interactions. Thus, day-to-day assessments of social networks might be a better predictor of adolescents' physical activity than a social network that are only measured once per measurement period.

## Limitations

Because of the novelty of the current study, several limitations should be discussed before drawing conclusions on the differences between the methods for collecting social network data. First, we noticed that participants did or could not always follow our instructions to have the smartphone with them at all times. In addition, no extra steps were taken to double-check whether the Bluetooth was working on all the research smartphones during data collection. As a result, fewer participants may have been included in the proximity network. Future research should explore whether wearables could also be used as beacons for the proximity network. This way, participants wear the beacon at all times and more proximity data will be available per participant. Also, the communication network was derived from the *Social Buzz* in the *MyMovez* app which was not their preferred social app and especially older adolescents already used WhatsApp or Facebook. Future studies should explore how the personal smartphone and social apps of participants could be used to generate social networks of adolescents.

Second, as a validation of the proximity network and the communication network, we looked at the segregation of connections by sex and the relationship of the network with the physical activity of adolescents. Additional measures of network properties, other sociometric questions, or other behaviors can be used to provide a more extensive test of validity. For example, this study used physical activity which seems to have a better fit with networks that capture interactions. However, other types of behaviors (e.g., smoking or alcohol consumption) might suit a nominated network better.

Third, every connection in the proximity network was treated as a relevant connection and we set the threshold for proximity connections at one. So every connection between two participants was included in the analyses. We did not systematically investigate how increasing the threshold would change the network and how this would relate to the nominated network. Also, not all participants provided equal amounts of data. For some, one interaction might be valuable because it is one of only three interactions that day. Yet, if another person has 300 interactions within its classroom, that one connection is only a small fraction of the total interactions and might be less meaningful. Future studies should investigate (personalized) thresholds for when proximity connections are meaningful, for example by basing the threshold on the total amount of connections an individual has within a wave. One study is already looking into optimizing the data of the proximity network and investigating how many days of proximity data are needed to reflect a social network based on nominations (Simoski et al., 2019).

## Conclusion

Altogether, the findings of this study indicate that nominated, communication, and proximity networks capture distinct types of connections between adolescents. The nominated networks is a stable network that includes relatively the most participants, but lacks the specificity of day-to-day measures and do not distinguish in the number of interaction in the relationship. Therefore, the nominated network can be seen as a solid type of relationships between participants that is least likely to fluctuate between days. The communication network is a very specific social network that includes many interactions per wave but includes the lowest number of participants. However, the communication network does not add many unique edges or unique explained variance. Therefore, the communication network can be seen as a collection of events within offline relationships. That is, this network could be used to quantify interactions as a measure of quality in nominated relationships. The proximity network measures many interactions per wave but includes fewer participants than the nominated network. The results indicate that the proximity network measures a different type of relationship, which can be considered as events. Therefore, this network is most useful when applied to behaviors that vary heavily from day to day. Also, the proximity network might reflect a broader range than deliberate peer interactions and, therefore, has a better fit with the many ways in which adolescents are influenced by peers. This idea is corroborated by the result that adolescents' physical activity is best explained by their peers' physical activity based on the proximity network.

With this in mind, the communication and proximity networks seem promising unobtrusive measures of peer interactions, with the additional benefit of multiple connections between participants within a measurement period. However, given the structural difference between the networks, the communication and proximity networks should not be used as a direct substitute for sociometric nominations. Researchers studying social networks should bear in mind what type of connections they wish to assess and use the best fitting network or combination of networks.

Chapter 3

# Simulated Social Network Interventions That Promote Physical Activity: Who Should be the Influence Agents?

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## Abstract

### Background

Social network interventions targeted at children and adolescents can have a substantial effect on their health-related behaviors, including physical activity. However, designing successful social network interventions is a considerable research challenge. For example, it is unclear which criteria should be used to select influence agents that serve as successful promoters of the targeted health behavior. Investigating this question through field experiments is a time consuming and infeasible process. Fortunately, advancements in computer science enable us to simulate these complex processes. In this work, we rely on social network analysis and agent-based simulations in order to better understand and capitalize on the complex interplay of social networks and health behaviors. More specifically, we investigate which criteria for selecting influence agents can be expected to produce the most successful social network health interventions. To test the differences between the selection criteria, a computational model is used to simulate different social network interventions and to observe the intervention's effect on the physical activity of primary and secondary school children within their classroom.

### Methods

We used a previously validated agent-based model to understand how physical activity spreads in social networks and who is influencing the spread of behavior. Based on the observed data of 460 participants collected in 26 school classes, we simulated multiple social network interventions ranging in selection criteria for the influence agents (i.e. *in-degree*, *betweenness* and *closeness centrality* and *random influence agents*) and a control condition (i.e. *no intervention condition*). Subsequently, we investigated

whether the detected variation of an intervention's success within classrooms could be explained by structural characteristics of the social networks (i.e. network density and network centralization).

## Results

The one-year simulations showed that the social network interventions were more effective compared to the control condition, $\beta = .30$, $t(100) = 3.23$, $p = .001$. In addition, the social network interventions that used a measure of centrality to select influence agents outperformed the random influence agent intervention, $\beta = .46$, $t(100) = 3.86$, $p < .001$. Also, the closeness centrality condition outperformed the betweenness centrality condition, $\beta = .59$, $t(100) = 2.02$, $p = .046$. The anticipated interaction effects of the network characteristics were not observed.

## Conclusions

Social network interventions can be considered a viable and promising intervention method to promote physical activity. We demonstrated the usefulness of applying social network analysis and agent-based modeling as part of the social network interventions' design process. We emphasize the importance of selecting the most effective influence agents and provide a better understanding of the role of network characteristics on the effectiveness of social network interventions.

Keywords: physical activity; social network intervention; influence agents; network centrality; agent-based models; simulations

## Introduction

There has been an increasing interest in the use of social network interventions to promote health relate behaviors. Social network interventions are based on the diffusion of innovations theory and capitalize on interpersonal influence to promote and catalyze desired behavioral changes (Valente & Davis, 1999). A few studies have used social network interventions to promote health behaviors in school settings (Valente, 2012). For example, the ASSIST study trained influence agents to encourage peers not to smoke in secondary schools (Campbell et al., 2008). Other studies have trained influence agents to stimulate peers to increase health behaviors such as drinking more water (Smit, de Leeuw, Bevelander, Burk, & Buijzen, 2016) or being more physically active (Sebire et al., 2017; van Woudenberg et al., 2018).

One of the most important assumptions of social network interventions is that some peers act as role models and can be important determinants of the behavior of the group (Valente & Fosados, 2006). By involving these important peers in the intervention, they can be used as an example for the rest of the social network, or ensure that the intervention message spreads among the individuals in the social network. In such an intervention, the health behavior is disseminated among the classmates through their network ties (Rogers, 2003) and this will lead to less resistance. Therefore, in most social network interventions, a subset of participants is selected as influence agents to initiate the diffusion of an idea or behavior. The influence agents can volunteer or be appointed by researchers, but many social network interventions rely on peer nominations to determine the influence agents (Valente & Davis, 1999). Participants nominate peers on a number of questions (e.g. “Who are your friends?”). Based on these nominations, 10% to 17.5% of individuals are approached to become influence agents (Valente & Davis, 1999). The influence agents are trained to adopt and spread a new or improved health behavior, or informally diffuse the intervention messages within their social network. Yet it is unclear which individuals in a network make for the most effective influence agents. In other words, what is the most optimal selection criterion to determine influence agents?

An ideal solution to this question would be to run a large-scale field experiment with different criteria for selecting the influence agents. However, this would be a costly undertaking, which is probably the reason why this question has remained unanswered. Fortunately, advancements in computer science enable us to simulate hypothetical social network interventions by using computational models (Badham, Kee, & Hunter, 2018; Jun Zhang, Shoham, Tesdahl, & Gesell, 2015). This contemporary approach is a big step forward in the intervention studies' design process. Computational models can be a promising method to understand the complex interplay between social influences and other factors that are driving certain health behaviors (Hammond, 2010). For example, researchers can collect baseline data, simulate a wide range of interventions and opt for the intervention strategy with the biggest changes in behavior, or the most cost-effectiveness. Also, computational models could be used in consultation with key stakeholders to determine priorities, create expectations about the interventions, and tackle issues regarding implementation early on. Lastly, simulations enable researchers to formulate data-driven hypotheses that can be tested in vivo. Therefore, computational models are a valuable addition to the toolbox of researchers and practitioners who aim to change behaviors.

Agent-based models (ABM) are used to model the interactions between individuals within a social network and therefore fit the theoretical underlying mechanisms of social network interventions. The behavior of influence agents has an effect on affiliating peers. To develop effective social network interventions, it is essential to understand how the behavior spreads in a social network and what is affects the spread of the desired behavior. ABM's are a helpful tool for this, as they enable researchers to experiment in simulated environments. In previous research, ABM's were used to find out what are effective ways of identifying important nodes in the network, e.g. (Beheshti, Jalalpour, & Glass, 2017; El-Sayed, Seemann, Scarborough, & Galea, 2013; Trogdon, Nonnemaker, & Pais, 2008; Jun Zhang et al., 2015). In addition, ABM simulations have been increasingly explored as an alternative approach for addressing health research questions. Also previous studies have shown that ABM's can be used to model physical activity behavior (Baker, Little, & Brownell, 2003; Yang & Diez-Roux, 2013; Yang, Roux, Auchincloss, Rodriguez, & Brown, 2011) or obesity (Widener, Metcalf, & Bar-Yam, 2013; J. Zhang et al., 2015) in a social network.

The aim of this paper was to test which selection criterion for determining influence agents in social network interventions resulted in the biggest increase in physical activity in the social network. In order to test the different selection criteria for the influence agents, an ABM was used to simulate different interventions and observe the intervention's effect on the physical activity within the classrooms. In this study, we relied on the methods and model specifications of our previous work (Araujo et al., 2018) to build the social networks and implement the computational model. The employed computational model builds on a previously validated model developed by Beheshti (2017) and Giabbanelli et al. (2012), and was applied to the observed data of primary and secondary school children collected in the *MyMovez* project (Bevelander et al., 2018), The model considers two factors as determinants for an individual's behavioral change: the classrooms social influence and the individual's socio-environment (for more information see Araujo et al., 2018). In the model, the behavior of influence agents has an effect on affiliating peers and the effect of the influence agents spreads from connection to connection.

To further investigate the applicability of ABM's for social network interventions, this study examined whether the simulated effectiveness of social network interventions is dependent on several network characteristics. We build upon Valente and Pumpuangs' idea that the interventionist should not just use the networks as intervention instrument but also learn from the available social network information in order to create better, meaningful interventions (Valente & Pumpuang, 2007). In addition, Giabbinelli et al. (2012) conclude that there are micro-level network structures to be investigated, that are involved in making the agents more resilient to change. Other works also state that interventions might be less effective if they neglect the impact of social networks (Bahr, Browning, Wyatt, & Hill, 2009). Therefore, we investigated if characteristics of social networks (classrooms) can affect the effectiveness of network-based health interventions.

### Selecting Influence Agents

To assess the predictive validity of the computational model, the simulated interventions were compared to a condition without an intervention. Based on social network theory and the overall positive outcomes of previous social network interventions (Campbell et al., 2008; Sebire et al., 2017; Smit et al., 2016; Starkey et al., 2009), we expected a bigger increase in physical activity in the intervention conditions than in the no-intervention condition.

Subsequently, we looked at selecting strategically placed influence agents, compared to having a random allocation of influence agents. Scholars have elaborated on different roles and positions of individuals within social networks (Freeman, 1978). Influence agents are often defined as individuals who are most *central* in the network (Valente, 2012). This means that those individuals hold a prominent place in the network. Thus, centrality is a measure of an individual's position relative to their social network. Yet, there are a handful of definitions and algorithms used to define and measure centrality (Freeman, 1978; Valente, 2012). These definitions all assume that in one way or another, being central in the social network means that an individual is more influential. Therefore, we assumed that having central individuals as influence agents (regardless of the used definition) should increase the effectiveness of a social network intervention. Thus, we defined our first hypothesis as (H1): The increase of physical activity will be higher in the simulated social network interventions based on centrality compared to the simulated random influence agent intervention.

As Freeman (Freeman, 1978) discussed, there is no consensus on a common definition of centrality or how it should be measured. There are three widely used definitions of centrality: *in-degree centrality*, *betweenness centrality* and *closeness centrality* (Borgatti, 2005; Valente, 2012).

**In-degree centrality.** The most often used centrality measure in the social network interventions literature is *in-degree centrality*. In-degree centrality is based on the number of peer nominations an individual receives. The more incoming peer nominations, the higher the in-degree centrality. So, individuals with high in-degree centrality can be seen as an important channel of information (Freeman, 1978). In school settings, most often the in-degree central influence agents are the most popular children or adolescents and are clustered together in the network. Therefore, the intervention could affect that small cluster of individuals and not reach the important subgroups or peripheral nodes in the network (who might benefit the most of the intervention). Also, popular peers may be reluctant to change their behavior or perform the role of an influence agent (Valente, 1995). The popular peers have a large contribution to the social norms within the network, and deviating from the established social norm could have a negative effect on their social status. Therefore, Borgatti (2005, 2006) argues that two other types of centrality are likely to be more important for the promotion of health behaviors: *betweenness centrality* and *closeness centrality*.

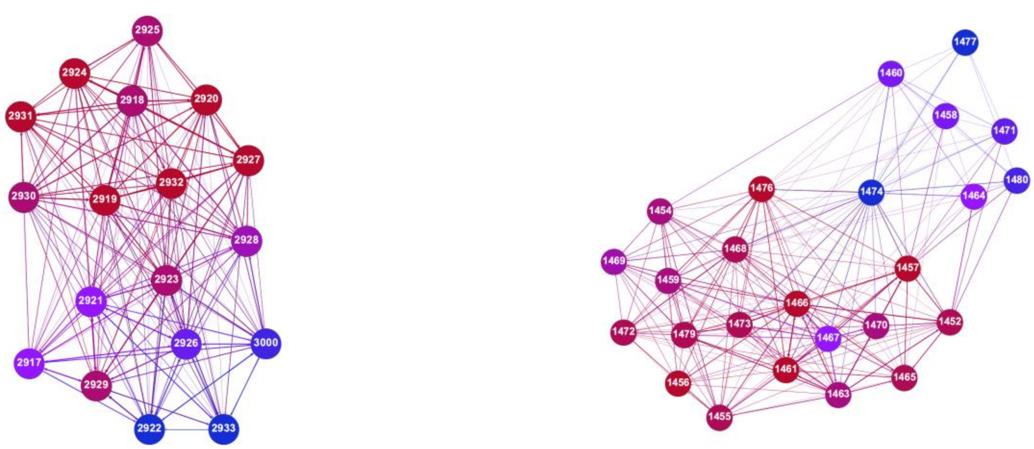
**Betweenness centrality.** Betweenness centrality focusses on the role of influence agents as a gatekeeper of information within social networks. These influence agents are important for linking different individuals or (sub)groups together and are referred to as being a *bridge*. More specifically, betweenness centrality is based on the frequency with which an individual is a link in the shortest path between two other peers. This means that this individual controls the flow of information between other peers in the network. Such an individual can influence the network by withholding or distorting information in the diffusion. If the betweenness central agents are not selected to disseminate the intervention message, entire subgroups could be withheld from the intervention (Freeman, 1978). In particular, Borgatti argues that betweenness central agents should be used when the goal is to disrupt the network's ability to spread unhealthy behavior (Borgatti, 2006). By removing these individuals from the social network, the residual network has the least possible cohesion and therefore will decrease the spread of negative behaviors in the network the most. In practice, it is not feasible to remove those individuals from a network, but we could try to increase their physical activity to prevent a potential negative behavior (low physical activity) form spreading in the social network.

**Closeness centrality.** Closeness centrality focuses on the reach of the influence agents within the social networks and the associated dissemination speed of the intervention. Closeness centrality represents the distance between the individuals and all other peers in a network. More specifically, closeness central individuals have on average the shortest path to all other peers in a network. This means that the intervention will reach the entire network in the least amount of links and it makes the intervention message most efficient. Therefore, Borgatti argues that closeness central influence agents should be used when the goal is to promote positive behaviors (Borgatti, 2006). The positive intervention message will reach all members of the social network in the most efficient way and will not exclude clusters of or subgroups from the intervention message. This approach fits within the notion that in order to reduce weight, it is more effective to promote a healthy behavior (e.g., physical activity) than to discourage negative behaviors (e.g., watching television; Salmon, Ball, Hume, Booth, & Crawford, 2008). Because the simulated social network interventions entail the promotion of physical activity (i.e. a positive behavior), we defined our second hypothesis (H2) as: The increase of physical activity will be higher for simulated social network intervention based on closeness centrality compared to simulated social network intervention based on in-degree and betweenness centrality.

## Network Characteristics

Next to the measurement of network properties on the individual level, social network analysis can also be used to describe network properties at the group level. It is important to understand group-level network information to create better and more meaningful interventions (Gesell, Barkin, & Valente, 2013; Valente & Pumpuang, 2007). Because all classes are unique in their network properties, social network interventions should keep the structure of the network in mind. Two of the most important network characteristics that could influence the effectiveness of a social network intervention are *density* and *centralization* (Sparrowe, Liden, Wayne, & Kraimer, 2001).

**Density.** The density of a social network is a measure of the cohesion in a network and can be defined as a ratio between the number of ties between participants and the number of all possible ties in a network. This means that dense classes have a relatively high number of connections between the individuals, thus having a high degree of cohesion. The left network in Figure 1 is a classroom with high density as 90% of all possible ties are connected. The right network scores low on centrality, as only 46% of all possible ties are connected.




(a) a class with high density (b) a class with low density

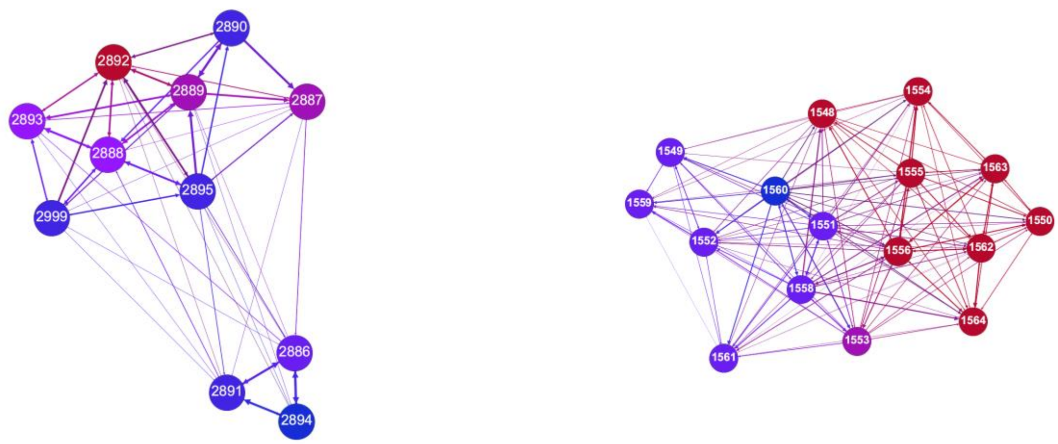
*Figure 1*: Example of social network density.

*Note*. The node color refers to the individual's in-degree centrality. Red means a higher in-degree, and blue means a low in-degree centrality. Ties between nodes are weighted based on 6 nomination questions and participants could nominate an unlimited number of peers.

Networks with high density imply more peer interactions, therefore maximizing the opportunities for spreading an intervention within a social network (Giordano, Cernkovich, & Pugh, 1986). We expected that this would also apply to social network interventions that promote physical activity, and therefore we defined our third hypothesis (H3) as: The effect of the simulated social network interventions will be higher in classes with high density compared to classes with low density.

**Centralization.** The *centralization* of a network describes the distribution of the individual centrality measures of the participants in a network. In contrast to centrality, centralization is a network-level measure. Freeman describes centralization as the skewness of the distribution of nominations in a social network (Freeman, 1978). That is, centralization defines the extent to which interactions are concentrated in a small number of individuals rather than distributed equally among all peers (Sparrowe et al., 2001). This means that in highly centralized networks, there is a pronounced subgroup of central individuals. Network centralization can be calculated for all the centrality measures (i.e. *in-degree*, *betweenness* and *closeness centrality*).

The left network in Figure 2 is an example of a class with high in-degree centralization. As can be visually observed, there is one individual (ID 2892) who received proportionally more nominations than the rest of the class. Therefore, this class scores a high in-degree centralization, and ID 2892 should be an effective influence agent in this class. In contrast, the network on the right has low in-degree centralization because it has a large subgroup of individuals who are high in in-degree centrality. The same principle applies to betweenness centralization and closeness centralization.




(a) a highly centralized class (b) a low centralized class

*Figure 2*: Example social networks of 2 classes.

*Note*. The node color refers to the individual's in-degree centrality. Red means a higher in-degree, and blue means a low in-degree centrality. Ties between nodes are weighted based on 6 nomination questions and participants could nominate an unlimited number of peers.

Previous research has shown the moderating role of centralization in the relationship between friendship networks and bullying in children (Ahn & Rodkin, 2014). More specifically, the centralization of the class predicted whether popularity relates to aggressive behavior in boys. However, it has not been studied before whether social network interventions have more effect in centralized classes than in classes in which the nominations are spread evenly. We argue that classes with high centralization lend themselves better for social network interventions because the influence agents are more pronounced and therefore easier to detect by the researcher. These influence agents in centralized classes will have relatively more influence on the network than the influence agents in non-centralized classes. We have defined our last hypothesis in three separate hypotheses, one for each centrality measure. The hypotheses are: (H4a) The effectiveness of the simulated social network interventions based on in-degree centrality will be greater in classes with high in-degree centralization than in classes with low in-degree centralization. (H4b) The effectiveness of the simulated social network interventions based on betweenness centrality will be greater in classes with high betweenness centralization than in classes with low betweenness centralization. And (H4c) the effectiveness of the simulated social network interventions based on closeness centrality will be greater in classes with high closeness centralization than in classes with low closeness centralization.

# Methods

## Participants and Procedure

The study used data from the *MyMovez* project (Bevelander et al., 2018), a large-scale cross-sequential cohort study among children and adolescents (8-12 and 12-15 years old) from 21 primary and secondary schools. In the project, participants received a smartphone with a research application on which they received daily questionnaires, and a wrist-worn accelerometer (Fitbit Flex®). This accelerometer has been shown to be a reliable measure of physical activity (Alharbi, Bauman, Neubeck, & Gallagher, 2016; Diaz et al., 2015). For this study, the first four waves of the *MyMovez* project were used: February/March 2016 (Wave 1), April/May 2016 (Wave 2), June/July 2016 (Wave 3) and February/March 2017 (Wave 4). In order to ensure that the influence agents are identified from a representative sample within each classroom, only classes with more than 60% of students participating were included. This resulted in 26 classes, with 460 participants ($M_{age}$ = 10.81, $SD_{age}$ = 1.28, 52.52% male) in total.

## Measures

**Physical Activity.** In each wave, participants wore the accelerometer on their non-dominant wrist for seven consecutive days. The first and the last day were excluded because these were partial days (handing out and giving back the accelerometer), resulting in five complete days of data. Additionally, days that did not add up to 1,440 minutes (24 hours) and days with less than 1,000 steps were excluded (e.g. caused by an empty battery or non-wear time).

The average physical activity per wave was calculated by taking the average steps per day of at least three days of valid data. If participants had less than three days of valid data per wave, daily step count was imputed with the same strategy as in van Woudenberg et al. (2018) by using single multilevel predictive mean matching imputation (Van Buuren, 2011). Missing data were imputed based on other physical activity data of the same participant, day of the week, measurement period, sex and age. On average, participants accumulated 10,505 steps per day (*SD* = 5.730).

The physical activity measure had to be scaled in order to fit the agent-based model (ABM). In the previous work with the same ABM, the mean value of physical activity was set at 1.53 (Beheshti et al., 2017). Therefore, we computed a new variable named the Physical Activity Level (PAL) by dividing the steps by 10,000 and multiplying by 1.53. The mean PAL value in our dataset was 1.50 with a minimum of 0.45 and a maximum of 4.27.

Family Affluence. A measurement of the influences of the social environment was needed as a second input parameter of the ABM. The Family Affluence Scale (FAS) was used as a measure of socioeconomic status (Torsheim et al., 2016). The FAS is a self-reported measure of family affluence and is an effective tool for assessing socioeconomic status in adolescents (Boyce, Torsheim, Currie, & Zambon, 2006). The participants were asked sets of questions (e.g. "How many cars does your family own", "How often do you go on a holiday outside of the Netherlands?"). All answers (range 0 – 13) were summed (*M* = 4.01, *SD* = 1.52), reflected and divided by the number of items to fit the model. This resulted in an environmental variable (*env*) with a value between 0 and 2 in which a higher *env* value reflects a lower family affluence.

**Sociometric Nominations.** In each wave, participants nominated peers from the same class by six sociometric questions based on the study by Starkey et al. (Starkey et al., 2009). Participants received the questions at a random time during the day and nominated peers by clicking on their names in a list on the research smartphone. They were required to nominate at least one other peer, and no maximum on the peers nominated was given (N.B. self-nominations were not possible). For an overview of the questions, see Appendix C.

**Centrality.** The social network characteristics at the individual level were calculated with the NetworkX package (Hagberg, Schult, & Swart, 2008) in Python3 (Van Rossum & Drake, 2003). For an overview of the centrality measures, see Table 1. The individual's betweenness centrality did not correlate with in-degree centrality or closeness centrality, but in-degree centrality did correlate with closeness centrality ($r(457) = 0.58$, $P < .001$).

**Density and Centralization.** The density and three centralization measures were calculated for each class. The density was calculated by taking the number of ties present in a social network and dividing this by the number of all possible ties, resulting in a number ranging from 0 (non-cohesive network) to 1 (very cohesive network). In-degree centralization, betweenness centralization, and closeness centralization were calculated with the *igraph* package (Csardi & Nepusz, 2005) in RStudio (2015), resulting in a number ranging from 0 (*non-centralized network*) to 1 (*very centralized network*). The density and centralization scores were normalized given the different network sizes. For an overview of the density and centralization scores, see Table 1.

Table 1

*Descriptive statistics for the individual and group level variables.*

| | *N* | Mean | *SD* | Min | Max |
|---|---|---|---|---|---|
| Individual Characteristics | | | | | |
| In-degree centrality | 451 | 12.27 | 4.15 | 4.00 | 27.00 |
| Betweenness centrality | 451 | .01 | .02 | .00 | .12 |
| Closeness centrality | 451 | .78 | .11 | .49 | 1.00 |
| Network Characteristics | | | | | |
| Density | 26 | .72 | .11 | .46 | .90 |
| In-degree centralization | 26 | .20 | .08 | .07 | .40 |
| Betweenness centralization | 26 | .04 | .03 | .01 | .09 |
| Closeness centralization | 26 | .22 | .08 | .09 | .39 |

## Design

**Social Networks.** Based on the sociometric nominations, one directed social network was constructed for each classroom. A directional social network consists of nodes that represent the participants within a class and edges representing (weighted) connection between two nodes. Because two participants could nominate each other, the edges in the network are directional (represented by the arrow of the edge). The weight was defined as the sum of nominations of one participant towards another, divided by the total number of nomination questions. Since participants nominated peers on multiple sociometric questions, each edge was associated with a connection weight ranging from 0 (zero nominations) to 1 (all six nominations). The more nominations one participant gave to another peer, the stronger the edge's connection weight. Duplicate nominations were omitted (as one participant could nominate the same peers on the same items across waves), resulting in a maximum of six nominations toward another peer within all four waves.

**Agent-Based Model.** Computational models can be defined "as an abstract and simplified representation of a given reality, either already existing or just planned. Models are commonly defined in order to study and explain observed phenomena or to foresee future phenomena" (Bandini, Manzoni, & Vizzari, 2009). Agent-Based Models (ABM) are a particular category of computational models for simulating the communication among the agents in a common environment in order to understand their behavior. For this work we rely on a previously validated ABM developed by Giabbanelli et al. (2012) and enriched by several adaptations (Araujo et al., 2018; Beheshti et al., 2017).

Giabbanelli's model (2012) was used as it accounts for the interaction of social networks with environmental factors, unlike earlier related computational models for social network interventions. In this model, individuals influence each other with respect to physical activity, which might change also depending on the agent's physical environment. Their factor analysis on synthetic and real-world social networks showed that the environment was crucial parameter for changes in body weight (their health behavior of interest). This particular model was favored as it was a fitted the collected data of the MyMovez project. Many prior studies are using more complex models incorporating multiple parameters, but base them on synthetic datasets. However, the purpose of this study was to use data collected from real human relations and behaviors, and this model was a good fit for the observed data.

The ABM simulates the spread of physical activity within social networks, that is, simulating the dissemination of the intervention throughout the classroom. We assumed that physical activity spreads throughout the relationships and depends on the physical environment. Each agent, in our case participants within a class, is assigned two input parameters before running the simulations - the physical activity and the environment parameter. One-year simulations were run for each of the social network intervention strategies and for each class. During each step (represented by a single day) of the simulation, physical activity is derived for each agent based on the social influence and the environmental influence. The social influence comes from the affiliating peers in the network and is based on the connection weights among agent's peers and the associated peers' physical activity. The environmental influence is the effect of the agent's family affluence. The ABM does not make assumptions regarding probability of diffusion across ties.

Each simulation step potentially updates the agent's PAL and is calculated in 3 phases, similarly as presented by Giabbanelli et. al (2012). First, the social influence parameter is calculated, coming from the adolescent's peers (dependent on peers' physical activity and connection weights). Second, the social influence with the agent's environmental influence is combined in a single parameter, called the socio-environmental influence. Third, the socio-environmental influence parameter is compared with a pre-defined threshold, to decide if agent's physical activity will be modified or remain the same.

Interventions. Five conditions were created based on four social network intervention strategies and a control condition (no intervention). In the centrality-based intervention conditions (i.e. *in-degree*, *betweenness* and *closeness centrality*), the top 15% of participants with the highest centrality were assigned as influence agents. When participants above and below the cutoff score had the same centrality scores, random participants from these cases were assigned as influence agents. In the *random agent* intervention condition, the 15% influence agents were randomly selected out of all participants in a classroom. To diminish the possible effect of selecting a particular set of influence agents in the random agent condition, 100 interventions were simulated and averaged afterward to provide a single outcome value. In the *control condition*, no intervention was simulated.

All interventions were based on the assumption that the training sessions of the social network interventions were able to increase the physical activity of the influence agents at the start of the intervention. Therefore, all influence agents received an artificial increase of 17% in their initial physical activity based on the outcomes of a previous behavioral intervention (Beheshti et al., 2017; Logue et al., 2005). After the increase in PAL of the influence agents, the intervention simulations were run for 365 days (day 0-364). The effectiveness of the health interventions is expressed as the *success rate*, the percentage of increase in a class's physical activity from the start (day 0) to the end (day 364) of the simulation.

## Results

The simulations were used to observe the spread of physical activity among peers in the classes and determine the success rate of the different interventions.

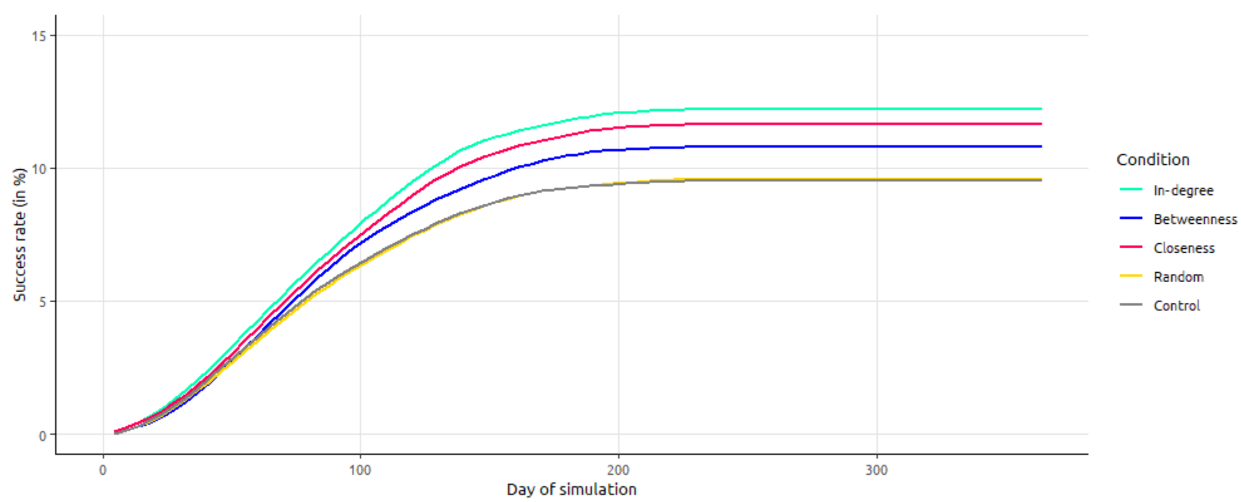



*Figure 3*: Intervention outcomes: Average success rate for the conditions over a one-year simulation.

Figure 3 illustrates the trajectory of the averaged physical activity for all the different simulated interventions for the one-year simulation period. What stands out form the figure is that all conditions increase in physical activity over time, but that are differences in the amount of the growth between the conditions. A detailed overview of the interventions' success rates for all conditions can be found in Appendix D.

As a first step, we tested the overall differences between all conditions. A linear mixed-effects model was run (Bates, 2010), with success rate as the dependent variable, condition as the predictor, and random intercepts per class. Mauchly's test indicated that the assumption of sphericity was not met, $W = 0.00$, $P < .001$, $\varepsilon = .41$. Therefore, all degrees of freedom were corrected by using the Huynh-Feldt estimation of sphericity. The repeated measures ANOVA showed that the simulated interventions differed from each other, $F(1.66, 41.42) = 7.72$, $P = .002$, $\varepsilon = .01$. To investigate differences between the conditions as proposed in the hypotheses, planned contrasts (Helmert coding scheme) were used. In addition, all *p*-values were corrected by using Satterthwaite's method as suggested by Luke (2017).

### Selecting Influence Agents

For the check of the model validity, the first planned contrast was used to compare the four social network intervention conditions with the control condition (no intervention). The contrast revealed that the success rates of the social network interventions (11.28%) were higher than the control condition (9.76%), $\beta = .30$, $t(100) = 3.30$, $p = .001$. This means that the interventions were more successful in increasing physical activity than having no interventions. Therefore, we presumed that the ABM is a valid tool to simulate social network interventions.

To test the first hypothesis (H1), the second planned contrast compared the three centrality social network intervention conditions (i.e. *in-degree*, *betweenness* and *closeness centrality* conditions) with the random agent condition. The averaged success rate of the centrality social network intervention conditions (11.74%) was higher than the success rate in the random agent condition (9.90%), $\beta = .46$, $t(100) = 3.86$, $p < .001$. This means that having central influence agents is more effective in increasing physical activity than having random sampled individuals in a network.

To test the second hypothesis (H2), the third and fourth planned contrasts compared the differences within the three centrality social network intervention conditions. The third contrast compared the *betweenness* and *closeness* centrality conditions (11.57%) with the *in-degree* condition (12.08%). The success rates did not differ from each other, $\beta = -.17$, $t(100) = -1.00$, $p = .32$. The fourth contrast compared the *closeness* centrality condition with the *betweenness* centrality condition. The success rates of the closeness centrality condition (12.16%) were higher than the betweenness centrality condition (10.98%), $\beta = .59$, $t(100) = 2.02$, $p = .046$. This means that we did not find evidence that the betweenness and closeness centrality conditions outperformed the in-degree centrality condition, but the betweenness centrality condition was less effective in increasing physical activity in the networks compared to the in-degree and closeness centrality conditions.

### Network characteristics

The success rates of the social network interventions varied between classes (as can be seen in Appendix D). Some of the networks did not change after the interventions or even negative effects occurred, while other networks showed an average increase of more than 30% in physical activity over one year of simulation.

Therefore, we investigated the effect of structural properties of the classes (i.e. *density*, *in-degree centralization*, *betweenness centralization,* and *closeness centralization*) on the success rates of the interventions. More specifically, we added the different structural properties as moderators to the mixed effect model. Table 2 displays the correlation coefficients of the four social network interventions and the four structural network properties. For an overview of the structural properties per class, see Appendix E.

Table 2

Correlations between social network interventions and network structures.

| | In-Degree | Betweenness | Closeness | Random Agent |
|---|---|---|---|---|
| Density | -.37 | -.33 | -.35 | -.34 |
| In-degree centralization | .58* | .57* | .58* | .56* |
| Betweenness centralization | .26 | .26 | .26 | .21 |
| Closeness centralization | .35 | .30 | .33 | .30 |

*Note*. * = $p < .05$

The third hypothesis (H3) predicted that the interventions would be more effective in classes with high density. To test whether the density of the class moderated the effectiveness of the different interventions, the same mixed model was run with the addition of the interaction effect of density (standardized). The analysis showed that there was no significant direct effect of density on the success rate, $\beta = -3.17$, $t(24) = -1.58$, $p = .077$. This means that the success rates were not higher in classes with high density than in classes with low density. In addition, no significant interaction effects of the planned contrasts of the social network conditions and the density of class were observed. This means that we did not find evidence to support the hypothesis (H3) that social network interventions are more effective in classes with high density compared to classes with low density.

The last three hypotheses (H4a, H4b, and H4c) predicted that the interventions would be more effective in classes with high centralization based on the centrality measure that was used. For these analyses, the contrasts were changed per hypothesis so that the centrality measure in focus was contrasted with the other social network interventions. For these three hypotheses, the same mixed model was used, with the addition of the interaction effect of centralization.

The first linear mixed-effects model investigated in-degree centralization (H4a) and showed that there was a direct effect of in-degree centralization on the success rate, $\beta = 5.27$, $t(9.94) = 3.55$, $P = .002$. As can be seen in Figure 4, the social network interventions were more effective in classes with high in-degree centralization. This means that social network interventions are more effective when the class is more centralized around some in-degree central individuals. Additionally, we looked at the interaction of in-degree centralization and the planned contrast of the in-degree centrality condition versus the other social network interventions. This interaction effect was non-significant, $\beta = .15$, $t(39.76) = 1.26$, $p = .210$. This means the effect of in-degree centralization on the success rates was not stronger in the in-degree centrality condition than in the other social network conditions.

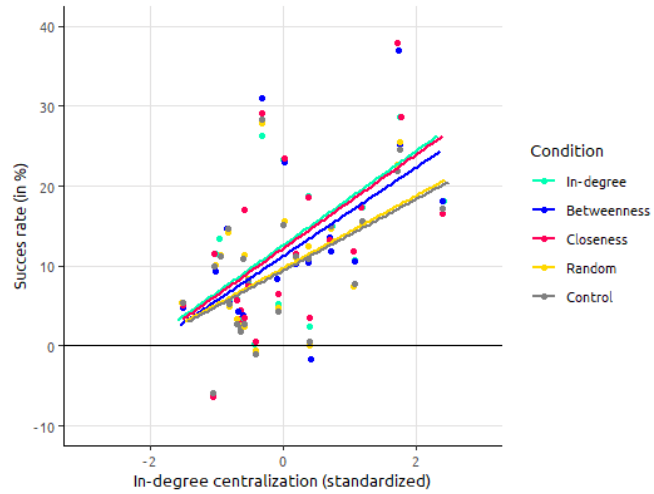



*Figure 4*: Effect of in-degree centralization on the success rates per condition.

The second linear mixed effect model investigated betweenness centralization (H4b) and showed that there was no direct effect of betweenness centralization on the success rate, $\beta = 2.22$, $t(9.94) = 1.25$, $p = .223$. This means that the social network interventions were not more effective in classes with high betweenness centralization compared to classes with low betweenness centralization. Additionally, the interaction effect was non-significant, $\beta = 0.09$, $t(39.76) = .73$, $p = .453$. This means that the effect of betweenness centralization on the success rates was not stronger in the betweenness centrality condition than in the other social network conditions.

The last linear mixed effect model investigated closeness centralization (H4c) and showed that there was no direct effect of closeness centralization on the success rate, $\beta = 2.88$, $t(9.94) = 6.66$, $p = .110$. This means that the interventions were not more effective in classes with high closeness centralization, compared to low closeness centralization. Additionally, the interaction effect was non-significant, $\beta = .11$, $t(39.76) = .93$, $p = .357$. This means that the effect of closeness centralization on the success rates was not stronger in the closeness centrality condition than in the other social network conditions.

Given these results, our hypotheses that the effectiveness of the simulated social network interventions would be greater in classes with high centralization than classes with low centralization were rejected. We only found evidence that social network interventions are more effective in high in-degree centralized classrooms, irrespective of the type of social network intervention used.

## Discussion

### Principal results

The aim of the current study was to test which influence agents are most effective in spreading an intervention message in a social network intervention. In order to test the different selection criteria for the influence agents, an ABM was used to simulate different selection criteria for social network interventions and to observe the intervention's effect on the physical activity within classrooms. In addition, the study investigated whether social network interventions are more effective in some classes than others based on their particular network characteristics.

The general effectiveness of social network interventions was compared with the control condition. The results showed that the increase in physical activity was of greater magnitude in social network interventions than the control condition. This demonstrates that an increase in physical activity of a small group of individuals has the potential to spread to peers in the social network. Therefore, the ABM produced results in line with the social network theory, which predicts that behaviors spread in social networks (Rogers, 2003; Valente, 1995). We, therefore, assumed that our model was a valid tool to test our hypotheses.

In addition, the effect was stronger for the centrality based social network intervention conditions compared to the random influence agents condition. This is not in line with the results of the first model of El-Sayed et al. (2013) who concluded (also based on simulations of literature-based parameters) that well-connected influence agents have little or no added value compared with randomly selected influence agents. This difference may be a result of the different model specifications in the two studies. In addition, the outcome variable in the study by El-Sayed et al. (2013) was the prevalence of obesity. On the contrary, the results of this study are in line with the second set of simulations of artificially high parameter models of El-Sayed et al. (2013) and Zhang et al. (2015). These results corroborate the idea that central individuals hold an important position within their social networks (Freeman, 1978). Taking a random sub-sample of the participants as influence agents is not as effective as strategically located influence agents. Therefore, researchers should carefully select influence agents based on their position in the social network, as suggested by Borgatti (2005), and Valente and Pumpuang (2007). When researchers are unable to strategically select the influence agents, Bahr et al. recommend increasing the percentage of random influence agents to obtain the same success rates as the centrality conditions with 15% of the class as influence agents (Bahr et al., 2009).

Contrary to expectations, no difference was observed between the in-degree centrality condition and the closeness centrality condition, as suggested by Borgatti (2005), and Valente and Pumpuang (2007). An explanation could be that Valente's (1995) argument, that in-degree agents are most often the popular individuals and not willing to change their behavior, does not hold for simulated intervention. In the simulations, the artificial increase of physical activity of the influence agents was the same for the in-degree centrality condition and the closeness centrality condition. In contrast, a difference between the closeness centrality condition and the betweenness centrality condition was observed. In accordance with Borgatti's (2006) reasoning that positive behavior should be promoted via closeness central agents, we observed that the closeness centrality condition had a higher success rate compared to the betweenness centrality condition. This corroborates the idea that when researchers want to increase positive behaviors, closeness centrality influence agents should be selected.

Lastly, this paper looked at the moderating role of network structures on the effectiveness of social network interventions. The results showed that the density of the class does not affect the success rates of the intervention. This is not in line with social network theory, which argues that innovations spread quicker through highly connected networks (Sparrowe et al., 2001). We also anticipated that the specific centrality conditions were most effective as the classes were more centralized on the relevant centrality measure. However, the results indicated that only in-degree centralization has a direct effect on the success rates. This means that social network interventions are more effective when classes have a small number of individuals who receive the most nominations. The subsequent analyses showed that this effect was not stronger in the in-degree centrality condition than in the other social network intervention conditions. Therefore, we can conclude that social network interventions work better in classes with high in-degree centralization irrespective of the selection criterion used.

The current study advanced the field of social network interventions and the use of ABMs in numerous ways. This study was one of the first that used simulations to test the difference between selection criteria for influence agents in social network health interventions. In addition, this study used empirical data as input for the model. The next step in the interplay between health interventions and computational models, will be to replicate these simulated results with empirical data of social network health interventions.

The study provides implications for future research and can advise social network researchers. First, this study supports the idea that social network interventions can be an effective strategy to increase physical activity in the classroom. Second, it stresses the importance of strategically selecting the most central individuals as influence agents. Third, the composition of the class can influence the effectiveness of social network interventions. In addition, the current study shows the applicability of simulations to help researchers design the most effective interventions

### Comparison with prior work

ABM's have been used previously to study the spread of health behaviors in simulated social environments after hypothetical interventions. For example, an ABM was used to investigate the spread of obesity in artificial participants after multiple obesity prevention campaigns (El-Sayed et al., 2013). Next, the use of ABM’s to investigate the spread of obesity was refined by using the BMI of an observed sample of participants and the addition of a socio-environmental factor (Giabbanelli et al., 2012). However, no behavioral data were available, so physical activity was imputed based on a random distribution. A subsequent study improved the previously mentioned ABM by incorporating individual thresholds for the change in health behaviors (Beheshti et al., 2017). Our previous work used this model, but here we applied it to observed behavioral and sociometric data (Araujo et al., 2018). The previously mentioned ABM’s (Araujo et al., 2018; Beheshti et al., 2017; Giabbanelli et al., 2012) showed similar results to this paper, in that the simulations of interventions showed an increase that attenuated over time.

Based on different ABM's, two other studies have used agent-based simulations to investigate the effectiveness of different types of influence agents in social network interventions (Badham et al., 2018; Jun Zhang et al., 2015), but both with a slightly different aim. The study by Zhang et al. (Jun Zhang et al., 2015) examined only the difference between randomly selected and in-degree central influence agents. Their conclusion aligns with the current findings that physical activity increases more in the intervention that uses influence agents based on centrality compared to the intervention that uses random influence agents.

The study by Badham et al. (2018) matches the research question of the current study more closely. That is, the study looked at the three different types of centrality measures. However, the outcome of the simulations was the amount of time (number of iterations) before the entire network adopted a behavior. In other words, the study by Badham et al. (2018) focused on the speed of adoption of the intervention, and not on the magnitude of the behavior change after the simulated interventions. Despite the different outcome variables, the studies showed comparable outcomes to the findings in this study. More specifically, the most effective interventions are those with influence agents based on centrality (in-degree, betweenness and closeness centrality). Although that study did not formally test the differences between the centrality measures, the observed steps to saturation do not indicate that there is a difference between them.

## Limitations

To interpret the results of the simulation of social network interventions, a number of limitations have to be discussed. First, this study was based on the assumption that researchers are able to increase the amount of physical activity of the influence agents. However, it could be that this does not reflect the field experiments that train influence agents to become more active. In addition, increasing the targeted health behavior is only part of the influence agents' training. For example, most training sessions on social network interventions also focus on how the influence agent could communicate the health message in an informal way. This type of health promotion was not a part of the ABM that we used. Future studies could also imitate other aspects of successful training. For example, researchers could consider increasing the number or the weight of the connections, to reflect the communication part of the influence agents' training. Along the same line, the success rates of the intervention are based on the embedded assumptions in the model of how people influence each other. In our model, the assumption was that the increase in physical activity diffuses over time. However, adopting a contagion framework, which looks at how many peers should increase in physical activity before the individual's physical activity increases, might lead to different success rates of the interventions.

Second, the employed ABM comes with a set of limitations. For example, based on the mathematical characteristics of the model, the ABM's outcome has an initial increase and reaches an equilibrium state after a particular time in the simulations, as shown in Figure 3. Consequently, the control condition also increased in physical activity, contrary to the usually observed decrease among youth (Cooper, Andersen, Wedderkopp, Page, & Froberg, 2005). Therefore, caution is warranted in interpreting the absolute increase in classes' physical activity. Rather, we want to emphasize that the results focused on the relative differences between the selection criteria. Also, the ABM outcomes enabled us to discuss the effects of *simulated* health interventions. Although the ABM has been validated and tuned to the empirical data, the presented simulation effects should be interpreted with caution. Following this limitation, in our next study, we intend to perform similar statistical analyses on the empirical data when the intervention outcomes of the *MyMovez* project are available.

Third, the applied analyses were all based on data aggregated on a classroom level. However, we realize the importance of conducting more elaborate individual-level analyses by including personal characteristics such as sex, personality traits, individual physical activity, or the role in the social network. These personal characteristics can moderate the effect of the health intervention. By including more personal information, the ABM can be better specified. Adopting personality traits could help us to understand how an individual perceives and reacts to peer behaviors and to learn about individuals' contributions to the class behavior.

## Conclusion

In conclusion, we demonstrated the advantages of applying social network analyses and simulations to understand social networks' characteristics, and performing detailed simulations on peer influences. We advise future researchers to perform such intervention simulations on peer influences, whenever possible, before doing real-world interventions to maximize the success rate of their interventions. This information can help in designing more effective social network health interventions.

Chapter 4

# A Randomized Controlled Trial Testing a Social Network Intervention That Promotes Physical Activity Among Adolescents.

This chapter is published as:

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Doi: 10.1186/s12889-018-5451-4

## Abstract

### Background

The current study examined the effectiveness of a social network intervention to promote physical activity among adolescents. Social network interventions utilize peer influence to change behavior by identifying the most influential individuals within social networks (i.e., influence agents), and training them to promote the targeted behavior.

### Method

A total of 190 adolescents (46.32% boys; $M_{age}$ = 12.17, age range: 11-14 years) were randomly allocated to either the intervention or control condition. In the intervention condition, the most influential adolescents (based on peer nominations of classmates) in each classroom were trained to promote physical activity among their classmates. Participants received a research smartphone to complete questionnaires and an accelerometer to measure physical activity (steps per day) at baseline, and during the intervention one month later.

### Results

A multilevel model tested the effectiveness of the intervention, controlling for clustering of data within participants and days. No intervention effect was observed, $b$ = .04, $SE$ = .10, $p$ = .66.

### Conclusion

This was one of the first studies to test whether physical activity in adolescents could be promoted via influence agents, and the first social network intervention to use smartphones to do so. Important lessons and implications are discussed concerning the selection criterion of the influence agents, the use of smartphones in social network intervention, and the rigorous analyses used to control for confounding factors.

## Trial registration

Dutch Trial Registry (NTR): NTR6173. Registered 5 October 2016 Study procedures were approved by the Ethics Committee of the Radboud University (ECSW2014-100614-222).

*Keywords:* social network intervention, physical activity, accelerometer, adolescents, smartphones

## Background

Physical activity in childhood and adolescence is linked to numerous health benefits, such as lower cholesterol, blood pressure and BMI (Janssen & LeBlanc, 2010). People who are more physically active at a young age are also more active adults (Telama et al., 2005). Unfortunately, young people are not physically active enough and physical activity declines with age (Nader et al., 2008; Riddoch et al., 2004). Nowadays, adolescents are even less physically active compared to previous generations (Boreham & Riddoch, 2001). According to the World Health Organization (2010), adolescents should accumulate at least 60 minutes of moderate-to-vigorous physical activity (MVPA) every day. Yet, a worldwide majority (80%) of adolescents, aged 13 to 15 year old, are not meeting these guidelines (Brusseau et al., 2013; Butcher et al., 2008; Hallal et al., 2012). In the United States, for example, 93% of adolescents (12- to 15-year-olds) do not meet the recommended amount of physical activity (Katzmarzyk et al., 2016) and in the Netherlands (the country of the current study), 72% of the adolescents (12- to 17-year-olds) do not adhere to the norm of 60 minutes of MVPA per day (Burghard et al., 2016).

Physical activity of adolescents is found to be influenced by peers (Maturo & Cunningham, 2013; Sawka et al., 2013). For example, studies have shown that adolescents are more active when they are together with peers (Salvy et al., 2012) and that adolescents are more often friends with others who are similar in terms of physical activity (Macdonald-Wallis et al., 2011). In addition, some studies have used a social network framework to predict physical activity in youth. For example, a study by De La Haye, Robins, Mohr, and Wilson (2011) showed that adolescents (12- to 14-year-olds) selected friends based on the amount of self-reported MVPA, but also influenced the amount of physical activity of their friends. Similarly, Simpkins, Schaefer, Price, and Vest

(2013) found evidence for these so-called selection and influence effects, based on self-reported physical activity in adolescents ($M_{age}$ = 15.97). Gesell, Tesdahl, and Ruchman (2012) observed only friendship selection effects in children and adolescents (5- to 12-year-olds), based on physical activity measured by accelerometer. Altogether, these studies show the relationship between adolescents' physical activity and the physical activity of friends and peers, and that it is plausible that physical activity can be influenced by their social network.

A social network framework can be used to design interventions for behaviors in which peer influence plays a crucial role (Valente, 2012). Social network interventions typically identify a small number of individuals within social networks, so-called *influence agents*, and train these agents to promote specific behaviors within their networks. There are a number of ways in which influence agents can be selected (Valente & Pumpuang, 2007). Usually, influence agents are selected by choosing participants that are nominated most frequently by all members of the social network on one or more sociometric questions (e.g., regarding who they respect, want to be like or who are their friends; Campbell et al., 2008; Starkey et al., 2009). Once the influence agents have been selected, they are approached and trained to promote the desired behavior in their network for intervention purposes. Previous research has shown promising results that influence agents can stimulate healthy behaviors, such as a healthy eating (Shaya et al., 2014) and water consumption (Smit et al., 2016), or discourage unhealthy behaviors, such as smoking (Campbell et al., 2008; Starkey et al., 2009) and substance use (Valente et al., 2007).

Despite the promising approach of using influence agents to promote health behavior, only two studies have tested a social network intervention to promote physical activity in adolescents (Bell et al., 2014; Sebire, Edwards, Campbell, Jago, Kipping, Banfield, Tomkinson, et al., 2016). Both studies were based on the ASSIST framework (Campbell et al., 2008), in which influence agents are trained to promote or discourage behavior among their peers. Bell et al. (2014) selected the most nominated adolescents as influence agents and trained them in a two-day training session to promote healthy eating and physical activity at the same time. After a 10-week intervention period, no behavioral differences were observed between the control and intervention conditions. The authors suggested that it was too complicated for the influence agents to promote both health-related behaviors at the same time. The second study (Sebire, Edwards, Campbell, Jago, Kipping, Banfield, Tomkinson, et al., 2016) focused solely on physical activity of adolescent females. The most nominated female adolescents in each classroom were selected as influence agents. The influence agents received a three-day training program about physical activity and interpersonal communication skills. After the training, the influence agents were asked to informally diffuse messages about physical activity for a period of 10 weeks. Preliminary results suggest that this intervention was successful (Sebire et al., 2017). That is, adolescent girls decreased less in MVPA compared to the control condition. These mixed findings show that more research is needed on social network interventions that promote physical activity.

## Current Study

This study extends research on social network interventions aimed at promoting adolescents' physical activity by (a) using a different selection criterion to determine the influence agents, and (b) training the influence agents via smartphones. First, this study used closeness centrality as the selection criterion to determine the influence agents. In previous social network interventions, influence agents have been selected by identifying participants in the network who received the most nominations on one or more sociometric questions. This selection criterion is referred to as *in-degree centrality*. In most cases, the participants with the highest in-degree centrality are the most popular individuals within a classroom. However, this might impair the effectiveness of the intervention, because popularity could be a detrimental characteristic of influence agents (Valente, 1995). For example, Valente argued that popular adolescents often depend on the social norms of the network to remain popular, and therefore may be reluctant to change their behavior or perform the role of an influence agent. As a solution, Borgatti (2005, 2006) reasoned that when an intervention aims to promote health behavior, one should select the influence agents based on *closeness centrality*. Based on this criterion, the influence agents are those in a classroom who are closely connected to all other classmates. More specifically, closeness refers to how many relationship ties are needed to link an individual to all others in a social network. Closeness centrality is calculated by taking the sum of the length of the shortest paths between each participant and all the classmates. People who have a small average path length, need fewer intermediaries to reach all members of a network. Therefore, it takes less time (i.e., fewer interactions) for the intervention message to reach the entire classroom (Borgatti, 2006). For this reason, the current intervention selected the influence agents based on closeness centrality.

Second, this study used smartphones to train the influence agents. Typically, influence agents are trained using repeated face-to-face meetings with trained experts. Delivering the training via smartphones increased the feasibility of social network interventions because it is a low-cost and less time-consuming method (Bell et al., 2014).

For example, the influence agents can be trained at any location and time without having to miss part of their school curriculum. In addition, the use of smartphones fits adolescents' lifestyle and the training of influence agents can be done covertly without raising suspicion of their peers because they do not have to leave the classroom to attend the training.

The aim of this study was to test the effectiveness of a social network intervention that promotes physical activity in adolescents, based on these two extensions. We hypothesized that adolescents who are exposed to the social network intervention would be more physically active than adolescents who are not exposed to the social network intervention.

## Methods

### Design

The study used a clustered randomized control trial design of two groups. Participating classes were randomly allocated to the intervention condition (social network intervention) or the control condition (no intervention). The study was registered a priori in the Dutch Trial Registry (NTR): TR6173 and the procedures were approved by the Ethics Committee of the Radboud University (ECSW2014-100614-222).

A priori sample size calculation was performed by using G*Power 3.1 (Faul, Erdfelder, Buchner, & Lang, 2009). For the calculation, the observed effect size in the study by Smit et al. (Smit et al., 2016) was used ($\eta^2 = .07$) and converted to Cohen's *F* ($f = 0.25$). The calculation showed that 130 participants were needed for a MANCOVA: repeated measures within-between interaction with two groups and two measurements (power = 0.80, $p = 0.05$). A larger number of participants were recruited due to the strictness of the inclusion criteria (i.e., active parental consent, minimum of 60% classroom participation) and to account for attrition (see Figure 1).

### Participants and Procedure

In total, 326 first-year pupils from 15 classrooms of a Dutch secondary school were approached in September – October 2016 to participate in the study via their school. Parents or legal guardians received an information letter about the project with the corresponding consent form. Active parental consent was obtained for 219 students. We limited participation to classrooms in which at least 60% of students provided consent. This was done to ensure a reliable assessment of the social networks (Marks et al., 2013). Four classes did not reach this threshold and were excluded from the study. After exclusion, the sample consisted of 11 classes with 190 participants (46% male) ranging from 11 to 14 years old ($M$ = 12.17 years, $SD$ = 0.50). The level of education of the classes varied, ranging from the lowest education level ("VMBO-kader", vocational training) to a moderate-high level ("HAVO/VWO", theoretical training). Five classes ($n$ = 93) were assigned to the intervention condition and six classes ($n$ = 97) to the control condition (see Figure 1). All participants signed assent before receiving the materials.

The baseline measures were administered over a seven day period (November 2016) followed by a seven-day intervention one month later (December 2016). At the start of the baseline measurement, the participants received instructions about the project and materials by the researchers in the classroom. For five weekdays and two weekend days, all participants received the *MyMovez Wearable Lab*: A smartphone with a tailor-made research application and a wrist-worn accelerometer.

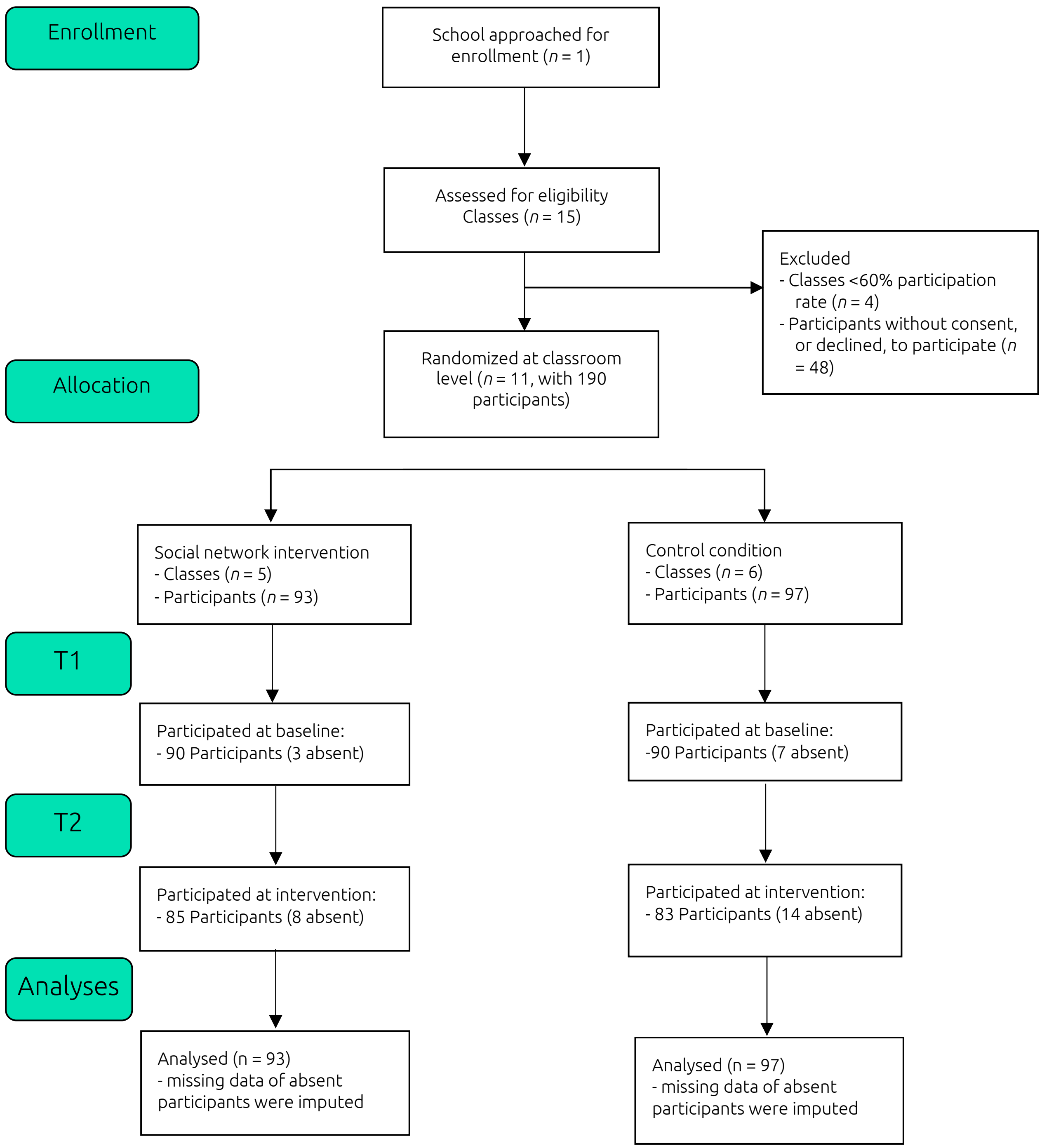


*Figure 1.* CONSORT flow diagram of participants.

The smartphone with the *MyMovez* application served as a measurement tool for the peer nomination and self-report items. Participants received daily questionnaires on these devices at random moments between 7:00 AM and 7:30 PM, except during school hours (i.e, they could receive questions during one of the school breaks).

## Measures

**Physical activity.** Physical activity was measured by a wearable accelerometer as the number of steps per day. Wearable accelerometers are accurate and detailed instruments to measure physical activity (Trost, Pate, Freedson, Sallis, & Taylor, 2000). The Fitbit Flex® was used to measure physical activity, which has shown to be an accurate and reliable measurement of physical activity (Alharbi et al., 2016; Diaz et al., 2015). Only complete measurement days were included, in which the accelerometer functioned the entire day and was worn by the participant. Therefore, measurements were only included if the total measured minutes equaled 1,440 minutes (24 hours), and at least 1,000 steps were recorded. The first and the last day of the measurement period were partial days because on these days the participants received or handed in the accelerometer. Therefore, the first and last days were excluded from the analyses. For analytical purposes, the steps per day variable was standardized across the remaining five days.

**Missing data.** In total, 73.37% of all possible data points were observed in the daily physical activity data (for a day-to-day overview, see Table 1). The Little's MCAR test indicated that the data were not missing completely at random, $x^2$ (7) = 205.79, $p <$ .001; relatively fewer data points were observed at the end of the week which was mostly caused by depleted batteries in the accelerometers. In addition, some participants had missing data for an entire week, caused by being absent at the start of the measurement period or a malfunction of the electronic devices (*n* = 18 at baseline, *n* = 28 during the intervention). Multilevel (predictive mean matching) imputation (Van Buuren, 2011) was used to generate multiple imputations (100 imputations based on 500 iterations each) of the missing physical activity data. The missing data points were imputed based on other physical activity data of the participant, day of the week, measurement period, sex, age and athletic competence of the participant.

Table 1

*Number (percentage) of valid data points for the physical activity data per day at baseline and intervention*

| | Day of measurement period | | | | |
|---|---|---|---|---|---|
| Measurement period | Day 1 | Day 2 | Day 3 | Day 4 | Day 5 |
| Baseline | 172 (90.53%) | 166 (87.37%) | 159 (83.70%) | 124 (65.26%) | 108 (53.16%) |
| Intervention | 162 (85.30%) | 148 (77.90%) | 147 (77.40%) | 112 (58.90%) | 103 (54.20%) |

*Note. N* = 1900.

**Sociometric nominations.** Influence agents within each classroom were identified on the basis of seven peer nomination questions. Three questions were based on ASSIST-based studies: friendship, advice, and leadership (Starkey et al., 2009). The remaining four questions (i.e., “With whom do you hang out?”; “To whom do you want to come across as an active person?”; “Who does sports or activities that you also would like to do?”; and “With whom do you talk about physical activity?”) were based on peer influence mechanisms involving physical activity (Salvy et al., 2012). Participants could nominate peers of the same grade, by clicking on their names that were presented in a list on the research smartphone. Also, a search field was provided so participants could easily find the names of the friend that they want to select. Participants were free to nominate an unlimited number of peers but were required to nominate at least one other schoolmate (N.B. self-nominations were not possible).

***Selection of influence agents.*** The most central participants were determined based on closeness centrality by entering all the sociometric nominations in the *KeyPlayer* package (An & Liu, 2016) in RStudio (2015). The package uses a 'greedy search algorithm' to identify a specified number of influence agents that collectively represent the most central subgroup, adjusting for overlapping nominations within each classroom network (An & Liu, 2016). This selection procedure differs from previous network interventions in which the researchers simply identified influence agents by selecting the participants that individually have the highest centrality without adjusting for redundant nominations. Additional analyses of the differences in selection criteria revealed that the overlap between influence agents identified using closeness centrality and those who would have been identified using the traditional criterion of in-degree centrality was low (29%). This means that the influence agents selected in this study had a different position in the social networks compared to the agents identified in previous studies.

Based on previous research (Rogers, 2003; Valente & Pumpuang, 2007), the top 15% of males and the top 15% of females in each classroom were identified as influence agents. In total, 24 participants were identified as influence agents. Of the approached influence agents, 19 participants (42% male, age: 12-13 y/o) accepted the role, 1 participant declined, and 4 participants did not respond to the invitation. This resulted in four intervention classes including 4 influence agents, and the other intervention classroom including 3 influence agents.

**Covariates.** A number of covariates were included to adjust for possible confounding effects. Sex and age were included because males tend to be more active than females, and younger adolescents tend to be more active than older adolescents (Sallis, Prochaska, & Taylor, 2000; Sherar, Esliger, Baxter-Jones, & Tremblay, 2007). In addition, athletic competence was measured by the *physical* subscale of the *self-perceived competence scale* (Nagai, Nomura, Nagata, Ohgi, & Iwasa, 2015). This scale consisted of 10 items describing competence and interest in physical activity (e.g., "Are you good at sports?" or "Do you have confidence in doing new sports for the first time?") that were measured on a 7-point likert scale (α = .84) ranging from "no, definitely not" (1) to "yes, definitely" (7).

## Social Network Intervention

The training adapted elements from a training stimulating healthy drinking behavior used by Smit et al. (2016). The training was based on insights from the self-determination theory (Deci & Ryan, 1985), targeting competence, autonomy, and relatedness to increase adolescents' motivation to be more physically active. In addition, the self-persuasion theory (Aronson, 1999) was used to stimulate ownership of the targeted behavior. After the adaptation, all authors agreed on the face validity of the intervention. The intervention was pretested on two males and two females from the first grade of an unrelated secondary school. Based on their feedback adjustments were made, including the suggestion to refer to the influence agents as *team captains*.

The training consisted of four components: introduction, knowledge, skills, and acceptance of the task. In the afternoon of the first day of the intervention, the influence agents received a message on their research phone that stated: "Based on the provided answers of the previous project week, you have been selected for a secret assignment. Together with a couple of classmates, you will carry out this assignment without the rest of the class knowing". Then, the role of the team captain (i.e., influence agent) was explained and questions about their own physical activity were asked to make the topic more salient. Subsequently, the training focused on knowledge about the benefits of physical activity. Based on self-persuasion theory (Aronson, 1999), participants were first asked to name benefits of being physically active and the perception of their own physical activity. Next, the influence agents received eight benefits of physical activity (e.g., health, academic performance, enjoyment). To raise competence as an influence agent (Deci & Ryan, 1985), the influence agents were thought influence strategies to promote physical activity in the classroom, based on Aronson (1999) and Salvy et al. (Salvy et al., 2012). More specifically, the influence agents learned about four strategies: S*ocial facilitation* (by organizing an activity), *modelling* (by being an example and acting as a role model), *impression management* (by telling others about the benefits of physical activity and asking them why they are physically active), and *self-persuasion* (by asking others why they think physical activity is important). To increase their autonomy, the intervention emphasized that the team captains were free to use one or multiple influence strategies, and were also free to come up with other strategies. Lastly, the participants were asked to accept or decline the role of team captain. After accepting the role, the researchers contacted the team captains via the smartphone to reveal the identity of the other captains in the class, and confirm that their assignment was clear. In the subsequent five days, all team captains received daily reminders on the benefits of physical activity and the four influence strategies.

**SNI evaluation.** After the intervention period, the influence agents filled out a questionnaire in which the intervention was evaluated. Specifically, the influence agents were asked about their role as a team captain, what types of strategies they used to performed their role and whether they thought they influenced the physical activity of their classmates.

## Strategy of Analysis

In this study, five consecutive days of physical activity per participant were measured, resulting in a hierarchical data structure. Days of physical activity (level 1) were nested within participants (level 2), and participants were nested within school classes (level 3). Because of the hierarchical structure, random adjustments for the different levels to the fixed intercept were included (Barr, Levy, Scheepers, & Tily, 2013). For that reason, we used a linear mixed-effects model approach to account for the nested hierarchical structure of the physical activity data. The multilevel approach simultaneously controls for clustering of the data and gives more weight to participants with more days of physical activity data (Singer & Willett, 2003).

The data were cleaned, structured and analyzed in RStudio (2015). Multilevel models were performed using the lme4 package (Bates, 2010). Alpha was set at $p < 0.05$. First, the clustering of the data was assessed by examining the intraclass correlation coefficient (ICC) of the different levels. Adjustments per level were made in an additive manner where necessary. Subsequently, a randomization check was carried out to ensure that participants in each condition did not initially differ in physical activity. Then, the main analyses were performed by adding all parameters to the mixed models. The mixed models were performed on the data that included the imputed values as well as on the data that included only those with complete information to detect if the imputed data led to different results. Lastly, additional analyses were carried out to inspect the effect the intervention had on the influence agents.

## Results

### Preliminary Analyses

**Clustering of data.** To examine the amount of variance in physical activity attributable to differences between classrooms, participants, and days of the week, three separate random-intercept models were performed and compared to the null model (only a fixed intercept). In each model, the standardized number of steps was included as the dependent variable. First, random intercepts per participant were added to the model specification. Likelihood ratio test indicated that the inclusion of random intercepts per classroom did not improve model fit, $x^2(1) = .44$, $p = .51$; but the inclusion of random intercepts per participant and per day did improve model fit ($x^2(1) = 150.55$, $p < .001$, and $x^2(1) = 154.64$, $p < .001$, respectively). That is, physical activity did not significantly vary between classrooms (ICC = .02), but did vary between participants (ICC = .24) and days (ICC = .12). Therefore, the subsequent models included random intercepts per participant and per day.

**Randomization check.** To test whether there were differences in physical activity at baseline between the conditions, a multilevel model was performed (that included random intercepts per participant and day). To check for possible differences between the influence agent and the non-influence agents in the social network intervention condition, the influence agents were treated as a separate condition. The control condition did not differ in physical activity from the influence agents, $b = -.03$, $SE = .18$, $p = .85$, or from the targeted adolescents, $b = -.19$, $SE = .11$, $p = .09$. This means that the randomization in terms of physical activity at baseline was successful. In addition, the participant characteristics in the different conditions were compared in sex, age, and athletic competence (Table 2). Adolescents were slightly older in the control condition, $F(2, 187) = 8.69$, $p < .001$. The difference in age between the conditions was accounted for in the subsequent analysis by including age as a covariate.

Table 2

*Randomization checks of the covariates for the influence agents, SNI condition and control condition.*

| | Condition | | | |
|---|---|---|---|---|
| | Influence Agents | SNI | Control | *P* value[a] |
| Boys/girls (n/n) | 8/11 | 32/42 | 48/49 | .67 |
| Age (y) | 12.16 ± .37 | 12.00 ± .37 | 12.31 ± .57 | <.001 |
| Athletic Competence [b] | 4.67 ± .82 | 4.68 ± .82 | 4.76 ± .75 | .83 |

*Note*. *N* = 190, [a] Reflects the differences in means between the conditions by Pearson's chi-square test or one-way ANOVA. [b] Likert scale [0-7].

**Main Analyses**In the main analyses, we added the fixed effects of the measurement period (baseline vs. intervention), condition (SNI vs. control), the interaction between the measurement period and condition, and the covariates (sex, age, and athletic competence) to the model with the random intercepts for days and participants.

The final model included random intercepts per participant and day (sum-to-zero coded), fixed effects for the measurement period, condition, the interaction of measurement period and condition, sex, age, and athletic competence. The number of steps was significantly predicted by measurement period ($b = -0.18$, $SE = .08$, $p = .033$). In both conditions, participants were more active at baseline ($M = 9{,}334.23$, $SD = 771.39$ steps per day) than during the intervention week ($M = 8{,}629.00$, $SD = 772.16$ steps per day). The number of steps was not predicted by the condition ($b = 0.14$, $SE = .10$, $p = .151$). Also, we did not observe a statistically significant interaction between the measurement period and condition in the data with imputed values ($b$ = .04, $SE$ = .10, $p$ = .66) nor in the data without imputed values ($b$ = .10, $SE$ = .09, $p$ =.27). This means that changes in physical activity between baseline and intervention did not differ between the SNI group and the control group (see Figure 2). Contrary to the hypothesis that adolescents in the SNI-condition would increase their physical activity over time compared to the control condition, no effect of the intervention was observed.

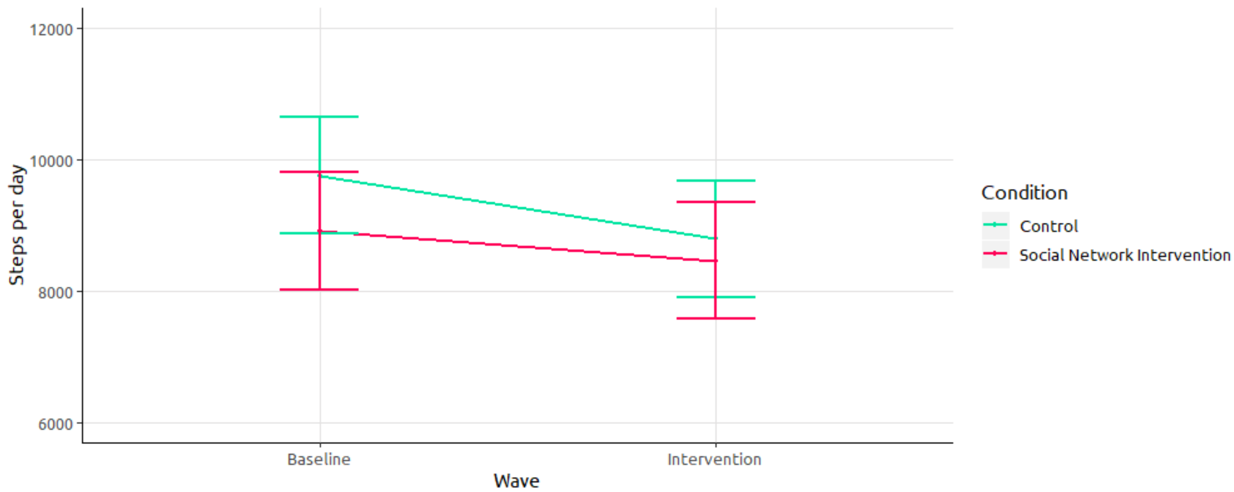


*Figure 2*. Estimated marginal mean steps per day for the two conditions.

*Note*. Unstandardized estimated marginal means are presented after controlling for the clustering in data and all covariates for interpretation purposes.

With regard to the covariates, the number of steps taken was significantly predicted by sex ($b$ = -0.39, $SE$ = .09, $p$ = .001). On average, boys ($M$ = 9,988.48, $SD$ = 798.52 steps per day) were more active than girls ($M$ = 7,974.75, $SD$ = 778.47 steps per day).

Table 3

*Linear mixed-effects model for standardized physical activity for the imputed dataset*

| | | | $s^2$ | *b* | *SE* | DF | *p* | 95% CI |
|---|---|---|---|---|---|---|---|---|
| Random | Participant | Intercept | 0.16 | | | | | |
| | Day | Intercept | 0.13 | | | | | |
| | | Residual | 0.62 | | | | | |
| Fixed | | Intercept | | .75 | 1.09 | 411.47 | .49 | [-1.39, 2.89] |
| | | M. period | | -.18 | .08 | 39.243 | .033* | [-.34, -.01] |
| | | Condition | | -.14 | .10 | 426.30 | .151 | [-.33, -.05] |
| | | Sex | | -.39 | .09 | 223.25 | <.001* | [-.56, -.21] |
| | | Age | | -.04 | .09 | 456.15 | .67 | [-.21, .14] |
| | | Athletic competence | | .18 | .04 | 455.43 | <.001* | [.09, .26] |
| | | M. Period * Condition | | .04 | .10 | 85.05 | .66 | [-.15, .24] |

*Note.* *N* = 190. CI = Confidence interval. Marginal $R^2$ = 0.07. Conditional $R^2$ is not applicable to multiple imputed mixed models.

Table 4

*Linear mixed-effects model for standardized physical activity for the complete cases dataset*

| | | | $s^2$ | *b* | *SE* | DF | *p* | 95% CI |
|---|---|---|---|---|---|---|---|---|
| Random | Participant | Intercept | 0.16 | | | | | |
| | Day | Intercept | 0.13 | | | | | |
| | | Residual | 0.62 | | | | | |
| Fixed | | Intercept | | .73 | 1.03 | 157.30 | .48 | [-1.28, 2.74] |
| | | M. period | | -.19 | .07 | 1159.50 | .004* | [-.32, -.06] |
| | | Condition | | -.17 | .09 | 245.60 | .07 | [-.35, .01] |
| | | Sex | | -.40 | .08 | 152.50 | .001* | [-.56, -.24] |
| | | Age | | -.03 | .08 | 153.70 | .70 | [-.19, .13] |
| | | Athletic competence | | .18 | .03 | 149.40 | <.001* | [.10, .26] |
| | | M. Period * Condition | | .10 | .09 | 1152.60 | .27 | [-.08, .28] |

*Note.* *N* = 190. CI = Confidence interval. Marginal $R^2$ = 0.06. Conditional $R^2$ = 0.08. Conditional $R^2$ = 0.37.

Likewise, athletic competence predicted the number of steps per day ($b = 0.18$, $SE = .04$, $p < .001$). Adolescents who were more athletically competent were more physically active. As can be seen in Table 3 (Table 4 for the complete case analysis), age did not affect physical activity.

Table 5

*Responses to the evaluations by the influence agents*

| | *M* | *SD* |
|---|---|---|
| How did you like being a team captain? | | |
| 0 = not at all, 100 = very much | 62.82 | 25.00 |
| How hard was the task of being a team captain? | | |
| 0 = very easy, 100 very hard | 42.73 | 31.37 |
| | % | |
| Which tactics did you use to promote physical activity | | |
| Impression management | 25.00 | |
| Modeling | 41.67 | |
| Social facilitation | 16.67 | |
| Self-persuasion | 16.67 | |
| At what time during the day did you carry out the role the most | | |
| Before school | 12.50 | |
| During the breaks | 25.00 | |
| During class | 31.25 | |
| After school | 31.25 | |
| Did you use social media for your role? | | |
| Yes | 9.09 | |
| No | 90.91 | |
| Do you think you were successful in increasing the physical activity of classmates? | | |
| Yes | 27.27 | |
| No | 9.09 | |
| Don't know | 63.64 | |

*Note.* $N = 11$

**Influence agents' evaluation.** After the intervention measurement period, the 19 influence agents received a post-intervention evaluation (Table 5) to which 57.9% responded. The qualitative data show that most of the influence agents indicated that they were neutral to positive about being a team captain and thought it was an easy task to perform, while some others did not like the role or thought it was hard to promote physical activity. Additionally, most influence agents indicated that they were not aware of their influence on others and not sure if they had increased physical activity among their classmates. The influence agents indicated that all the different tactics from the training to promote physical activity were used, with modeling being the most popular. The influence agents performed their tasks throughout the day, so not only during school hours. Lastly, almost all influence agents indicated that they did not use social media to perform their tasks.

## Discussion

This study was one of the first to test the effectiveness of a social network intervention to promote physical activity among adolescents. In addition, the study selected the influence agents based on their closeness centrality within the social networks and used an innovative approach to train the influence agents via smartphones. Contrary to our expectation, we did not find an effect of the social network intervention on the physical activity of adolescents.

The findings are not in line with previous social network interventions promoting other types of health behaviors than physical activity (Campbell et al., 2008; Smit et al., 2016; Starkey et al., 2009; Valente et al., 2007). In these studies, social network interventions have shown promising results to promote a variety of health behaviors. When focusing on physical activity, our findings are not in line with Sebire et al. (2017)

who was successful in promoting physical activity in adolescent females via a social network intervention. However, our study shows similar results as Bell et al. (2014), who observed no social network intervention effect on dietary intake or physical activity. Their main recommendation was that the training should be relatively simple and the intervention message should be easy to pass on. Bell et al. (2014) advised focussing the intervention on one health behavior at a time. Our study followed this advice and focused only on physical activity. However, this did not increase the effectiveness of the social network intervention. In our view, there are two plausible explanations for the discrepancy between our study and the previously discussed social network interventions.

One explanation for our finding is that we adjusted the existing social network interventions to a smartphone environment to increase feasibility and make the intervention more fun and suitable for large-scale deployment. This study was the first to incorporate smartphones in a social network intervention. Influence agents were approached and trained via the research app in the *Wearable Lab*. This is a less personal approach compared to previous social network intervention studies in which the influence agents met face-to-face with their trainers and other influence agents (Bell et al., 2014; Campbell et al., 2008; Smit et al., 2016; Starkey et al., 2009). Also, because of the smartphone-based training, the instructions took less time compared to previous studies. It might have resulted in less commitment and team effort to perform their tasks. Although the influence agents indicated at the end of the intervention that they liked their role, it was unclear whether they completely understood the training and were motivated to be influence agents. In order to decrease the psychological distance between the researchers and the influence agents, we added a photograph of the researcher who gave the instruction in the school to the training and contacted the influence agents personally via the smartphone after completing the training. A more personal approach has been successfully used by Smith et al. (2014) in a smartphone obesity prevention trial to promote physical activity for boys with an increased risk of obesity. Apart from three interactive seminars at school focusing on increasing physical activity and decreasing screen-time, participants used a smartphone application to receive feedback and to keep in touch with the researchers. Future research could adapt this to social network interventions by combination between personal contact (e.g., at the start of or during the intervention) and contact via the smartphone (e.g., during the intervention), and test whether this approach is a feasible tool for training and a way to keep in contact with the influence agents.

Another explanation for our findings involves our approach to use closeness centrality as a means of identifying the influence agents. Previous social network interventions have exclusively used in-degree centrality to identify influence agents (Bell et al., 2014; Campbell et al., 2008; Sebire et al., 2017; Smit et al., 2016; Starkey et al., 2009). Based on the idea that individuals who receive the most nominations would be reluctant to change behavior because they want to remain popular (Valente, 1995), we opted to use closeness centrality because these individuals were expected to have more influence within the entire network when it comes to the promotion of health behavior (Borgatti, 2006). A possible consequence is that the influence agents in our study were closely connected to all the other classmates, but were not effective in persuading others because they did not have a high status. Future research should further investigate the selection of the influence agents by systematically evaluating the effectiveness of influence agents identified by these (and other) selection criteria. By doing so, the generalizability of the diffusion mechanism of the health campaign will become more clear.

## Limitations

Innovative studies go along with a number of limitations and several limitations should be discussed in interpreting the results. First, active parental consent was required for participants to be included in this study due to ethical and legal considerations. As a result, there were some students in each classroom that did not participate, which may have influenced the identification of the influence agents in the social network. That is, the adolescents who did not participate did not provide nominations nor could they be nominated by participants. It also remains unclear whether non-participants differed in their physical activity compared to the participants. It could be that the non-participants did not want to participate because of their sedentary lifestyle. To reduce this potential confound, however, classes with a high percentage of non-participants (participation lower than 60%) were excluded.

Second, only one large school was approached to participate in order to reduce potential differences between the classes in the control condition and in the intervention condition. This may have had an effect on external validity. Future research should include multiple schools to examine whether differences occur between different locations or school types, and make the results more generalizable.

Third, compared to other social network studies, the intervention period was rather short. In previous studies, the intervention period lasted for multiple weeks. A longer intervention period enables more opportunities for the influence agents to perform their role and influence the behavior of the rest of the class. Due to time constraints of the participating school and limited availability of the research material, the intervention period in this study was only one week. Future research should consider using a longer intervention period than a week to provide more time for the influence agents to promote the health behavior among their classmates.

## Conclusion

Despite these limitations, this study advanced the field of social network interventions in three ways. First, the present study was the first social network intervention that used a 'greedy search algorithm' to identify influence agents based on closeness centrality. Although we did not directly compare influence agents identified using a different criterion, our study extended social network theory by using an alternative selection criterion that reflects the main tenets of social network theory. Our study provides implications for future research to build on this extended way of thinking about the role of influence agents.

Second, this study was the first that used smartphones to train the influence agents in a social network intervention to promote physical activity in adolescents. Evaluations showed that research using smartphones is a feasible research tool to not only collect various types of data but also to train and keep in touch with the influence agents. Nevertheless, maintaining personal contact with influence agents is still an important aspect to consider.

Third, the present study used a sophisticated analytic procedure utilizing multilevel analyses and multiple multi-level imputations, to adjust for the nested structure of the data and to include individuals with missing values. This procedure provided a more stringent test of the intervention effect by accounting for variance in physical activity due to daily fluctuations in activity levels and to individual differences.

In this study, we did not observe an effect of the social network intervention on the physical activity of adolescents. However, given that social network interventions in physical activity (as well as other health behaviors) are relatively underutilized and understudied, we encourage continued research applying social network interventions among adolescents to promote health behaviors and advance behavioral health science.

Chapter 5

# Testing a Social Network Intervention using Vlogs That Promotes Physical Activity among Adolescents: A Randomized Controlled Trial.

This chapter is in review as:

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## Abstract

### Background

There is a need to stimulate physical activity among adolescents, but unfortunately, they are hard to reach with traditional mass media interventions. Given the popularity and the networked structure of social media, social network intervention seems to be a promising alternative. In social network interventions, a small group of individuals (*influence agents*) is selected to promote health behaviors within their social network. This study investigates whether a social network intervention is more effective to promote physical activity, compared to a mass media intervention and no intervention.

### Method

Adolescents ($N = 446$; $M_{age} = 11.35$, $SD_{age} = 1.34$; 47% male) were randomly allocated by classroom ($N = 26$) to one of three conditions: social network intervention, mass media intervention, or control condition. In the social network intervention, 15% of the participants (based on peer nominations) were approached to become an influence agent, who then created several vlogs about physical activity. During the intervention period, participants were able to view the vlogs on a research smartphone. In the mass media intervention, participants were exposed to vlogs made by unfamiliar peers (i.e., the vlogs of the social network intervention). The control condition did not receive vlogs about physical activity. All participants received a research smartphone to complete questionnaires and a wrist-worn accelerometer to measure physical activity.

### Results

There were no differences between the social network intervention and the control condition in the short-term, and an unexpected increase in the control condition

compared to the social network intervention in the long-term. No differences between the social network intervention and mass media intervention were observed either. Exploratory analyses suggest that the social network intervention increased the perceived social norm toward physical activity and responses to the vlogs were more positive in the social network intervention than in the mass media intervention.

### Conclusion

The current study does not provide evidence that a social network intervention is more effective in increasing physical activity in adolescents than a mass media intervention or no intervention. However, exploratory results suggest that the social network intervention has a positive effect on the perceived descriptive norm and the responses towards the vlogs. These first results warrant further research to investigate the role of the perceived social norms and the added benefit of using influence agents in social network interventions.

### Trial Registration

Dutch Trial Registry (NTR): NTR6903. Registered 14 December 2017. Study procedures were approved by the Ethics Committee of the Radboud University (ECSW2014-100614-222).

*Keywords:* social network intervention, physical activity, accelerometer, adolescents, vlogs

## Background

Physical activity has a positive effect on youth's physical (Janssen & LeBlanc, 2010) and mental health (Biddle & Asare, 2011). However, 80% of adolescents worldwide do not adhere to the recommended amount of daily physical activity (Hallal et al., 2012). This is problematic, because (un)healthy habits formed in childhood can persevere into adulthood (Boreham & Riddoch, 2001). Therefore, there is a substantial need for effective interventions to promote physical activity among adolescents.

Public health agencies and researchers have used mass media intervention campaigns to promote physical activity at a community level (Cavill & Bauman, 2004; Dobbins, DeCorby, Robeson, Husson, & Tirilis, 2009). Mass media interventions use standardized messages to increase knowledge, influence attitudes and beliefs, and change behavior (Kahn et al., 2002), and are a relatively inexpensive way of reaching a large audience and, therefore, suitable for large scale implementation (Redman, Spencer, & Sanson-Fisher, 1990). Although there are examples of mass media interventions that have increased physical activity in adolescents (e.g., Huhman et al., 2005), a systematic review of mass media campaigns concludes that there is insufficient evidence to assess whether mass media interventions are an effective strategy to promote physical activity in this particular population (Kahn et al., 2002). One of the reasons that mass media interventions do not succeed in increasing physical activity is that people, especially youth, are resistant to information from outside sources (Laverack, 2017). In addition, today's adolescents are less likely to use traditional mass media and more likely to use online social media (Valkenburg & Piotrowski, 2017; Wartella, Rideout, Montague, Beaudoin-Ryan, & Lauricella, 2016). Potentially, interventions can be more effective when utilizing the impact that adolescents have on each other's physical activity by having intervention messages that are communicated by the adolescents themselves in these (online) social networks (Valente, 2012).

Social network interventions is an emerging and promising approach to counteract the decline in physical activity, by capitalizing on the influence youth has on each other's behaviors (Valente, 2012). In social network interventions, a small group of individuals, so-called *influence agents*, are identified based on their central position within each social network, which is assumed to involve substantial influence on the behavior of peers (Thoits, 2011). The influence agents are asked to either promote or discourage the targeted behavior within their social network (e.g., classroom), by serving as role models or advocates of the health behaviors. Previous work has shown that social network interventions can stimulate health-related behaviors, such as healthy eating (Shaya et al., 2014) and water consumption (Smit et al., 2016), or discourage unhealthy behaviors, such as smoking (Campbell et al., 2008; Starkey et al., 2009) and substance use (Valente et al., 2007).

Only a few studies have adopted the social network approach to promote physical activity among adolescents (Bell et al., 2014; Brown et al., 2017; Jong et al., 2018; Owen et al., 2018; Sebire, Edwards, Campbell, Jago, Kipping, Banfield, Kadir, et al., 2016; Sebire et al., 2018; van Woudenberg et al., 2018), varying in intervention method, target audience, influence agent selection strategy, and training method. For example, different forms of nominations have been used to select the influence agents (Bell et al., 2014; Brown et al., 2017; Jong et al., 2018; Sebire, Edwards, Campbell, Jago, Kipping, Banfield, Kadir, et al., 2016; Sebire et al., 2018; van Woudenberg et al., 2018), and two studies focused on female adolescents only (Owen et al., 2018; Sebire, Edwards, Campbell, Jago, Kipping, Banfield, Kadir, et al., 2016; Sebire et al., 2018). In most studies, influence agents received intensive face-to-face training sessions to teach them how they could promote the behavior within their classroom (Bell et al., 2014; Brown et al., 2017; Jong et al., 2018; Sebire, Edwards, Campbell, Jago, Kipping, Banfield, Kadir, et al., 2016; Sebire et al., 2018). One study did not use face-to-face training but trained the influence agents on how to promote physical activity within their classroom via online training on a research smartphone (van Woudenberg et al., 2018). The majority of the studies, apart from the studies by Bell et al. (2014) and van Woudenberg et al. (2018), successfully increased physical activity in the target group.

However, all previous social network intervention studies on physical activity have used designs in which the effectiveness of the intervention was compared to a control condition that did not receive an intervention. Therefore, these studies cannot provide insights on whether the social network intervention was effective due to the spread of the intervention messages led by the influence agents or just the exposure to the promotion of physical activity. No previous studies compared a social network intervention to a similar intervention without a social network component (e.g., mass media intervention) to determine the additional benefit of using the social network intervention approach. Therefore, the aim of the current study was to investigate whether a social network intervention is more effective in promoting physical activity than a mass media intervention or no intervention.

In the current study, influence agents created video blogs (‘*vlogs*’) about physical activity. Generally, vlogs are short user-generated videos that are available online, for example on YouTube (Gao, Tian, Huang, & Yang, 2010). Using vlogs as intervention messages connects seamlessly to the purposes of this study, not only because watching vlogs online has become immensely popular among adolescents (Snelson, 2015), but also because it allows for testing the social network intervention principles in a unique and unprecedented way in which the social network intervention condition is exposed to the exact same intervention messages as the mass media intervention. Specifically, to test whether the social network intervention is more effective in increasing physical activity than a mass media intervention or no intervention, participants were exposed to vlogs created by influence agents within their class (social network intervention) or unfamiliar peers (mass media intervention), or were not exposed to vlogs about physical activity. The hypotheses were that (1) participants in the social network intervention condition would increase more in physical activity than participants in the mass media intervention condition and (2) participants in the social network intervention condition would increase more in physical activity than participants in the control condition.

Moreover, because no previous studies have investigated the underlying mechanisms of social network interventions, this study has taken the first step by exploring secondary outcomes of the intervention. Based on the theory of planned behavior (Ajzen, 1991) and the self-determination theory (Ryan & Deci, 2017), four important secondary outcomes of the intervention were defined: social norms on physical activity, enjoyment of physical activity, self-efficacy of physical activity and motivation to be physically active. Likewise, because of the novelty of using vlogs as intervention messages, there is no precedence in research on how adolescents respond to these types of intervention messages. Therefore, the current study explored the responses to the vlogs (i.e., exposure to the vlogs, linking of the vlogs and perceived closeness to the vloggers) in the social network intervention and the mass media intervention.

# Method

## Design

This study used a clustered randomized control trial design with three groups. A priori, the study was registered in the Dutch Trial Registry (NTR): TR6903 and procedures were approved by the Ethics Committee of the Radboud University (ECSW2014-100614-222). The required sample size was based on the previous study by Sabire et al (2018) that found an effect of the social network intervention in a study with 272 adolescents in the sample (intervention and control condition). This number was multiplied by 1.5 to add the third condition, which resulted in a minimum number of 408 participants (approximately 21 classrooms of 20 participants per class). To account for non-response in the active consent procedure and associated strict exclusion criteria for classes, we approached more than 21 classrooms for participation in the project, see Figure 1.

## Participants and Procedure

The study is part of a two-phase project called the *MyMovez* project. In the first phase, 21 primary and secondary schools were enrolled (Bevelander et al., 2018). All participating schools were invited for the second phase (intervention phase), and new schools were approached to complement the sample, of which six new schools agreed to participate. The schools sent out information letters and consent forms to the parents or legal guardians of students in the targeted classrooms. To obtain representative samples within each classroom, only classrooms could participate in which at least 60% of students had active parental consent (Marks et al., 2013). As a result, 43 classes were enrolled in the sample. In total, active parental consent was obtained for 745 students.

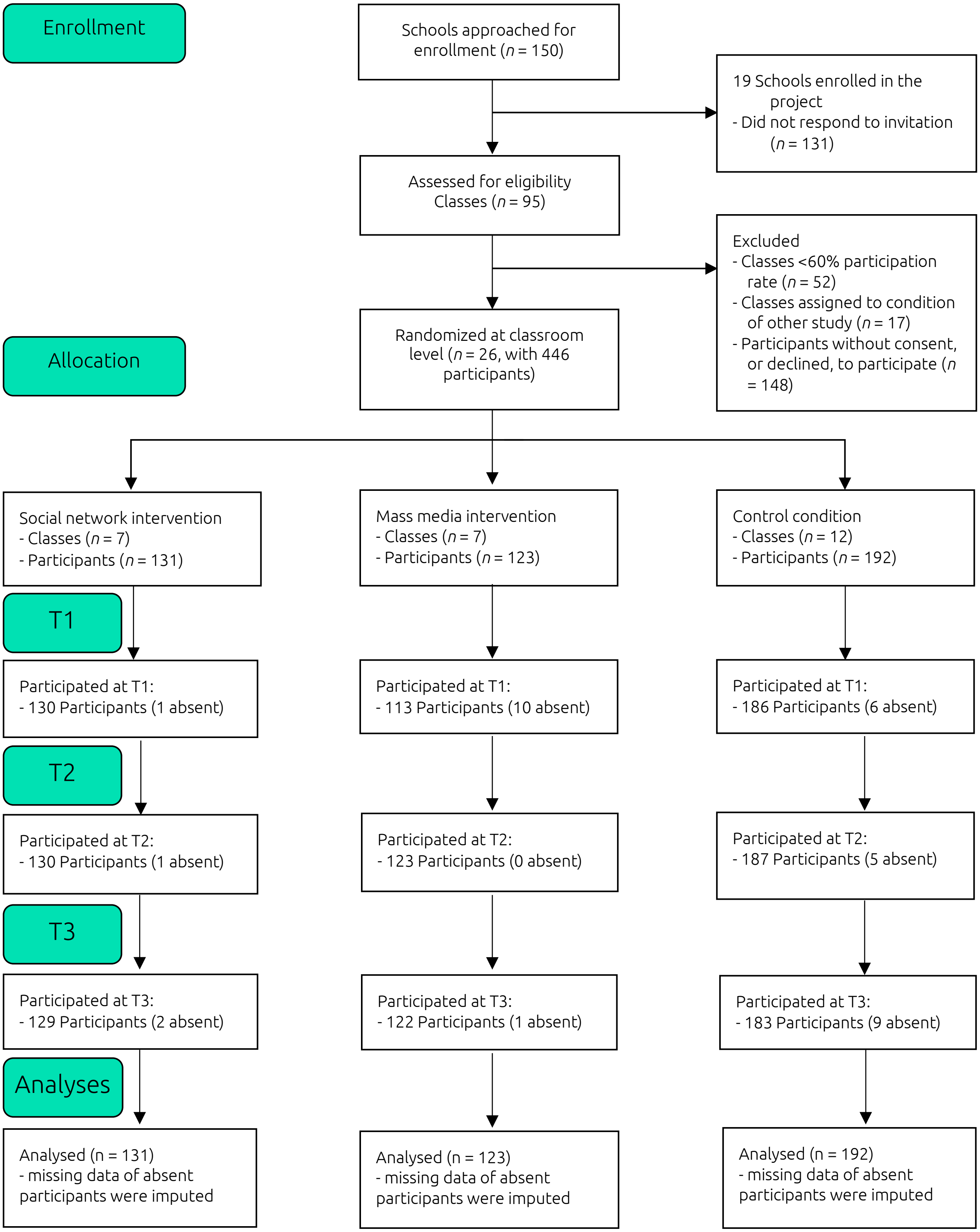


*Figure 1.* CONSORT flow diagram of participants.

In the *MyMovez* project, two separate intervention studies were conducted with a shared control group (i.e., promoting water consumption and promotion of physical activity). A total of 19 schools (43 classes) were assigned to one out of the five conditions (two water-drinking conditions, two physical activity conditions, and a control condition). Because only four secondary schools participated in the project, the two smallest secondary schools were combined, and the secondary schools were randomly assigned to one of the intervention conditions or control condition. Thereafter, the primary schools were stratified based on size and randomly assigned over all five conditions. The control condition received relatively more classes because that condition was also part of the other intervention study that only focused on primary schools.

The study reported here included three conditions (two physical activity intervention conditions and the control condition). The sample consisted of 446 participants (47.31% male) ranging from 9 to 16 years old ($M$ = 11.35 years, $SD$ = 1.34). Seven classes ($n$ = 131) were assigned to the social network intervention condition, seven classes ($n$ = 123) were assigned to the mass media intervention condition, and 12 classes ($n$ = 192) to the control condition. Before receiving the materials, participants provided informed assent.

Participants provided data for seven consecutive days at each of the three assessments: in February-March 2018 (T1), April-May 2018 (T2), and May-June 2018 (T3). At the beginning of the study (T1), all participants received instructions about the usage of the *Wearable Lab*: a smartphone with a tailor-made research application and a wrist-worn accelerometer. The smartphone was used as an assessment tool, an online social platform for participants within the class, and means of communication between the researchers and the participants. On the smartphone, participants received daily questionnaires at random moments between 7:00 AM and 7:30 PM, excluding hours that participants were in school. During the intervention week (T2), participants received the *Wearable Lab* again and were able to watch one new vlog per day on the smartphone. Five weeks after the intervention, participants received the *Wearable Lab* for the last time (T3).

## Measures

**Physical activity.** The wearable accelerometer (Fitbit Flex®) measured the number of steps per day. Incomplete days (<1,000 steps or <1,440 minutes per 24 hours) of measurement were excluded from the analysis. Reasons for incomplete days were the first and last day of the measurement week, the device was not worn, or the battery was empty. In total, 76.5% of all possible data points were observed in the daily physical activity data. When participants had less than 3 days of observed data but at least one day of data, single multilevel predictive mean matching imputation (Van Buuren, 2011) was used to generate imputed physical activity data (based on 500 iterations). The data points were imputed based on other physical activity data of the participant, class, school, day of the week, sex, age, BMI, weather conditions of that day, and psychosocial measures of the participant (i.e., athletic competence, perceived social norms; enjoyment; self-efficacy and motivation). On average, participants accumulated 9849.69 ($SD$ = 5838.63) steps per day and were moderate-to-vigorously active for 55.13 ($SD$ = 50.89) minutes per day. The imputed values did not differ from the observed values of physical activity, $t(9548) = 1.62$, $p = .11$.

**Sociometric nominations.** Participants nominated peers on five sociometric questions. Three questions (i.e.: “Whom do you ask for advice?”; “Who in your classroom are leaders, or take the lead often?"; "Who do you want to be like?") were based on previous studies that used peer nominations to identify influence agents (Campbell et al., 2008; Starkey et al., 2009). The remaining two questions were included to cover the times when adolescents are most likely together (i.e. "With whom do you hang out during the breaks?") and communicate about physical activity (i.e. "With whom do you talk about physical activity?"), based on the study by Salvy et al. (2012). Participants nominated peers within the same grade at school. In addition, participants could search for names in the provided search field and were required to nominate at least one other peer (self-nominations were impossible).

***Closeness centrality.*** Participants with the highest *closeness centrality* were selected as influence agents (van Woudenberg et al., 2019). Closeness centrality is the average distance between the participant and all other peers in a network. More specifically, closeness central individuals have the shortest paths to all other peers, making them the most strategic influence agents to disseminate the intervention message in a social network in the least amount of time (Borgatti, 2005). The KeyPlayer package (An & Liu, 2016) in RStudio (2015) was used to determine a specified number of influence agents that collectively represented the most central subgroup, adjusting for overlapping nominations within each classroom network (An & Liu, 2016). Based on previous studies (Rogers, 2003; Valente & Pumpuang, 2007), 15% of males and 15% of females were identified as influence agents in each classroom (Araujo et al., 2018). All 22 of the participants who were approached accepted the role of influence agent. In one school, three participating classes shared one room in the building (as part of the teaching philosophy). Therefore, students in these three classes were combined into one large network for the influence agent selection procedure. This resulted in four intervention classes with four influence agents, and the last intervention classroom with six influence agents.

**Social norms.** Perceived descriptive norms of classmates was measured by a single item: 'How many days per week are your classmates physically active for more than an hour per day?' Perceived injunctive norms of classmates was measured by a single item: 'How many days per week do your classmates think that you should be physically active for more than an hour per day?' For both questions, participants could answer in a range between 0 and 7 days per week (Pedersen, Grønhøj, & Thøgersen, 2015).

**Enjoyment.** Enjoyment was measured by a Visual Analogue Scale (VAS). Participants were asked to indicate how much they enjoyed sports and physical activity, and could answer by placing their finger on a slider ranging from 0 ('not at all fun') to 100 ('very much fun').

**Self-efficacy.** Self-efficacy was measured by two items (van der Horst et al., 2007): 'Do you think you are able to be more physically active?' and 'Does being more physically active seem difficult to you?'. Participants could answer on a 6-point Likert scale ranging from 'No, definitely not' to 'Yes, definitely'. The two items ($r$ = .62, $p$ < .001) were averaged into one variable.

**Motivation.** Motivation was measured by 12 items, in four subdomains as described in the self-determination theory (Ryan & Deci, 2017): extrinsic, introjected, identified and intrinsic motivation. Participants read statements describing the different types of motivation (e.g. 'I am physically active because I think this is important') and could answer on a 6-point Likert scale ranging from 'No, not at all' to 'Yes, definitely'. The extracted means at each time point are reported in Table 1.

**Vlogs exposure.** Vlog exposure was measured by how many times, and seconds a participant watched the vlogs. The first vlog (introduction vlog) was excluded because it did not promote physical activity. The five remaining vlogs had an average length of 50.36 seconds (*SD* = 22.00). On average, the vlogs were watched 1.67 times (*SD* = 3.06) per participant per day, with an average viewing time of 60.22 seconds per participant per day (*SD* = 116.64).

**Liking of the vlogs.** The liking of the vlogs was measured at the end of each day on which the vlog became available. Participants indicated on a VAS how much they liked the vlog, ranging from 'not fun' (0) to 'very much fun' (100). On average, the vlogs were evaluated slightly positive (*M* = 58.14, *SD* = 34.31).

**Perceived closeness with the vloggers.** The perceived closeness with the vloggers was assessed on the last day of T2 (when participants had received all the vlogs) and was measured by using the *Inclusion of Other in the Self*-scale (Aron, Aron, & Smollan, 1992). Participants indicated which image best represented the overlap between themselves and the vloggers ranging from an image with two circles that do not overlap (1) to an image with two almost completely overlapping circles (7). Participants reported a moderate degree of closeness to the vloggers (*M* = 4.09, *SD* = 1.90).

**Covariates.** Sex and age were included to correct for possible confounding effects because males tend to be more active than females, and younger adolescents tend to be more active than older adolescents (Sallis et al., 2000; Sherar et al., 2007). In addition, participants' weight and height were measured individually by a trained research assistant according to standard procedures (with clothes, but without shoes) at T1. Based on the weight, height, sex, and age, a standardized measure of the Body Mass Index was calculated, *M* = 18.05, *SD* = 3.15 (5.2% overweight, 0.7% obese) which accounts for variations in growth curves of youth (Schönbeck et al., 2011). The type of school (primary and secondary) was also added as a covariate to control for structural differences between the two school types. And because adolescents are less active in the weekend, a variable that identified whether a day was a weekday or a weekend was added as a covariate (Lee, Stodden, & Gao, 2016).

Also, the perceived athletic competence was added as a covariate, measured at T1 and T3 by the *physical* subscale of the *Children's Perceived Competence Scale* (Nagai et al., 2015). The subscale consisted of 10 items measuring the perceived level of in physical activity (e.g., "Are you good at sports?" or "Do you have confidence in doing new sports for the first time?") measured on a 6-point Likert scale (α = .78) ranging from "no, definitely not" to "yes, definitely" (Cronbach's $\alpha = .78$, $M = 4.34$, $SD = .87$).

Table 1
*Overview of measures at the three time-points.*

| | | *items* | *α* | Range | $M_{T1}$ | $SD_{T1}$ | $M_{T2}$ | $SD_{T2}$ | $M_{T3}$ | $SD_{T3}$ |
|---|---|---|---|---|---|---|---|---|---|---|
| Steps per day | | - | - | [1,000 – 44,560] | 9181 | (5038) | 1091 0 | (6506) | 9479 | (5781) |
| Social norms | *Descriptive* | 1 | - | [0-7] | 3.84 | (1.76) | 3.77 | (1.81) | 3.74 | (1.92) |
| | *Injunctive* | 1 | - | [0-7] | 3.47 | (2.20) | 3.65 | (2.21) | 3.62 | (2.15) |
| Enjoyment | | 1 | - | [1-6] | 5.13 | (1.05) | 5.18 | (.94) | 5.13 | (1.02) |
| Self-efficacy | | 2 | - | [1-6] | 4.93 | (1.09) | 4.88 | (1.18) | 4.52 | (1.34) |
| Motivation | *Extrinsic* | 3 | .68 | [1-6] | 1.48 | (.94) | 1.71 | (1.24) | 1.75 | (1.27) |
| | *Introjected* | 3 | .78 | [1-6] | 2.03 | (1.23) | 2.1 | (1.35) | 2.05 | (1.40) |
| | *Identified* | 3 | .85 | [1-6] | 4.91 | (1.12) | 4.93 | (1.13) | 4.72 | (1.31) |
| | *Intrinsic* | 3 | .59 | [1-6] | 5.37 | (.90) | 5.27 | (.94) | 5.16 | (1.07) |

*Note.* $N$ =446.

## Conditions

**Social network intervention.** The influence agents were approached on the last day of T1 and were invited to create vlogs about physical activity. The influence agents who accepted their role (100%) watched six short video instructions on a laptop, presented by a famous Dutch vlogger. In the instruction, they were taught how to write scenarios, present, and film the content of the vlogs. They did not receive training on how they can influence the physical activity of peers. After watching the videos, the influence agents received an example script and a range of topics that they could use for each vlog. These ideas were based on social influence components, such as social norms, enjoyment, self-efficacy, and motivation (Ajzen, 1991; Ryan & Deci, 2017; Salvy et al., 2012, 2008). The topics targeted the increase in social norms by showing how physically active the influence agents are, increasing enjoyment by showing fun ways to be active, increasing ability to be physically active by providing new activities or increasing the motivation to be physically active by providing challenges. The influence agents filmed the content for the first vlog with the help of the researcher. Afterward, the influence agents could ask questions and schedule meetings with the other influence agents to film the remaining vlogs. In addition, each group of influence agents also received a sheet with crude ideas for the remaining vlogs. During the process, it was stressed by the researcher that the assignment should remain a secret to the rest of their classrooms until the vlogs were shown. All influence agents promised to keep their assignment a secret.

On the first day of the intervention period, all participants were instructed in the classroom that a select group of influence agents had created vlogs about physical activity and that the participants were able to see the vlogs on the provided research smartphone. Each morning (at 7:00 AM) a new vlog became available under the 'vlog tile' in the *MyMovez* app. Participants could watch the vlogs as often as they wanted, give *likes* to the vlogs and send the vlogs to classmates via the *Social Buzz*. On average, the participants in the social network intervention conditions watched the vlogs 15.69 times (*SD* = 20.60) across the entire week, with a total viewing time of 515 seconds (*SD* =

641) per participant, but 22 participants in the social network intervention conditions (8.6%) did not watch any of the vlogs.

**Mass media intervention.** Similar to the social network intervention, all participants were instructed on the first day of T2 in the classroom that vlogs about physical activity would become available daily on the provided smartphone. The vlogs from the social network intervention condition were used and matched in terms of school type (primary and secondary). As a result, the vloggers were unfamiliar peers, resembling a mass media campaign that adolescents are exposed to on the internet. Each vlog was presented once in the social network intervention condition and once in the mass media intervention condition. On average, participants in the mass media intervention condition watched the vlogs 7.21 times ($SD$ = 14.60), with an average viewing time of 218 seconds ($SD$ = 444), 40 participants in the mass media intervention condition (32%) did not watch any of the vlogs.

**Control.** The control condition was not exposed to vlogs about physical activity. In the research application, other short videos were available (which were available for all conditions).

## Strategy of Analysis

The data were handled and analyzed in RStudio (2015). To control for the hierarchical structure of the data, a mixed-effects model approach was used (Barr et al., 2013; Singer & Willett, 2003). Mixed-effects models were performed with the lme4 package (Bates, 2010). Statistical significance ($p$-values) were determined using the Satterthwaite approximation (Luke, 2017).

**Preparatory analyses.** The preparatory analyses were used to identify the most appropriate random effects structure for the data. More specifically, variance in physical activity explained by each level (i.e., school type, school, class, participant, weekend, date) was compared separately to an intercept-only model. Based on the intraclass correlation coefficient (ICC), each level was added in a stepwise approach when the model fit improved significantly as indicated by a statistically significant chi-square difference test. After the random effects structure was identified, a mixed-effects model with condition (social network intervention, mass media intervention, and control) included as a fixed effect was performed on the physical activity data of T1 to test whether the randomization was successful.

Main analysis. The primary analysis used a mixed effect model to test differences between conditions on physical activity over time. More specifically, condition, time, the interaction between condition and time, as well as several covariates (i.e. sex, age, BMI, athletic competence, and weather conditions) were included as fixed effects in the model. Because condition and time were categorical variables with three factor levels, two planned contrasts were used to test differences between conditions and between time periods. For condition, the first contrast compared the social network intervention to the control condition, and the second contrast compared the social network intervention to the mass media intervention. For time, the first contrast compared T1 with T2 to assess short-term effects, and the second contrast compared T1 with T3 to assess long-term effects. As sensitivity analyses, the same analysis was repeated twice, once without the imputed data and once without the data of the influence agents.

Exploratory analyses. Additional mixed effect models tested differences between the three conditions over time on several secondary outcomes namely: perceived social norms, physical activity enjoyment, self-efficacy, and motivation. For each outcome, an identical model specification was used as in the main analyses, with the only adjustment being the physical activity variable was substituted for the respective secondary outcome variable.

The last set of analyses were limited to participants in the two conditions that were exposed to the physical activity vlogs (i.e., the control conditions was excluded). The analyses investigated whether the amount of exposure to the vlogs, liking of the vlogs and the perceived closeness to the vloggers was higher in the social network intervention condition compared to the mass media intervention condition, by using t-tests.

## Results

### Preparatory Analyses

**Clustering of data.** Due to the complex design of the study, the amount of variance in physical activity that could be attributed to differences between the levels of data (i.e. school type, school, class, participant, weekend, date) was initially assessed. Per level, a separate random-intercept model was performed and compared to an intercept-only model (no random intercept) and the ICC per level was calculated. The variance in physical activity could mostly be attributed to differences between participants (ICC = .19), and a likelihood ratio test indicated that the addition of a random intercept per participant improved the model fit, $x^2(1) = 551.23$, $p < .001$. Second, the random intercept of the date (ICC = .08) was added, which improved the model fit again, $x^2(1) = 325.98$, $p < .001$. Lastly, the random intercept of classroom (ICC = .03) was added, which also improved the model fit, $x^2(1) = 6.72$, $p = .009$. Other levels did not significantly improve the model fit. To conclude, subsequent models included random intercepts per class, participant and date.

**Randomization check.** To test whether there were differences in physical activity at T1 between the conditions, a mixed-effects model showed that, after adjusting for multiple testing, the social network intervention condition did not differ in physical activity from the mass media intervention, $b$ = 844.71, $se$ = 783.12, $p$ = .533, or the control condition, $b$ = 81.88, $se$ = 557.23, $p$ = .988. Also, the mass media intervention condition did not differ from the control condition, $b$ = 762.83, $se$ = 721.24, $p$ = .546. Thus, this analysis indicated that the randomization was successful.

## Main Analyses

Table 2 presents the unstandardized model estimates for the primary analysis. Only one of the four interaction effects testing differences between conditions over time emerged as statistically significant.

Specifically, the interaction (labeled *Long term * control vs SNI*) indicated that the increase in physical activity from T1 to T3 was greater for participants in the control condition compared to those in the social network intervention. Therefore, there is no evidence that the social network intervention is more effective in increasing physical activity in adolescents compared to the mass media intervention or no intervention. A main effect for the short-term contrast also emerged as statistically significant, indicating that participants in all three conditions increased in physical activity from T1 to T2. Figure 2 presents the estimated means and standard errors for physical activity separately for the three conditions and three time-points. The short-term contrasts comparing differences between the conditions from T1 and T2 are depicted by the solid lines in Figure 2. The long-term contrasts comparing the differences between the conditions from T1 and T3 are depicted by the dotted lines in Figure 2.

*Table 2*
Estimates of the mixed-effects model

| | | $s^2$ | *B* | *SE* | *DF* | *t*-value | *p* |
|---|---|---|---|---|---|---|---|
| Random | Class | .003 | | | | | |
| | Child | .18 | | | | | |
| | Date | .05 | | | | | |
| | Residual | | | | | | |
| Fixed | (Intercept) | | 9,525.63 | 235.70 | 49.49 | 40.41 | <.001 |
| | Condition: MMI vs SNI | | -200.23 | 406.91 | 20.48 | -.49 | .628 |
| | Condition: control vs SNI | | 1,099.32 | 518.85 | 33.81 | 2.12 | .042 |
| | Short term | | 2,460.11 | 866.12 | 64.75 | 2.84 | .006 |
| | Long-term | | 904.33 | 870.56 | 64.71 | 1.04 | .303 |
| | Sex: male vs female | | 847.19 | 271.06 | 431.44 | 3.13 | .002 |
| | Age (c) | | -472.17 | 147.49 | 100.86 | -3.20 | .002 |
| | BMI (z) | | -180.07 | 118.71 | 431.27 | -1.52 | .130 |
| | Mean temperature (c) | | -102.67 | 56.23 | 64.99 | -1.83 | .072 |
| | Hours of sunshine (c) | | 154.38 | 56.30 | 62.04 | 2.74 | .008 |
| | Hours of precipitation (c) | | -152.56 | 137.28 | 60.70 | -1.11 | .271 |
| | Humidity (c) | | 65.17 | 19.98 | 58.42 | 3.26 | .002 |
| | Athletic competence (c) | | 787.73 | 160.09 | 434.47 | 4.92 | <.001 |
| | Weekend | | -,081.61 | 362.17 | 57.97 | -2.99 | .004 |
| | Type: prim vs sec | | 61.18 | 490.88 | 48.65 | .12 | .901 |
| | Short term * Con vs SNI | | -197.63 | 482.24 | 2068.60 | -.41 | .682 |
| | Short term * MMI vs SNI | | -,287.78 | 860.40 | 100.96 | -1.50 | .138 |
| | Long-term * Con vs SNI | | -,484.66 | 484.38 | 1929.41 | -3.07 | .002 |
| | Long-term * MMI vs SNI | | -,172.62 | 925.66 | 124.55 | -1.27 | .208 |

*Note.* $N_{participants}$ = 446, $N_{observations}$ = 5388. Marginal $R^2$ = 0.08, Conditional $R^2$ = .29. MMI = Mass media intervention, SNI = Social network intervention, Con = Control condition, (c) = centered, (z) = standardized.

As sensitivity analyses, the same model was performed on a subsample of complete data (i.e., excluding the imputed values) and on a subsample that excluded the influence agents. Both of these models revealed an identical pattern of short and long-term interaction effects. Likewise, no significant interaction effects were observed with a planned contrast that compared the mass media intervention and the control condition, meaning that there is no evidence that the mass media intervention outperformed the control condition.

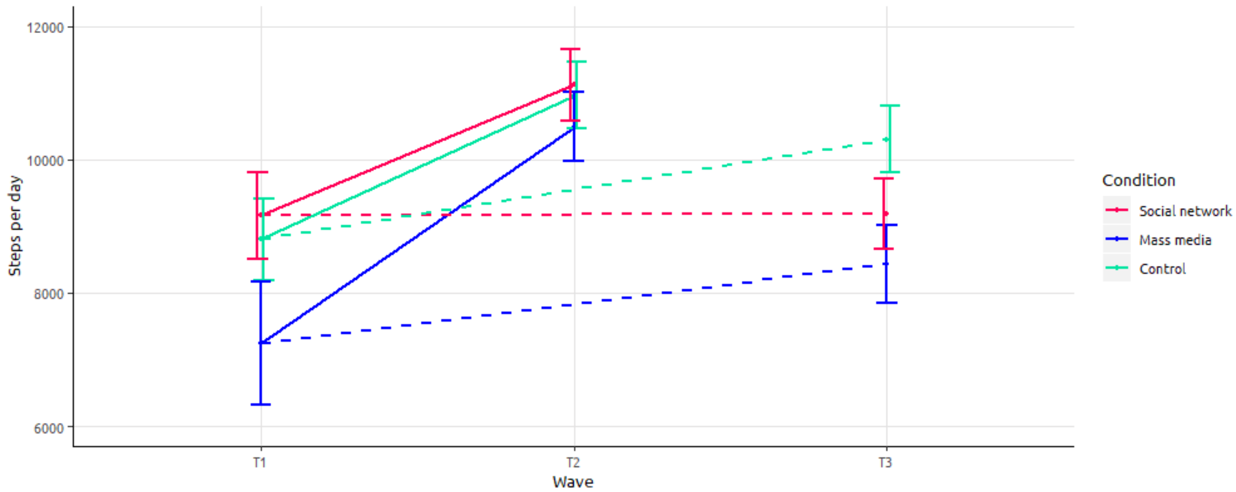


*Figure 2*. Estimated marginal mean steps per day for the three conditions at the three time-points, controlling for the clustering in data and all covariates. Error bars represent standard errors.

## Exploratory Analyses

**Secondary outcomes.** The same mixed-effect models were used to explore differences between the conditions in the secondary outcomes (perceived social norms, physical activity enjoyment, self-efficacy, and motivation). For each variable, a separate model was performed with the secondary outcome as the dependent variable. Figure 3 presents the differences between conditions over time. Only one of the thirty-two interaction effects emerged as statistically significant. For descriptive norms, participants in the social network intervention differed from those in the mass media intervention from T1 to T3, $b$ = .83. $se$ = 0.32, $p$ = .009 (not corrected for multiple testing). The estimated means, presented in Figure 3, suggest that descriptive norms involving physical activity increased in the social network intervention and decreased in the mass media intervention. Additional explorative structural equation modeling showed no significant cross-lagged paths between physical activity at T1 and T3, and the secondary outcomes at T2. Therefore, there is no indication that the secondary outcomes mediated the effect of the intervention.

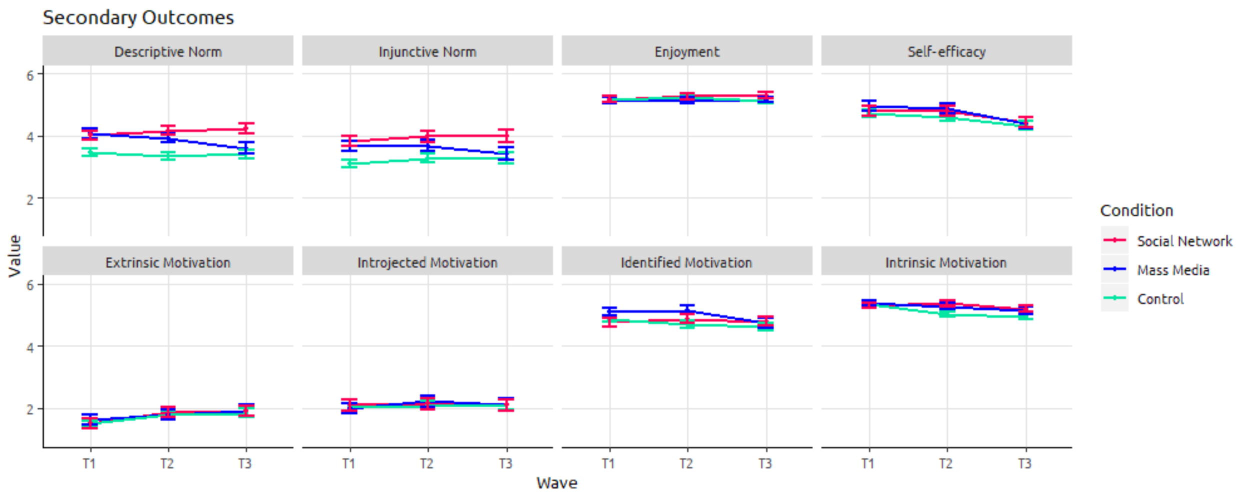


*Figure 3.* Estimated marginal means for the secondary outcome variables for the three conditions at the three time-points. Descriptive and injunctive norm and enjoyment variables were scaled to a score in the range between 1 and 6, similar to the range of the other variables. Error bars represent standard errors.

**Responses to the vlogs.** The last set of analyses explored whether exposure, liking of the vlogs, and the perceived closeness to the vloggers differed for participants in the social network and mass media interventions ($n$ = 254). The first analysis investigated whether participants in the social network intervention were exposed more often to the vlogs than participants in the mass media intervention condition. Participants in the social network intervention condition watched the vlogs more often during the intervention week ($M$ = 15.69, $SD$ = 20.60) than participants in the mass media intervention condition ($M$ = 7.21, $SD$ = 14.60), $t$(1000) = 7.67, $p$ < .001.

The second analysis investigated whether participants in the social network intervention liked the vlogs more than participants in the mass media intervention. On average, the vlogs were rated significantly more positively in the social network intervention ($M$ = 69.09. $SD$ = 30.42) compared to the mass media intervention ($M$ = 40.20. $SD$ =32.72), $t$(306.73) = 8.88, $p$ < .001.

The third analysis investigated whether participants in the social network intervention perceived the vloggers as closer to them than participants in the mass media intervention. On average, the perceived closeness to the vloggers was higher in the social network intervention ($M = 4.68$. $SD = 1.61$) than in the mass media intervention ($M = 3.46$. $SD = 1.97$), $t(739.75) = 9.54$, $p < .001$. So overall, responses to the vlogs were more positive in the social network intervention than in the mass media intervention.

## Discussion

This study was the first to investigate the additional benefit of implementing a social network approach to promote physical activity by comparing a social network intervention to a mass media intervention and a control condition. In addition, the study was the first social network intervention study using vlogs as intervention messages. While all adolescents increased their physical activity in the short term (from T1 to T2), those in the social network intervention increased *less* in the long term compared to the control condition (from T1 to T3). No differences between the social network intervention and mass media intervention were observed, in either the short or the long term. Therefore, the study does not provide evidence that a social network intervention is more effective in increasing physical activity in adolescents than a mass media intervention or no intervention.

Our findings are not in line with the majority of social network interventions on physical activity (Brown et al., 2017; Jong et al., 2018; Owen et al., 2018; Sebire, Edwards, Campbell, Jago, Kipping, Banfield, Kadir, et al., 2016; Sebire et al., 2018). A possible explanation is that in those effective interventions, influence agents received extensive training on how they could promote physical activity. One of the previous studies that did not find an effect of the social network intervention only used an online training of influence agents (van Woudenberg et al., 2018) and discussed that less personal contact might have resulted in a lack of commitment and team effort within the group of influence agents. In the current study, the influence agents did have face-to-face interaction with the researcher and were supported in making the vlogs, but did not receive formal training on how they could promote physical activity within their network. Possibly, a key factor to the effectiveness of social network interventions is face-to-face meetings in combination with a training for the influence agents. This would explain why no differences between the two intervention conditions were observed, because in both intervention condition participants did not receive a formal training on how to promote physical activity. Future studies should test this in a design in which a face-to-face training and an online training is compared to a condition without any training of influence agents.

It was surprising that the physical activity of adolescents in the control condition also increased over time, and even more so than the two intervention conditions. Despite our efforts to find a potential explanation of why the control condition increased the most in physical activity, we could not find a reasonable explanation. For example, we controlled for possible confounding effects of school type (primary and secondary school), differences between the timing of the measurements by including a random intercept per date and specifying the effects of the weather on physical activity as covariates in the model. Likewise, we ruled out an effect of timing of the measurements because they were evenly allocated between the different conditions over time. Lastly, we eliminated possible experimenter and novelty effects because participating classes of phase 1 of the project and participating classes that were new to the project were equally divided over the conditions and showed similar patterns of physical activity. Apart from the control condition, the patterns in physical activity of both interventions correspond to a pattern that might be expected for an intervention that is effective in the short term. That is, there is an increase in physical activity as a result of the intervention from T1 to T2, but there is a decrease in physical activity from T2 to T3 because the effect of the intervention dissipates over time. Replication of this study is warranted to corroborate this idea or confirm that in order for a long term effect of the intervention, several boosters or reminders are required to maintain the short term increase in physical activity.

Exploration of secondary outcomes indicated that the social network intervention increased the descriptive norm of physical activity while the mass media intervention decreased the descriptive norm. No other differences were observed in the secondary outcomes between the three conditions. The general lack of statistically significant differences between conditions in these analyses provides some indication of why no differences between the conditions were observed for physical activity. For example, participants reported high levels of enjoyment, self-efficacy, and motivation to be physically active in all conditions, indicating a possible ceiling effect. Possibly, the participants in both interventions already enjoyed physical activity, were able to be physically active, and were sufficiently intrinsically motivated and, therefore, the interventions could not increase these dimensions. However, the exploratory analyses also suggested that descriptive norms increased after exposure to the vlogs in the social network intervention, whereas the descriptive norms in the mass media intervention condition decreased. Potentially, when adolescents watch their classmates being physically active, their perceived norm for physical activity increases because they observe that peers from their social group are more physically active than initially perceived. In contrast, when adolescents watch vlogs about physical activity made by unfamiliar peers (who are part of another social group), they perceive another social group as more physically active, and their own social group as less physically active. Future studies should investigate the role of perceived social norms (both descriptive and injunctive) in social network interventions and test whether changes in perceived social norms operate as an underlying mechanism of social network interventions.

The exploratory analyses on the responses to the vlog indicated that in the social network intervention condition, the vlogs were watched more often, rated higher, and the vloggers were perceived as closer to the participants. This is in line with the expectations, because in the social network intervention, the vloggers were classmates of the participants, whereas in the mass media intervention, the vloggers were unfamiliar peers. Potentially, having adolescents within each classroom that create the intervention messages will ensure that participants will be more often exposed to the intervention message and enjoy the intervention more. Nevertheless, this difference did not affect the effectiveness of the interventions.

## Strengths and Limitations

The most important strengths of this randomized controlled trial are that both the design and the intervention messages enabled us to compare a social network intervention and a mass media intervention with identical intervention messages. Additionally, advanced statistical methods have been used to impute missing values, account for the clustering of data within the different levels, and systematically investigate the research questions and exploratory analyses. However, a number of limitations should be discussed when interpreting the results.

First, compared to other social network interventions on physical activity (Bell et al., 2014; Brown et al., 2017; Jong et al., 2018; Owen et al., 2018; Sebire, Edwards, Campbell, Jago, Kipping, Banfield, Kadir, et al., 2016; Sebire et al., 2018), the measurement periods were rather short (i.e. 5 days of physical activity data), because of the limited battery life of the accelerometers. Longer measurement periods could ensure a more complete measure of physical activity. In addition, it was not feasible to have more than six vlogs per group of influence agents; otherwise the burden for the influence agents would be too high. As a result, we were limited in the length of the intervention. A longer intervention period might have had a significant effect on physical activity of adolescents. On the contrary, a shorter intervention period increased external validity. In practice, schools have only a limited time to spend on projects outside of their curriculum and more days of data gathering will lead to an increased burden for the participating adolescents, potentially causing additional attrition.

Second, because active consent was required for participation, a sampling bias might have occurred. During the consent procedure, we were under the impression that parents of healthier participants (in terms of lower BMI) were more likely to provide consent, and that less healthy adolescents were less likely to participate. As a result of the strict inclusion criterion (participation > 60%), the sample could have been biased toward relatively healthy classrooms. Likewise, in each classroom, the relatively healthy adolescents of the class could have participated. Because we did not have information on non-participants, we could not test this. However, the percentage of participants in our sample that was overweight (5%) was lower than the national average of 13-14% (Centraal Bureau voor de Statistiek, 2018), supporting this supposition. Possibly, the two interventions tried to increase physical activity in a sample that was already healthy and potentially more physically active to start with and did not target adolescents who could benefit the most from a physical activity intervention. This would explain why no differences were found between the social network intervention and the control condition in the short term.

## Conclusion and Implications

In conclusion, our study did not provide evidence that exposing adolescents to vlogs made by influential classmates increased physical activity more than when adolescents were exposed to vlogs made by unfamiliar peers, or no vlogs at all. However, the social network intervention might have a positive effect on the perceived descriptive norm. Likewise, responses to the vlogs were more positive when the vloggers were influential classmates compared to unfamiliar peers. Potentially, this could be the added benefit of implementing a social network intervention over a mass media intervention.

Altogether, social network interventions may be a promising intervention type to promote physical activity in adolescents, but certain conditions must be satisfied before such interventions are effective. Future studies should investigate more closely when and why social network interventions work by investigating the training aspect of the intervention, the feasibility of online interventions for large-scale implementation, and the underlying mechanisms of social network interventions. Also, future studies should investigate the role of the perceived social norms and the added benefit of having influence agents within a social network intervention.

Chapter 6

# Discussion of the Research Findings, Conclusions, and Implications.

# General Discussion

The aim of this dissertation was to understand, test and improve social network interventions that promote physical activity among adolescents, while addressing several gaps in the literature on social network interventions. In addition, it tried to improve the design of social network interventions by investigating solutions that may decrease the burden of the intervention for all the parties involved (i.e., the influence agents, the participants, the schools, and the researchers). Although the two social network intervention studies did not provide evidence that the intervention brought about an increase in physical activity, this dissertation provided new insights into the design of social networks. First, we demonstrated that the physical activity of adolescents is influenced by the physical activity of their peers. Second, this dissertation provided some indication that social network interventions affect the descriptive norms about physical activity and the responses towards the vlogs. Third, we showed two modern alternative ways to measure relationships in adolescents' social networks. Last, we revealed that using a social network intervention with influence agents based on in-degree centrality or closeness centrality results in the most effective physical activity interventions. The current chapter reflects on the findings of the studies that were performed on the basis of the three stages of social network interventions. Subsequently, the general limitations of the research and the *MyMovez* project are discussed. The dissertation ends by providing scientific and societal implications.

## Overview of the Studies

**Mapping.** Study 1 (chapter 2) aimed to investigate the mapping stage of social network interventions by comparing three types of social networks. More specifically, the study investigated the use of a nominated network based on peer nominations, a communication network based on instant messages on an online platform, and a proximity network based on Bluetooth connections. The study also aimed to validate the proximity and communication networks in reference to the nominated network, based on sex segregation and the role of the networks in relation to physical activity in adolescents. The study showed that the three types of social networks were partially similar but differed in several interesting ways. The communication and proximity networks included fewer participants per class than the nominated networks but provided more connections per measurement period. More specifically, the communication and proximity networks provided multiple connections per day, which allows for weighted connections between individuals. The proximity network was also less stable over time and showed less sex segregation than the nominated networks. This indicates that a proximity network does not portray network characteristics that are similar to those of traditional nominated networks. Furthermore, social influence was more prevalent in the proximity network than in the other two networks. These findings indicate that communication and proximity networks measure different concepts than nominated networks, and therefore should not be used as direct substitutes for sociometric nominations. Instead, future studies could use a communication or proximity network to quantify the relationships in nominated networks. Researchers should keep in mind what type of relationships are to be assessed in the social network and use the best fitting network or combination of networks.

Selecting. Study 2 (chapter 3) aimed to investigate the best selection criterion for determining influence agents in social network interventions. More specifically, the study investigated the outcomes of simulated social network interventions that used different criteria for selecting influence agents (in-degree centrality, betweenness centrality, closeness centrality, random agent or no intervention). Five different interventions were simulated for a one-year period and the average change in physical activity was compared. The study showed that implementing a social network intervention approach increases the amount of physical activity more than not implementing such an approach and that randomly selecting participants as influence agents is the least effective strategy for social network interventions. Also, the simulations revealed that selecting influence agents based on in-degree centrality or closeness centrality resulted in the highest increase in the average physical activity of the class. This means that popular adolescents (i.e., those who are most often nominated) and adolescents who have close connections with all the others in the network could increase the physical activity of a social network the most. Finally, the study indicated that social networks in which a small number of adolescents receive a large proportion of all connections (i.e., the nominations have a skewed distribution) are more susceptible to social network interventions than social networks in which the connections are evenly distributed among the members of the network.

**Training.** The last two studies investigated the training stage of social network interventions. Study 3 (chapter 4) aimed to test the effectiveness of a social network intervention in which the influence agents were trained via online training. The randomized controlled trial investigated whether influence agents could be trained via their research smartphone to promote physical activity within their class. The study found no evidence that the social network intervention could increase the amount of physical activity of the class. Potentially, training influence agents online lacks the personal interaction that ensures that influence agents can successfully promote physical activity in the classroom. In addition, the study indicated that the influence agents did not use one particular strategy to promote physical activity but mostly preferred to model the targeted behavior.

In order to incorporate personal interaction and use the preference for modeling physical activity, Study 4 (chapter 5) used face-to-face meetings with the influence agents and vlogs as intervention messages. The study again aimed to test the effectiveness of a social network intervention, but this time the influence agents created vlogs about physical activity as intervention messages. In addition, this study aimed to test whether using a social network intervention was more effective than using a mass media intervention. The study found no evidence that the social network intervention was more effective in increasing the amount of physical activity of the class than a mass media intervention or no intervention. It did, however, indicate that the strength of the perceived social norm about physical activity increased in the social network intervention and decreased in the mass media intervention. Moreover, responses to the vlogs were more positive when the vlogs were created by classmates (social network intervention condition) than when they were created by unfamiliar adolescents (mass media intervention condition). To conclude, there are some indications that, as expected, a social network intervention has some benefits compared to a mass media intervention, but it appears that the social network intervention was not effective in changing actual behavior.

**Capitalizing on social norms.** The two intervention studies showed that, although adolescents have an effect on each other’s physical activity, in practice it is hard to capitalize on these naturally occurring social influences and to utilize them to increase the amount of physical activity of an entire group. Also, the interventions demonstrated the delicate relation between theory and the real world. More importantly, the link between social norms and physical activity is not as straightforward as proposed by the four relevant dominant theories. More specifically, Study 4 did not observe a direct increase in physical activity after the social norm had increased.

A possible explanation of the absence of the causal link between social norms and behavior is suggested by Cialdini et al. (Cialdini et al., 1990; Reno, Cialdini, & Kallgren, 1993) who performed research on how social norms can reduce littering. In their studies, the authors showed that people are more likely to adhere to injunctive norms (what people approve and disapprove ) than descriptive norms (the observation of what other people do). More specifically, the researchers exposed participants to a confederate who dropped litter in a clean room. In this situation, the descriptive norm would promote littering, because the participants observed and could imitate the behavior of the confederate. The injunctive norm would be to not litter because that would be disapproved of in the society. The studies showed that the participants did not simply imitate or model the behavior of others, but adhered to their perceived injunctive norm. In our study, only the descriptive norm increased significantly after the social network intervention, meaning that our participants observed an increase in what most people did, but did not change their perception of what was approved of or disapproved of by others.

Another possible explanation of the absence of an intervention effect is also provided by Cialdini et al. (Cialdini et al., 1990; Reno et al., 1993). They proposed that, in order for people to adhere to a social norm, this social norm has to be salient (even if it is made so by exposing subjects to a counter-normative act). In our study, the participants only watched the vlogs about physical activity a small number of times. Potentially the social norm was not sufficiently explicit and salient in the participants' minds to change their behavior. This explains why participants in the social network intervention increased their perception of the descriptive norm but did not increase their physical activity. Therefore, future studies should aim to make the injunctive norm more explicit and salient for the participants, in order to change behavior.

## Limitations, Implications and Future Directions

In the following section, general limitations are discussed that do not relate specifically to one individual study in this dissertation but had an impact on the *MyMovez* project. Based on these limitations, recommendations for future research are made and the theory is interpreted. The limitations are divided into methodological, practical, and theoretical limitations.

**Methodological.** One of the limitations of social network analysis is that the boundary for the social network (i.e., who should be included and excluded from the social network) must be set. In social network research on adolescents, setting the classroom as a boundary is universally followed, because the classroom covers the largest part of their social network and behaviors can easily be transferred in a school setting (e.g., smoking behavior in ASSIST). Therefore, we decided to focus on classrooms as social networks and used the schools' infrastructure to approach and enroll participants in the project. However, opting for the classroom as a boundary can be a limitation because in the Netherlands most physical activities take place outside of the school. For example 74% of Dutch adolescents participate in organized sports outside school (Burghard et al., 2016). This percentage is comparable to that of Australia but is higher than the figures for the United States or the United Kingdom.

Therefore, future research on physical activity in (offline) social networks could broaden the scope by utilizing the physical boundaries of the social networks. For example, researchers could study a cross-section of one small city in which almost all social interactions occur (e.g., Kerr, Stattin, & Kiesner, 2007; Tilton-Weaver, Burk, Kerr, & Stattin, 2013). If all the schools and sports clubs in that village participate, researchers can get a more accurate representation of the relevant social influences on adolescents' physical activity. An extreme case of such a remote village with physical boundaries would be an island (e.g., Rutter, Tizard, Yule, Graham, & Whitmore, 1976). For example, the Dutch islands in the Waddenzee or the Dutch Caribbean islands can be used, because they have a small number of primary and secondary schools and a range of sports clubs. Although such a design would not have a control condition (or a control island is needed), adolescents living on these islands would be an outstanding sample for mapping the broad range of offline social interaction when it comes to physical activity.

**Practical.** In the *MyMovez* project, we aimed for a diverse and representative sample of primary and secondary schools, distributed over different locations in the Netherlands. However, in the project we found that it was hard to obtain complete social networks because of the sampling method and the required active consent and inclusion criteria. Therefore, sampling biases might have occurred at the level of the participating schools, classrooms, and individuals. More specifically, schools were invited by cold calling, via health institutions or personal contact (Bevelander et al., 2018). Potentially, more health-conscious schools or schools that attributed more importance to scientific research participated in the project.

Once the schools were enrolled in the project, the parents were approached to provide active parental consent and the assent of the students were needed before students could participate in the project. It was our impression that adolescents with higher BMIs were less likely to have parental consent or were willing to participate themselves. It is conceivable that the parents expected that these children would feel threatened by a health-related project. In addition, only classrooms were included when the inclusion criterion of 60% of the members of the class was met (Marks et al., 2013). Potentially, this has resulted in a sample of relatively healthy participants in relatively healthy classrooms. This was corroborated in Study 4, in which the number of overweight participants was considerably lower than the national average in the Netherlands. This sampling bias might have had an effect on the results of all the studies in this dissertation. On the one hand, the sample was not representative of the prevalence of overweight adolescents in the Netherlands. On the other hand, the adolescents who were not included in the sample could potentially have benefitted most from the *MyMovez* project. It is conceivable that we tried to make relatively physically active adolescents even more physically active.

Future research should aim to obtain complete social networks and draw representative samples from the population. A number of steps could be taken to increase parental consent and participation. First, parental consent could be increased by studying less pressing behaviors that relate better to the interests of adolescents but are still deemed important by their parents. For example, the spread of behaviors related to fashion, movies, pop culture or new technologies could be studied. Second, parental consent could be increased by making the project information easier for the parents to access and comprehend. Researchers could add a small informative video clip next to the information letter to reduce the effort of understanding what the study is about. In addition, the recruitment of participants could be improved by using real-world influence agents (e.g., famous vloggers) in promotional videos. Third, in the current project, participating schools and adolescents were not rewarded for participating. We tried to make participation as much fun as possible by having additional features in the research application and asking fun questions between the more serious questionnaires. It is possible that incentivizing the participation of schools and adolescents would increase participation.

**Theoretical.** The last limitation has to do with social network theory (Valente, 2015), which played an important role in the studies in this dissertation. Social network theory proposes that individuals' behavior is influenced by the social network on three levels, but it does not specify the working mechanisms of the influences. The predictive value of social network theory is hence rather low compared to the dominant theories that propose causal relationships on behavior (Ajzen, 1991; Bandura, 1986; Bandura & Walters, 1977). However, these dominant theories lack the integration of the behavior of peers. For example, the theory of planned behavior (Ajzen, 1991) could be extended with a *social loop*. The behavior of person A affects the subjective norm of person B. The subjective norm of person B predicts the intention to be physically active and, subsequently, the physical activity of person B. In turn, the behavior of person B affects the subjective norm of person A again, which completes the social loop.

Because of its low predictive value, social network theory cannot easily be represented in a conceptual model, as it is not a prediction of the antecedents and outcomes of an individual. For this reason, some scholars even debate whether social network research constitutes a theory or is a method that builds upon other theoretical constructs (Valente, 2015). Borgatti and Halgin (2011) aimed to remedy this confusion by clarifying two different perspectives, which they term "network theory" and "theory of networks." The first perspective refers to the mechanisms and processes of network structures, and how these can influence individuals or groups. This means that the network characteristics are the independent variables that predict an outcome. The second perspective refers to the processes that determine the structures in networks and the antecedents of the network properties. This means that the network characteristics are the outcomes of the antecedents of the network properties.

In this dissertation, the social network theory (the first perspective) was used as a comprehensive paradigm that contained numerous ways in which peers can affect adolescents' behaviors and because social network theory was used as the foundation of the studies, it is hard to shed light on the extent to which social norms, social facilitation, modeling, and impression management (Salvy et al., 2012) play a role in the dissemination of physical activity within adolescents' social networks. Future studies should aim to integrate these mechanisms in social network analyses. For example, future social network studies could investigate whether impression management tactics explain why peers become more similar in physical activity over time, by asking participants not only to nominate others according to certain relationships but also to rate, for each peer who they nominate, the extent to which they use self-presentation motives towards that person.

## Closing Remarks

The studies in this dissertation extend the small body of scientific literature that uses social network interventions to promote health-related behaviors in young people. This dissertation stands out because it has a strong focus on technological innovations. One of the most important implications of this dissertation, and of the *MyMovez* project, is that it demonstrates the feasibility of doing research with modern technologies. Using *the Wearable Lab* ensured that participating in the project appealed to young people.

Because of the use of smartphones, we were able to use innovative ways to measure behaviors and relationships, to train influence agents online, and to spread the intervention messages in the form of vlogs, while the participants were engaged with using the smartphone app. Our experiences with the *Wearable Lab* have taught us that integrating modern technologies in research requires more preparation time, but that this effort is eventually repaid in the form of the scale and possibilities of the research. Although we recognize that not every researcher has the opportunity to use smartphones, we encourage the implementation of smartphones and wearables in research on children and adolescents.

A second important and repeated finding in this dissertation is that adolescents' physical activity does not occur in a social vacuum and that adolescents' behaviors are affected by their peers in their social network. Studies 1 and 2 replicate the existing literature (de la Haye et al., 2011; Long et al., 2017; Ommundsen et al., 2010; Shoham et al., 2012; Simpkins et al., 2013) by demonstrating that the physical activity of peers who share a connection with an adolescent predicts the amount of physical activity of that adolescent. These results show that trying to increase physical activity of individual adolescents is less effective when the behavior of their peers is not increased. If the behavior of the peers remains the same, the increase in physical activity of the individual adolescent is counteracted by the relatively lower levels of physical activity of the peer group, and thus the individual will relapse towards the health behaviors of the peers. For example, an overweight adolescent is often referred to a health practitioner, who then asks the adolescent to keep a food diary and to start exercising. This process takes a lot of effort, and motivation is required to adhere to the new regime. In addition, these individual adolescents should also be, in some sense, brave, because they have to go against the current social norm on health behaviors. That is why it is so incredibly hard for adolescents to lose weight successfully when they are targeted individually (McLean, Griffin, Toney, & Hardeman, 2003). However, by targeting the social environment and the social norm, adolescents who need to change their health behaviors will swim with, rather than against, the current.

Therefore, an integrated approach is needed in which not only those adolescents who are the least physically active are targeted, but a community-level perspective is taken towards promoting physical activity. Because of this, schools and governments share the enormous responsibility of creating a healthy social environment in which healthy behaviors are seen as the norm. In recent years, schools have responded to this call by working on a healthy food environment. For example, primary schools have restricted parents in what their child is allowed to bring in their lunch box, and secondary schools have changed the range of products in their cafeterias. However, for physical activity, schools have reacted rather ambivalently. On the one hand, some schools have changed to standing desks or incorporated active learning in their curriculum. On the other hand, we observed during our data collections at schools that physical education lessons are treated as secondary and are among the first classes to be canceled when needed. Therefore, more effort has to be put into integrated approaches for schools and governments to prevent young people from following unhealthy and sedentary lifestyles. The findings and suggestions in this dissertation could be used to develop, measure, and test preventions and interventions to make and keep young people physically active.

# Miscellaneous

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## Appendix A

| Class description | | | | | | Nominated network | | | Proximity network | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Level | Class | Participants | % male | $M_{age}$ | Wave | Participants | Edges | % data | Participants | Edges | % data |
| Secondary | 67 | 18 | .50 | 12.56 | 1 | 15 | 104 | .83 | 14 | 269 | .78 |
| Secondary | 67 | 18 | .50 | 12.56 | 2 | 13 | 88 | .72 | 15 | 702 | .83 |
| Secondary | 67 | 18 | .50 | 12.56 | 3 | 14 | 88 | .78 | 14 | 355 | .78 |
| Secondary | 71 | 20 | .65 | 12.80 | 1 | 18 | 108 | .90 | 18 | 678 | .90 |
| Secondary | 71 | 20 | .65 | 12.80 | 2 | 16 | 100 | .80 | 14 | 223 | .70 |
| Secondary | 71 | 20 | .65 | 12.80 | 3 | 17 | 124 | .85 | 15 | 340 | .75 |
| Secondary | 72 | 20 | .70 | 12.85 | 1 | 18 | 114 | .90 | 16 | 561 | .80 |
| Secondary | 72 | 20 | .70 | 12.85 | 2 | 13 | 78 | .65 | 10 | 77 | .50 |
| Secondary | 72 | 20 | .70 | 12.85 | 3 | 9 | 67 | .45 | 6 | 30 | .30 |
| Primary | 74 | 12 | .50 | 11.00 | 1 | 8 | 50 | .67 | 7 | 86 | .58 |
| Primary | 74 | 12 | .50 | 11.00 | 2 | 8 | 56 | .67 | 8 | 46 | .67 |
| Primary | 74 | 12 | .50 | 11.00 | 3 | 9 | 54 | .75 | 4 | 10 | .33 |
| Primary | 77 | 19 | .32 | 11.53 | 1 | 12 | 64 | .63 | 2 | 4 | .11 |
| Primary | 77 | 19 | .32 | 11.53 | 2 | 19 | 119 | 1.00 | 14 | 86 | .74 |
| Primary | 77 | 19 | .32 | 11.53 | 3 | 17 | 109 | .89 | 4 | 28 | .21 |
| Primary | 78 | 20 | .50 | 10.20 | 1 | 19 | 166 | .95 | 19 | 172 | .95 |
| Primary | 78 | 20 | .50 | 10.20 | 2 | 20 | 222 | 1.00 | 19 | 186 | .95 |
| Primary | 78 | 20 | .50 | 10.20 | 3 | 19 | 200 | .95 | 13 | 27 | .65 |
| Primary | 79 | 25 | .48 | 10.44 | 1 | 15 | 117 | .60 | 3 | 10 | .12 |
| Primary | 79 | 25 | .48 | 10.44 | 2 | 8 | 77 | .32 | 7 | 13 | .28 |
| Primary | 79 | 25 | .48 | 10.44 | 3 | 9 | 91 | .36 | 3 | 14 | .12 |
| Primary | 81 | 28 | .54 | 10.50 | 1 | 28 | 384 | 1.00 | 22 | 548 | .79 |
| Primary | 81 | 28 | .54 | 10.50 | 2 | 27 | 407 | .96 | 22 | 456 | .79 |
| Primary | 81 | 28 | .54 | 10.50 | 3 | 26 | 383 | .93 | 22 | 221 | .79 |
| Primary | 83 | 14 | .50 | 10.50 | 1 | 14 | 87 | 1.00 | 13 | 114 | .93 |
| Primary | 83 | 14 | .50 | 10.50 | 2 | 13 | 85 | .93 | 11 | 80 | .79 |
| Primary | 83 | 14 | .50 | 10.50 | 3 | 12 | 86 | .86 | 7 | 12 | .50 |
| Primary | 86 | 16 | .50 | 10.62 | 1 | 14 | 120 | .88 | 8 | 18 | .50 |
| Primary | 86 | 16 | .50 | 10.62 | 2 | 15 | 115 | .94 | 8 | 16 | .50 |
| Primary | 86 | 16 | .50 | 10.62 | 3 | 12 | 132 | .75 | 2 | 2 | .12 |
| Primary | 100 | 21 | .52 | 10.24 | 1 | 9 | 90 | .43 | 10 | 140 | .48 |
| Primary | 100 | 21 | .52 | 10.24 | 2 | 14 | 154 | .67 | 5 | 22 | .24 |
| Primary | 100 | 21 | .52 | 10.24 | 3 | 14 | 134 | .67 | 12 | 117 | .57 |
| Primary | 101 | 18 | .39 | 10.44 | 1 | 17 | 120 | .94 | 16 | 158 | .89 |
| Primary | 101 | 18 | .39 | 10.44 | 2 | 17 | 109 | .94 | 10 | 72 | .56 |
| Primary | 101 | 18 | .39 | 10.44 | 3 | 14 | 118 | .78 | 10 | 40 | .56 |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Primary | 103 | 17 | .71 | 10.29 | 1 | 17 | 125 | 1.00 | 15 | 429 | .88 |
| Primary | 103 | 17 | .71 | 10.29 | 2 | 17 | 141 | 1.00 | 10 | 91 | .59 |
| Primary | 103 | 17 | .71 | 10.29 | 3 | 15 | 130 | .88 | 9 | 62 | .53 |
| Secondary | 121 | 14 | .71 | 11.86 | 1 | 13 | 78 | .93 | 13 | 203 | .93 |
| Secondary | 121 | 14 | .71 | 11.86 | 2 | 10 | 61 | .71 | 7 | 30 | .50 |
| Secondary | 121 | 14 | .71 | 11.86 | 3 | 10 | 66 | .71 | 6 | 26 | .43 |
| Secondary | 122 | 11 | .82 | 12.27 | 1 | 11 | 52 | 1.00 | 11 | 220 | 1.00 |
| Secondary | 122 | 11 | .82 | 12.27 | 2 | 11 | 69 | 1.00 | 8 | 38 | .73 |
| Secondary | 122 | 11 | .82 | 12.27 | 3 | 11 | 45 | 1.00 | 5 | 46 | .45 |
| Primary | 125 | 17 | .41 | 10.59 | 1 | 11 | 86 | .65 | 11 | 104 | .65 |
| Primary | 125 | 17 | .41 | 10.59 | 2 | 14 | 114 | .82 | 12 | 70 | .71 |
| Primary | 125 | 17 | .41 | 10.59 | 3 | 14 | 125 | .82 | 9 | 58 | .53 |
| Primary | 126 | 11 | .64 | 11.00 | 1 | 8 | 35 | .73 | 9 | 31 | .82 |
| Primary | 126 | 11 | .64 | 11.00 | 2 | 8 | 40 | .73 | 10 | 76 | .91 |
| Primary | 126 | 11 | .64 | 11.00 | 3 | 6 | 45 | .55 | 10 | 22 | .91 |
| Primary | 127 | 14 | .64 | 10.86 | 1 | 6 | 28 | .43 | 3 | 22 | .21 |
| Primary | 127 | 14 | .64 | 10.86 | 2 | 7 | 50 | .50 | 8 | 67 | .57 |
| Primary | 127 | 14 | .64 | 10.86 | 3 | 5 | 49 | .36 | 5 | 20 | .36 |
| Primary | 129 | 9 | .67 | 12.11 | 1 | 9 | 47 | 1.00 | 9 | 78 | 1.00 |
| Primary | 129 | 9 | .67 | 12.11 | 2 | 6 | 26 | .67 | 3 | 8 | .33 |
| Primary | 129 | 9 | .67 | 12.11 | 3 | 1 | 4 | .11 | 0 | 0 | .00 |
| Primary | 131 | 21 | .52 | 10.24 | 1 | 9 | 36 | .43 | 5 | 24 | .24 |
| Primary | 131 | 21 | .52 | 10.24 | 2 | 11 | 44 | .52 | 9 | 76 | .43 |
| Primary | 131 | 21 | .52 | 10.24 | 3 | 11 | 41 | .52 | 6 | 60 | .29 |
| Primary | 133 | 20 | .40 | 10.55 | 1 | 15 | 84 | .75 | 12 | 132 | .60 |
| Primary | 133 | 20 | .40 | 10.55 | 2 | 18 | 137 | .90 | 17 | 112 | .85 |
| Primary | 133 | 20 | .40 | 10.55 | 3 | 13 | 125 | .65 | 7 | 10 | .35 |
| Primary | 135 | 20 | .45 | 10.30 | 1 | 17 | 116 | .85 | 15 | 394 | .75 |
| Primary | 135 | 20 | .45 | 10.30 | 2 | 18 | 154 | .90 | 15 | 190 | .75 |
| Primary | 135 | 20 | .45 | 10.30 | 3 | 17 | 191 | .85 | 5 | 10 | .25 |
| Secondary | 130 | 20 | .45 | 13.15 | 1 | 21 | 109 | 1.05 | 12 | 204 | .60 |
| Secondary | 130 | 20 | .45 | 13.15 | 2 | 21 | 118 | 1.05 | 15 | 140 | .75 |
| Secondary | 130 | 20 | .45 | 13.15 | 3 | 17 | 110 | .85 | 4 | 10 | .20 |
| Secondary | 138 | 20 | .35 | 13.10 | 1 | 18 | 138 | .90 | 13 | 139 | .65 |
| Secondary | 138 | 20 | .35 | 13.10 | 2 | 19 | 130 | .95 | 16 | 144 | .80 |
| Secondary | 138 | 20 | .35 | 13.10 | 3 | 17 | 117 | .85 | 6 | 28 | .30 |
| Secondary | 139 | 19 | .32 | 13.16 | 1 | 10 | 41 | .53 | 8 | 76 | .42 |
| Secondary | 139 | 19 | .32 | 13.16 | 2 | 10 | 41 | .53 | 11 | 136 | .58 |
| Secondary | 139 | 19 | .32 | 13.16 | 3 | 8 | 51 | .42 | 8 | 66 | .42 |

## Appendix B

| | Class description | | | | Nominated network | | | Communication network | | | Proximity network | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Level | Class | Nodes | % male | $M_{age}$ | Nodes | Edges | % data | Nodes | Edges | % data | Nodes | Edges | % data |
| Primary | 73 | 7 | .29 | 11.14 | 5 | 11 | .71 | 1 | 1 | .14 | 4 | 12 | .57 |
| Primary | 74 | 13 | .46 | 11.31 | 9 | 71 | .69 | 1 | 2 | .08 | 0 | 0 | .00 |
| Primary | 78 | 29 | .48 | 10.41 | 28 | 233 | .97 | 11 | 79 | .38 | 11 | 56 | .38 |
| Primary | 81 | 28 | .5 | 10.54 | 26 | 328 | .93 | 8 | 19 | .29 | 25 | 298 | .89 |
| Primary | 82 | 14 | .43 | 10.79 | 11 | 66 | .79 | 6 | 15 | .43 | 10 | 172 | .71 |
| Primary | 86 | 17 | .53 | 10.65 | 12 | 81 | .71 | 3 | 49 | .18 | 6 | 12 | .35 |
| Primary | 100 | 20 | .60 | 10.50 | 20 | 140 | 1.00 | 17 | 237 | .85 | 17 | 334 | .85 |
| Primary | 103 | 17 | .59 | 10.41 | 14 | 145 | .82 | 7 | 33 | .41 | 2 | 4 | .12 |
| Primary | 124 | 19 | .37 | 10.37 | 19 | 188 | 1.00 | 16 | 273 | .84 | 19 | 436 | 1.00 |
| Primary | 125 | 17 | .41 | 10.59 | 17 | 136 | 1.00 | 12 | 419 | .71 | 14 | 254 | .82 |
| Primary | 131 | 21 | .52 | 10.24 | 21 | 110 | 1.00 | 8 | 111 | .38 | 13 | 98 | .62 |
| Primary | 133 | 20 | .40 | 10.55 | 15 | 118 | .75 | 9 | 23 | .45 | 9 | 12 | .45 |
| Primary | 135 | 20 | .45 | 10.3 | 20 | 225 | 1.00 | 4 | 10 | .20 | 11 | 30 | .55 |
| Primary | 141 | 18 | .56 | 10.44 | 16 | 115 | .89 | 5 | 13 | .28 | 4 | 6 | .22 |
| Primary | 250 | 8 | .38 | 9.50 | 7 | 21 | .88 | 7 | 252 | .88 | 5 | 16 | .62 |
| Primary | 251 | 13 | .62 | 10.54 | 12 | 72 | .92 | 11 | 103 | .85 | 7 | 40 | .54 |
| Secondary | 256 | 24 | .46 | 12.21 | 24 | 128 | 1.00 | 10 | 53 | .42 | 19 | 532 | .79 |
| Secondary | 258 | 25 | .44 | 12.48 | 25 | 200 | 1.00 | 11 | 35 | .44 | 18 | 512 | .72 |
| Secondary | 259 | 17 | .47 | 12.29 | 17 | 80 | 1.00 | 10 | 43 | .59 | 16 | 240 | .94 |
| Primary | 261 | 17 | .65 | 10.29 | 17 | 102 | 1.00 | 17 | 276 | 1.00 | 17 | 568 | 1.00 |
| Primary | 262 | 15 | .53 | 10.6 | 15 | 64 | 1.00 | 15 | 135 | 1.00 | 14 | 432 | .93 |
| Primary | 263 | 22 | .36 | 10.45 | 20 | 149 | .91 | 18 | 688 | .82 | 20 | 924 | .91 |
| Primary | 272 | 27 | .59 | 9.59 | 24 | 275 | .89 | 25 | 1929 | .93 | 26 | 1200 | .96 |
| Primary | 273 | 25 | .52 | 10.48 | 25 | 309 | 1.00 | 21 | 744 | .84 | 20 | 248 | .80 |
| Secondary | 277 | 13 | .23 | 12.23 | 12 | 72 | .92 | 8 | 22 | .62 | 11 | 146 | .85 |
| Secondary | 279 | 19 | .53 | 12.21 | 17 | 109 | .89 | 6 | 16 | .32 | 15 | 282 | .79 |
| Primary | 290 | 14 | .14 | 9.64 | 13 | 102 | .93 | 13 | 1574 | .93 | 13 | 220 | .93 |
| Primary | 291 | 16 | .44 | 10.75 | 14 | 101 | .88 | 13 | 359 | .81 | 13 | 418 | .81 |
| Primary | 292 | 21 | .24 | 9.62 | 21 | 119 | 1.00 | 20 | 1684 | .95 | 21 | 828 | 1.00 |
| Primary | 296 | 19 | .37 | 9.68 | 19 | 131 | 1.00 | 17 | 912 | .89 | 18 | 966 | .95 |
| Primary | 297 | 25 | .48 | 10.36 | 18 | 168 | .72 | 14 | 199 | .56 | 18 | 886 | .72 |
| Primary | 298 | 22 | .41 | 9.41 | 21 | 181 | .95 | 21 | 4294 | .95 | 20 | 1410 | .91 |
| Primary | 299 | 19 | .53 | 10.42 | 18 | 169 | .95 | 19 | 2047 | 1.00 | 19 | 870 | 1.00 |
| Primary | 300 | 19 | .47 | 10.42 | 19 | 132 | 1.00 | 17 | 300 | .89 | 19 | 546 | 1.00 |
| Primary | 301 | 24 | .71 | 9.38 | 24 | 172 | 1.00 | 24 | 1906 | 1.00 | 23 | 788 | .96 |
| Primary | 302 | 19 | .32 | 10.84 | 19 | 152 | 1.00 | 17 | 355 | .89 | 19 | 632 | 1.00 |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Primary | 303 | 27 | .44 | 10.30 | 27 | 295 | 1.00 | 25 | 2235 | .93 | 27 | 460 | 1.00 |
| Secondary | 304 | 8 | .50 | 12.88 | 7 | 18 | .88 | 5 | 35 | .63 | 7 | 68 | .88 |
| Secondary | 305 | 6 | .50 | 12.67 | 4 | 11 | .67 | 5 | 44 | .83 | 6 | 34 | 1.00 |
| Secondary | 306 | 10 | .70 | 14.00 | 9 | 33 | .90 | 8 | 28 | .80 | 8 | 42 | .80 |
| Secondary | 307 | 12 | .42 | 15.25 | 12 | 76 | 1.00 | 12 | 105 | 1.00 | 12 | 192 | 1.00 |
| Primary | 308 | 14 | .71 | 10.50 | 14 | 100 | 1.00 | 14 | 764 | 1.00 | 14 | 792 | 1.00 |
| Secondary | 310 | 14 | .36 | 12.36 | 13 | 33 | .93 | 7 | 35 | .50 | 8 | 52 | .57 |

## Appendix C

*Peer nomination questions*

| Measure Description | Literature Reference | Survey |
|---|---|---|
| Advice | Campbell et al., 2008 | 1 item assessing to who participants go for advice |
| Friends | Brechwald & Prinstein, 2011 | 1 item assessing to who participants are friends |
| Leadership | Campbell et al., 2008 | 1 item assessing who participants consider as leaders |
| Respect | Campbell et al., 2008 | 1 item assessing who participants respect |
| Social facilitation | Salvy et al., 2012 | 1 item assessing who participants hang out / have contact with |
| Want to be like | Campbell et al., 2008 | 1 item assessing who participants want to be like |

## Appendix D

*Success rates per class of one year simulations of the interventions (in percentages)*

| Class ID | In-degree centrality | Betweenness centrality | Closeness centrality | Random agent | Control |
|---|---|---|---|---|---|
| 67 | 10.70 | 10.60 | 11.80 | 7.50 | 7.69 |
| 71 | 13.22 | 13.51 | 13.22 | 14.66 | 14.93 |
| 72 | 26.31 | 30.95 | 29.12 | 27.85 | 28.35 |
| 74 | 2.34 | -1.69 | 3.56 | 0.00 | 0.58 |
| 77 | 5.24 | 8.32 | 6.44 | 4.70 | 4.27 |
| 78 | 11.59 | 10.26 | 11.59 | 11.12 | 11.24 |
| 79 | 5.50 | 5.42 | 5.01 | 4.86 | 5.29 |
| 81 | 14.66 | 14.62 | 14.66 | 14.23 | 14.69 |
| 83 | 7.62 | 7.62 | 7.62 | 8.43 | 8.16 |
| 86 | 4.72 | 4.74 | 5.03 | 5.35 | 5.46 |
| 100 | 4.40 | 3.19 | 4.40 | 2.54 | 1.81 |
| 101 | 0.27 | -0.62 | 0.61 | -0.55 | -0.96 |
| 103 | 23.31 | 22.98 | 23.45 | 15.56 | 15.10 |
| 121 | 37.95 | 36.91 | 37.95 | 22.61 | 21.99 |
| 122 | 3.36 | 3.36 | 3.36 | 2.35 | 2.27 |
| 125 | 17.01 | 11.42 | 17.01 | 11.37 | 10.94 |
| 126 | 5.83 | 4.33 | 5.74 | 3.36 | 2.80 |
| 127 | 3.48 | 3.83 | 3.48 | 2.49 | 2.66 |
| 129 | -6.08 | -6.08 | -6.41 | -5.88 | -5.88 |
| 130 | 17.26 | 15.67 | 17.26 | 15.37 | 15.54 |
| 131 | 18.18 | 18.18 | 16.51 | 17.12 | 17.16 |
| 133 | 18.73 | 10.49 | 18.65 | 12.41 | 10.89 |
| 135 | 13.42 | 11.15 | 11.15 | 11.40 | 11.17 |
| 136 | 11.51 | 9.33 | 11.51 | 10.08 | 9.97 |
| 138 | 28.60 | 25.20 | 28.60 | 25.44 | 24.59 |
| 139 | 14.94 | 11.87 | 14.94 | 13.01 | 13.15 |

## Appendix E

Structural network parameters per class based on the weighted ties.

| Class ID | Number of participants | % Male | Edges | Density | In-degree Centralization | Betweenness Centralization | Closeness Centralization |
|---|---|---|---|---|---|---|---|
| 67 | 18 | 50 | 205 | 0.67 | 0.29 | 0.05 | 0.25 |
| 71 | 20 | 65 | 247 | 0.65 | 0.26 | 0.03 | 0.25 |
| 72 | 20 | 70 | 238 | 0.63 | 0.17 | 0.06 | 0.27 |
| 74 | 12 | 50 | 104 | 0.79 | 0.23 | 0.03 | 0.19 |
| 77 | 19 | 31 | 223 | 0.65 | 0.19 | 0.05 | 0.26 |
| 78 | 20 | 50 | 303 | 0.80 | 0.21 | 0.02 | 0.16 |
| 79 | 25 | 48 | 275 | 0.46 | 0.13 | 0.05 | 0.39 |
| 81 | 28 | 53 | 663 | 0.88 | 0.13 | 0.01 | 0.10 |
| 83 | 14 | 50 | 142 | 0.78 | 0.15 | 0.04 | 0.17 |
| 86 | 16 | 50 | 192 | 0.80 | 0.07 | 0.05 | 0.15 |
| 100 | 20 | 50 | 288 | 0.76 | 0.14 | 0.02 | 0.22 |
| 101 | 18 | 38 | 205 | 0.67 | 0.16 | 0.07 | 0.24 |
| 103 | 17 | 70 | 221 | 0.81 | 0.20 | 0.01 | 0.15 |
| 121 | 14 | 71 | 110 | 0.60 | 0.34 | 0.09 | 0.30 |
| 122 | 11 | 81 | 84 | 0.76 | 0.14 | 0.02 | 0.22 |
| 125 | 17 | 41 | 200 | 0.74 | 0.15 | 0.01 | 0.26 |
| 126 | 11 | 63 | 96 | 0.87 | 0.14 | 0.02 | 0.11 |
| 127 | 14 | 64 | 129 | 0.71 | 0.15 | 0.05 | 0.25 |
| 129 | 9 | 66 | 65 | 0.90 | 0.11 | 0.02 | 0.09 |
| 130 | 21 | 47 | 259 | 0.62 | 0.30 | 0.08 | 0.27 |
| 131 | 11 | 72 | 70 | 0.64 | 0.40 | 0.08 | 0.30 |
| 133 | 20 | 40 | 217 | 0.57 | 0.23 | 0.07 | 0.31 |
| 135 | 18 | 44 | 272 | 0.89 | 0.12 | 0.01 | 0.09 |
| 136 | 19 | 47 | 268 | 0.78 | 0.11 | 0.02 | 0.16 |
| 138 | 20 | 35 | 255 | 0.67 | 0.35 | 0.03 | 0.25 |
| 139 | 19 | 31 | 201 | 0.59 | 0.26 | 0.09 | 0.29 |

## Declarations

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## Data Management

The Radboud University and the Behavioural Science Institute (BSI) have set strict conditions for the management of research data. All research data is handled in accordance with the university's research data management policy (https://www.ru.nl/rdm/) and the BSI's General Data Protection Regulations (GDPR; https://www.radboudnet.nl/bsi/gdpr/), which is approved by the ERC ethical review board. All research data is archived in an encrypted workgroup folder on the Radboud University server and stored for 10 years after completion of the project. All data suitable for reuse will be made available to the scientific community, together with their accompanying metadata and documentation necessary to understand the data. To this end, the services of the Research Information System (RIS) of Radboud University is used. Via RIS, data sets are made available at DANS, a long-term data archive to which access may be open, restricted, or both. Data of the study in chapter 2, 3, and 5 can be found on: https://doi.org/10.17026/dans-zz9-gn44. The data for the study in chapter 5 can be found on: https://doi.org/10.17026/dans-zxr-qm28.

# Dutch Summary

Jongeren wereldwijd bewegen te weinig (Nader et al., 2008; Riddoch et al., 2004). Jongeren gaan minder sporten en bewegen naarmate ze ouder worden, en de hedendaagse jeugd beweegt minder in vergelijking met de jeugd van vorige generaties (Boreham & Riddoch, 2001; Kohl et al., 2012; Tudor-Locke et al., 2011). Volgens de World Health Organization (WHO; 2010) zouden adolescenten tussen de 12 en 15 jaar tenminste 60 minuten per dag matig tot intensief moeten bewegen. Het merendeel van de jongeren wereldwijd (80%) haalt dit echter niet (Brusseau et al., 2013; Butcher et al., 2008; Hallal et al., 2012). In Nederland is dat met 85% zelfs nog net iets hoger (Burghard et al., 2016; Katzmarzyk et al., 2016).

Dit hoge percentage is alarmerend te noemen, aangezien een tekort aan sporten en bewegen een belangrijke risicofactor is voor gezondheidsproblemen, zoals obesitas (Jiménez-Pavón et al., 2010; Rey-López et al., 2008), verschillende psychische en sociale problemen (Biddle & Asare, 2011), fysiologische aandoeningen (Ebbeling et al., 2002; Ekelund et al., 2012; Janssen & LeBlanc, 2010) en zelfs vroegtijdig overlijden (Füzéki et al., 2017; Reilly & Kelly, 2011). Daarnaast is bekend dat bewegen een positief effect heeft op de fysieke en mentale gesteldheid (Biddle & Asare, 2011; Brooks et al., 2014; Füzéki et al., 2017; Janssen & LeBlanc, 2010), en de schoolprestaties van adolescenten (Trudeau & Shephard, 2008). Het is dus cruciaal dat adolescenten voldoende sporten en bewegen.

## Sociale Netwerkinterventies

Uit de wetenschappelijke literatuur is bekend dat adolescenten veelal hetzelfde beweegpatroon hebben als hun vrienden in hun sociale netwerk (de la Haye et al., 2011; Long et al., 2017; Shoham et al., 2012; Simpkins et al., 2013). Dit kan komen doordat ze nieuwe vrienden maken die vooral op henzelf lijken (selectie), maar ook doordat adolescenten elkaars fysieke activiteit beïnvloeden (beïnvloeding). Onderzoekers hebben geprobeerd om deze invloed in sociale netwerken te gebruiken om gezond gedrag van adolescenten te bevorderen. De sociale netwerktheorie (Valente, 2015) veronderstelt dat sociale invloeden in een sociaal netwerk op verschillende niveaus effecten hebben op het gedrag: (a) Individuen worden beïnvloed door andere leden van een sociaal netwerk, (b) de rol van het individu in het sociale netwerk voorspelt het eigen gedrag van het individu en (c) de eigenschappen van het sociale netwerk bepalen in hoeverre groepsgedragingen veranderen door de tijd heen. De sociale netwerktheorie is de basis voor het ontwikkelen van interventies die gebruik maken van deze sociale invloeden, die sociale netwerkinterventies worden genoemd (Valente, 2012, 2015).

In sociale netwerkinterventies worden de belangrijkste personen in een sociaal netwerk gebruikt als beginpunt van een interventie. Ze worden bijvoorbeeld gevraagd om een gezondheidsgedraging te verspreiden door anderen te informeren of overtuigen, het goede voorbeeld te geven, of het gezonde gedrag te faciliteren (Valente, 2012, 2015). Deze invloedrijke personen worden ‘influence agents’ genoemd. Er zijn verschillende soorten sociale netwerkinterventies (Valente, 2012). Eén van de bekendste sociale netwerkinterventies is de ASSIST (A Stop Smoking In School Trial) methode (Campbell et al., 2008; Starkey et al., 2009). Hierin krijgen participanten een lijst met de namen van klasgenoten voorgelegd en kunnen ze hun klasgenoten nomineren op een aantal vragen, bijvoorbeeld “Wie zijn jouw vrienden in de klas?” of “Welke klasgenoten vraag je om advies?”. De meest genoemde leerlingen worden aangewezen als influence agents. Vervolgens worden zij getraind hoe ze het gedrag kunnen verspreiden in hun klas. Sinds ASSIST hebben enkele onderzoeken deze methode toegepast om het beweeggedrag te stimuleren bij kinderen en adolescenten (Bell et al., 2014; Brown et al., 2017; Jong et al., 2018; Owen et al., 2018; Sebire, Edwards, Campbell, Jago, Kipping, Banfield, Kadir, et al., 2016; Sebire et al., 2018). Deze onderzoeken, variërend in doelgroep en resultaten, waren sterk gebaseerd op het ontwerp van de ASSIST-studie en de daarbij behorende onderzoekskeuzes. Daarnaast waren de studies erg arbeidsintensief voor de participerende scholen, de influence agents en de onderzoekers, waardoor de sociale netwerkinterventies niet op grote schaal geïmplementeerd kunnen worden.

## Doel van dit Proefschrift

Het doel van dit proefschrift is om sociale netwerkinterventies beter te begrijpen, de methode te verbeteren en de effectiviteit ervan te toetsen om het beweeggedrag van adolescenten te stimuleren. Hierbij is gekeken naar de drie fases van sociale netwerkinterventies: (1) Het *in kaart brengen* van sociale netwerken, (2) het *selecteren* van de influence agents en (3) het *trainen* van de influence agents. In vier empirische studies hebben we de drie fases onderzocht en getracht te optimaliseren. Daarnaast is geprobeerd om sociale netwerkinterventies te ontwerpen die alle betrokken partijen zo min mogelijk belasten. Al deze studies maken onderdeel uit van het *MyMovez* project.

## Het *MyMovez* project

Het *MyMovez* project is een grootschalig onderzoeksproject dat zich richt op de sociale omgeving van adolescenten (tussen de 9 en 15 jaar) en drie belangrijke gezondheidsindicatoren: voeding, media gebruik, en fysieke activiteit (Bevelander et al., 2018). In het project krijgen participanten het ‘Wearable Lab’: een onderzoekstelefoon met de *MyMovez* applicatie (app) en een bewegingsmeter die aan de pols gedragen wordt (Fitbit™ Flex). De bewegingsmeter registreert het aantal stappen per minuut en ook het aantal minuten per dag waarop er intensief bewogen wordt. Op de *MyMovez* app kunnen participanten een puzzelspel spelen, een persoonlijke avatar aanmaken en ontvangen ze dagelijks vragenlijsten.

Een bijzonder type vragenlijsten die aan de participanten gesteld worden, zijn de zogenaamde nominatie vragen. In dit type vraag krijgen participanten de namen van de klasgenoten te zien en kunnen ze antwoord geven op een vraag door de desbetreffende namen aan te vinken. Zo kunnen ze bijvoorbeeld aangeven met welke klasgenoten ze omgaan in de pauzes of wie ze zien als leider in de klas. Op basis van deze antwoorden hebben we de sociale netwerken gecreëerd. Deze genomineerde netwerken zijn onder andere gebruikt om de influence agents te bepalen in de interventies.

Daarnaast konden participant in de laatste twee jaar van het project ook gebruik maken van de ‘Social Buzz’ in de app. De Social Buzz is een sociaal platform waarmee de participanten een-op-een met klasgenoten kunnen chatten, berichten kunnen plaatsen in de klassenpagina en vragen kunnen stellen aan de onderzoekers. Op basis van de een-op-een chatgesprekken zijn ook sociale netwerk in kaart gebracht. In het project worden deze netwerken de communicatienetwerken genoemd.

Tot slot dient de onderzoekstelefoon ook als ‘beacon’ om door andere onderzoekstelefoons gevonden te worden. De onderzoekstelefoon detecteert om de 15 minuten per dag andere toestellen die zich binnen het bereik van Bluetooth bevinden (ongeveer 10 meter). Met deze gegevens kunnen interacties tussen participanten passief worden meten. In het project worden deze interacties het ‘proximity-netwerk’ genoemd.

## Opbouw van het Proefschrift

Dit proefschrift bestaat uit een introducerend hoofdstuk, vier empirische hoofdstukken die gepubliceerd (of in review) zijn in academische tijdschriften, en een afsluitend hoofdstuk waarin conclusies worden getrokken en de resultaten bediscussieerd.

### Hoofdstuk 2: Een vergelijking van verschillende methodes om sociale netwerken te meten: nominatie vragen, onlinecommunicatie en 'proximity' data.

Hoofdstuk 2 beschrijft een studie waarin het *in kaart brengen* van sociale netwerken centraal stond. In deze studie werden drie verschillende methodes om sociale netwerken te meten met elkaar vergeleken. Daarbij is gekeken naar de drie sociale netwerken zoals ze zijn gemeten in het *MyMovez* project, namelijk (1) nominatienetwerken, (2) communicatienetwerken, en (3) proximity-netwerken. De sociale netwerken werden gemaakt voor twee (grotendeels) verschillende steekproeven: een voor het eerste jaar van het project (25 klassen, 444 adolescenten, 8-14 jaar oud) en een voor het derde jaar van het project (43 klassen, 774 adolescenten, 8-15 jaar oud). Vervolgens zijn de netwerken op verschillende eigenschappen (responspercentages, stabiliteit en overlap) vergeleken. Tevens is onderzocht in hoeverre geslachtssegregatie aanwezig was in de sociale netwerken en in welke mate de netwerken beweeggedrag konden voorspellen.

De resultaten van deze studie lieten zien dat de netwerken inhoudelijk van elkaar verschillen. De nominatienetwerken waren stabiel en leken te verwijzen naar vriendschapsrelaties. De proximity-netwerken veranderen veel en leken te verwijzen naar interactierelaties, hetgeen ook het meest specifiek de fysieke activiteit kon voorspellen. De communicatienetwerken zaten daartussenin, maar bevatten het minste aantal participanten (niet alle participanten maakte gebruik van de Social Buzz). De studie concludeerde dat onderzoekers niet zomaar proximity-netwerken kunnen gebruiken om vriendschapsrelaties in kaart te brengen. Communicatie en proximity-netwerken zouden wel gebruikt kunnen worden om een vriendschapsnetwerk meer specifiek te maken (bijvoorbeeld, welke vrienden vaker met elkaar omgaan of praten veel met elkaar).

## Hoofdstuk 3: Gesimuleerde sociale netwerkinterventies die fysieke activiteit bevorderen: wie zouden de 'influence agents' moeten zijn?

Hoofdstuk 3 beschrijft een studie waarin het *selecteren* van influence agents centraal stond. Er was onderzocht welke adolescenten in een sociaal netwerk de meest effectieve influence agents zouden zijn. Met andere woorden, welke adolescenten konden er het best voor zorgen dat de rest van de klas meer ging sporten en bewegen? Om dit te onderzoeken werd gebruik gemaakt van de data van 26 klassen ($N$ = 460 adolescenten) in het eerste jaar van het *MyMovez* project. Op basis van de nominatievragen werd per klas een sociaal netwerk gemaakt. Vervolgens werden er vijf scenario's geschetst op basis van verschillende criteria om influence agents aan te wijzen, namelijk (1) degenen die het meest genomineerd zijn (*in-degree centrality)*, (2) degenen die het vaakst een tussenpersoon zijn (*betweenness centrality)*, (3) degenen die de kortste vriendschapspaden heeft met de rest van de klas (*closeness centrality*), (4) willekeurig aangewezen influence agents en (5) geen influence agents (de controlegroep). Tot slot werd het beweeggedrag van de influence agents kunstmatig verhoogd en hebben we gesimuleerd hoe het beweeg gedrag zich verspreidde in de klas in de vijf verschillende scenario's.

De resultaten van deze studie lieten zien dat het beweeggedrag van de klas het minst verhoogd werd in de controle conditie (geen influence agents), wat een indicatie is dat het zin heeft om een sociale netwerkinterventie uit te voeren. Daarnaast liet deze studie zien dat van de vier sociale netwerkinterventies, het scenario met willekeurige influence agents het kleinste effect had. Het beste resultaat werd behaald in de scenario's met influence agents gebaseerd op *in-degree centrality* of *closeness centrality*. Dit zijn respectievelijk de adolescenten die het meest genoemd werden door anderen, of degenen die de kortste vriendschapspaden had met de rest van de klas. Tot slot liet deze studie zien dat niet elke klas even geschikt is voor sociale netwerkinterventies. Wanneer in een klas er maar een paar adolescenten het overgrote deel van de nominaties kreeg, waren sociale netwerkinterventies het meest effectief, ten opzichte van klassen waarin alle adolescenten ongeveer hetzelfde aantal nominaties kregen.

**Hoofdstuk 4: Het effect van een sociale netwerkinterventie die de fysieke activiteit van adolescenten bevordert door middel van een onlinetraining.**

Hoofdstuk 4 beschrijft een studie waarin het *trainen* van influence agents centraal stond. In de studie werd het effect van een sociale netwerkinterventie getoetst. De opzet van de studie was grotendeels in lijn met de ASSIST-studie, alleen kregen de influence agents geen tweedaagse training. Daarentegen kregen ze een korte training via de onderzoekstelefoon over hoe ze fysieke activiteit konden promoten in de klas. Daarnaast werden de influence agents geselecteerd op basis van hun *closeness centrality* in plaats van *in-degree centrality*. In de studie deden 11 klassen mee met 190 leerlingen van één middelbare school die niet deelnam aan het *MyMovez*-project. De klassen werden willekeurig in de interventie of in de controle groepen geloot. In de interventie werden per klas vier adolescenten die het hoogst scoorden op *closeness centrality* via de onderzoekstelefoon benaderd om influence agents te worden. De 19 van de 24 benaderde adolescenten die de rol accepteerden, kregen vervolgens een training op de telefoon die ongeveer een half uur duurde. Vervolgens mochten ze hun eigen strategieën bepalen om de rest van de klas meer te laten bewegen.

De resultaten van deze studie lieten zien dat de sociale netwerkinterventie er niet in slaagde om het beweeggedrag van de klasgenoten te verhogen. De beide groepen gingen minder bewegen in de interventieweek in vergelijking met de voormeting. Uit evaluaties van de influence agents bleek dat ze hun rol als redelijk leuk beschouwden en dat ze niet zozeer één strategie gebruikten, maar een combinatie van alle strategieën toepasten. Een mogelijke verklaring waarom de interventie niet effectief was, is dat door de online trainingen de afstand tussen de onderzoeker en de influence agents te groot was. Persoonlijk contact kan er mogelijk voor zorgen dat de influence agents hun rol beter kunnen uitvoeren.

### Hoofdstuk 5: Het effect van een sociale netwerkinterventie die de fysieke activiteit van adolescenten bevordert door middel van vlogs.

Hoofdstuk 5 beschrijft een studie waarin het *trainen* van influence agents centraal stond. In de studie werd het effect van een sociale netwerkinterventie werd getoetst. Daarnaast werd in deze studie ook gekeken of een sociale netwerkinterventie een groter effect heeft op beweeggedrag dan een traditionele interventie (door middel van een mediacampagne gericht op de gehele doelgroep). De opzet van de studie was vergelijkbaar met de opzet van de studie in hoofdstuk vier, met het verschil dat er meer participanten meededen en de influence agents niet via de onderzoekstelefoon werden getraind. In deze studie hadden de influence agents meer persoonlijk contact met de onderzoeker en werden ze uit de les meegenomen om ze een korte instructie te geven hoe ze vlogs (videoblogs) konden maken. De influence agents maakten vlogs over sporten en bewegen, die vervolgens werden getoond aan de klasgenoten (sociale netwerkinterventie conditie) of aan adolescenten van een niet gerelateerde klas (traditionele media interventie conditie). Adolescenten in de derde conditie (de controle conditie) werden niet blootgesteld aan vlogs over sporten en bewegen.

De resultaten van deze studie lieten zien dat alle condities gemiddeld meer gingen bewegen en dat er op de korte termijn geen verschillen waren tussen de drie condities. Op de lange termijn was er een omgekeerd effect. De toename in beweeggedrag was groter in de controle conditie dan in de sociale netwerkinterventie conditie. Daarentegen vonden we een indicatie dat de sociale netwerkinterventie wel een positief effect had op de sociale norm. Na blootstelling aan de sociale netwerkinterventie gaven de adolescenten aan dat hun sociale omgeving meer was gaan bewegen, terwijl adolescenten na blootstelling aan de traditionele interventie rapporteerden dat hun sociale omgeving juist minder was gaan bewegen. Dit suggereert dat de perceptie van de sociale norm hoger werd als adolescenten klasgenoten zagen bewegen in vlogs, maar lager als ze onbekende adolescenten zagen bewegen in vlogs. Tot slot werden de vlogs ook beter ontvangen (kijktijd, waardering en ervaren afstand tot de vlogger) door de adolescenten in de sociale netwerkinterventie dan in de traditionele interventie.

## Hoofdstuk 6: Discussie

Dit proefschrift sluit af met een hoofdstuk waarin de conclusies worden getrokken. Allereerst zijn in dit proefschrift nieuwe methodes ontwikkeld om de relaties tussen adolescenten in kaart te brengen. We vonden dat de sociale netwerken op basis van de communicatienetwerken en proximity-netwerken structureel anders zijn dan die van genomineerde netwerken, die vaak gebruikt worden in sociale netwerkanalyses. Ten tweede hebben we in dit proefschrift op basis van simulaties laten zien dat sociale netwerkinterventies het beweeggedrag van adolescenten het meest kunnen verhogen als de influence agents strategisch worden geselecteerd. Influence agents die het meest genomineerd worden, of de kortste vriendschapspaden hebben met de rest van de klas, zorgen voor de grootste toename van sporten en bewegen in een klas. Tot slot is dit proefschrift er niet in geslaagd om door middel van twee verschillende sociale netwerkinterventies het beweeggedrag van adolescenten te stimuleren. Echter lijkt het er wel op dat sociale netwerkinterventies de sociale norm positief beïnvloeden en als je adolescenten vlogs laat maken deze wel beter ontvangen worden door de klasgenoten.

Vervolgens bediscussieerd dit hoofdstuk hoe bepaald aspecten van het *MyMovez* project de resultaten hebben kunnen beïnvloeden. Allereerst is de klas gebruikt als grens van de sociale netwerken. Het is goed voorstelbaar dat er ook belangrijke sociale interacties bestaan buiten de klas die hierdoor niet zijn meegenomen. Daarom zou toekomstig onderzoek natuurlijke grenzen kunnen gebruiken door bijvoorbeeld sociale netwerken op eilanden te onderzoeken. Ten tweede hebben we een strenge toestemmingsprocedure gehanteerd, die mogelijk heeft geleid tot een relatief gezonde steekproef. Toekomstig onderzoek zou naar nieuwe manieren moeten vinden om ouders te motiveren om toestemming te geven voor deelname aan onderzoeken. Tot slot kan de gehanteerde sociale netwerktheorie gezien worden als een overkoepelende theorie die kan worden in- en aangevuld door andere theorieën. Zo heeft de sociale netwerktheorie geen sterke voorspellende capaciteit (bijvoorbeeld X leidt tot Y) en gaat de theorie ook niet verder in op onderliggende mechanismes van sociale beïnvloeding (bijvoorbeeld faciliteren, sociale normen of voorbeeldfuncties). Toekomstige studies zouden kunnen proberen om afzonderlijke processen in de sociale netwerktheorie te isoleren om zo meer inzicht te krijgen in deze mechanismes en een hogere voorspellende waarde te kunnen creëren.

Het hoofdstuk sluit af met de sterke punten van dit proefschrift. Allereerst hebben de studies in dit proefschrift een sterke technologische inslag. Eén van de belangrijkste implicaties van het project is dat het laat zien dat het mogelijk is om grootschalige veldstudies bij jongeren te doen met telefoons en bewegingsmeters. Technologische innovaties maken het aan de ene kant aantrekkelijker voor adolescenten om aan onderzoek mee te doen, en maken het aan de andere kant mogelijk om nieuwe methodes toe te passen en nieuwe onderzoeksvragen te beantwoorden. Daarnaast laat dit proefschrift op verschillende manieren zien dat het beweeggedrag van jongeren zich niet afspeelt in een sociaal vacuüm en dat het sociale netwerk hier een invloed op heeft. Het is daarom van belang dat toekomstige interventies niet alleen op adolescenten die te weinig sporten of bewegen focussen, maar een integrale aanpak te hanteren waarbij complete sociale netwerken elkaar bevorderen om meer te sporten en bewegen. Het is echter lastig gebleken om deze sociale netwerkinvloeden daadwerkelijk te gebruiken om het beweeggedrag te bevorderen bij adolescenten. Daarom is meer onderzoek nodig om te onderzoeken hoe de sociale netwerken ingezet kunnen worden om sporten en bewegen te bevorderen in jongeren.

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--- Mic drop ---

## About the Author

Thabo Joshua van Woudenberg was born on 29 August 1989 in Leiden, the Netherlands. In 2012, he obtained a bachelor's degree in communication science at the Radboud University in Nijmegen, the Netherlands. Two years later, he completed the research master at the Behavioral Science Institute at the same university, after studying self-persuasion to promote advertising literacy and the feeling of presence in a virtual environment. Subsequently, Thabo started to work as a research assistant to lay the groundwork for the *MyMovez* project, led by Professor Buijzen. In 2015, Thabo started his PhD project in the same project, of which the current dissertation is the end product.

At present, Thabo works as a Post-doctoral Researcher at the Communication and Media research program of the Behavioral Science Institute at Radboud University, the Netherlands. In the current project, Thabo further investigates effective and responsible health campaigns for adolescents using online social networks. For a full scientific curriculum vitae, please visit http://www.tvanwoudenberg.com.