

Network Distance and Centrality Shape Social Learning in the Classroom

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Social learning can help individuals to efficiently acquire knowledge and skills. In the classroom, social learning often takes place in structured settings in which peers help, support, and tutor each other. Several protocols have been developed to make peer-assisted learning (PAL) more efficient. However, little attention has been devoted to how the transfer of knowledge is shaped by the social relationship between peers, and their relative positions in the social network. To address this gap, we combined social network analysis with an experimental social learning task, in which pupils ($N = 135$; aged 11–19) could use social information from their peers to improve their performance. We show that pupils' tendencies to use social information substantially decrease with the peer's distance in the social network. This effect is mediated by subjective closeness: pupils report feeling much closer to their friends than to their non-friends, and closeness strongly enhances social learning. Our results further show that, above and beyond these effects of network distance, social information use increases with the peer's social status (network centrality) and perceived smartness. Our results provide empirical evidence in a naturalistic setting for the role of specific network attributes in shaping pupils' willingness to learn from their peers. These findings illustrate the value of a social network approach for understanding knowledge transfer in the classroom and can be used to structure more effective peer learning.

Impact and Implications

This study shows how social network analyses can help teachers and practitioners boost learning outcomes. Social network data can inform matching of pupils for peer learning, and can help cultivating social cohesion in the classroom. Collecting social network data is a fast and cheap procedure, and may be easily incorporated in existing protocols aimed at promoting peer learning, knowledge transfer and positive school culture.

Keywords: social learning, social networks, peer learning, eigenvector centrality, high school


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Social learning can help individuals acquire useful knowledge and make better and more accurate decisions (Hoppitt & Laland, 2013). In everyday life, social learning occurs through the observation and modeling of specific behaviors (Bandura & McClelland, 1977) from a multitude of sources (Kendal et al., 2018). The transfer of social knowledge can be broadly categorized as vertical when stemming from older generations (e.g., parents, grandparents, teachers), or horizontal when occurring between same-aged peers. Within the school context, horizontal social learning is often formalized as peer-assisted learning (PAL; Palincsar & Brown, 1984), which can be defined as the acquisition of knowledge and skills through helping


and supporting among pupils (Topping, 2005). In the past decades, researchers have identified ways of structuring peer learning to make it more efficient and cost-effective, benefiting both the tutor and tutee (see Topping et al., 2017, for an overview). One of the outstanding challenges remains how to best select pairs of tutee and tutor to optimize learning outcomes. Here we present a behavioral experiment that aims at leveraging insights from social network analysis to improve peer learning in adolescence.

During adolescence, which starts almost simultaneously with the transition to middle school, peers become more important while the influence of parents wanes (Rubin et al., 2006). As a result, there is a

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shift from vertical to horizontal social learning. Over this period, friendships become more intimate (Berndt, 1982), and a drive emerges to stand out (status) and fit in (belonging) the social group (Crone & Dahl, 2012). These motives can create positive feedback loops that affect the learning process: strong friendships can increase the motivation for schooling, and friendship status may even directly impact the efficacy of peer learning (Riese et al., 2012). Furthermore, the performance of closer friends predicts students' future grades (Blansky et al., 2013). This is thought to be a result of both selection (good students befriending each other) and social influence (peers motivating each other to perform; Rambaran et al., 2017). In addition, numerous studies show that in adolescence, high-status individuals have a disproportionate influence on their peers' behavior (Dijkstra et al., 2008), in domains such as risk-taking (Rambaran et al., 2013), health behavior, and substance abuse (Helms et al., 2014). Taken together, the transition from vertical to horizontal social learning, and the qualitative shift in peer relations during adolescence, highlight the importance of understanding the role of social relations in peer learning in this specific age group.

Current studies on learning mostly focused on identifying factors other than social relations that positively contribute to the learning outcome. For instance, a fruitful pairing strategy for complex topics, such as mathematics, is to match a higher achieving student with a less performing one. This strategy has been shown to produce an increase in grades (Alegre et al., 2019), and greater confidence in own capabilities (Moliner & Alegre, 2020) for both students. Another established method is cross-age tutoring, in which older tutors support younger tutees (Robinson et al., 2005; Topping & Bryce, 2004; Topping et al., 2004, but see Alegre et al., 2019). Tutoring strategies should also consider gender differences: for instance, in an academic context female students indicated a stronger preference for peer tutoring and joined tutoring activities more often than male students did (Sobral, 2002). Despite these extensive investigations, little work has focused on the social relationship between the peers involved in peer learning in the classroom. There is some evidence that in some cognitive tasks pairs of elementary school friends perform better than pairs of non-friends (Zajac & Hartup, 1997), but thus far, this has not been structurally investigated in adolescents.

The paucity of research on the impact of social relations on social learning in adolescents is surprising. Adolescents are especially sensitive to their social environments (see above, Blakemore & Mills, 2014), and the broader literature on social learning presents ample evidence that the social relationship between peers is an important factor in learning. Studies from across the biological and social sciences suggest that learners tend to use social information strategically, being selective as to who they turn to for useful knowledge (Hoppitt & Laland, 2013; Kalkstein et al., 2016; Kendal et al., 2018). The extent to which a peer guides an individual's behavior often depends on the peer's (a) social distance, (b) social status, and or (c) achievement (Kalkstein et al., 2016; Kendal et al., 2018). The main aim of this study is to examine if the impact of these three fundamental elements identified in laboratory experiments translate to the classroom environment and can actively shape peer learning. We set out to ask: Do pupils preferentially learn from peers who (a) are closer to them in their social network (b) have high-status and (c) are perceived as high achievers?

Our research strategy was as follows. We combined an experimental approach with social network analyses in high school classrooms to

examine who are the peers that pupils are most likely to learn from. Pupils completed a numerical judgment task and could adjust their responses upon observing the responses of a classmate. The magnitude of adjustments quantifies pupils' tendency for social information use—a basic building block of social learning (Molleman, Kurvers, & van den Bos, 2019). We used social network analyses and peer nomination data to identify attributes of social relationships that facilitate the transmission of information. By using social network analyses in combination with experimental methods, we provide insights that can help structuring dyads for effective peer learning.

First, we investigated the relationship between social learning and distance in social networks. We hypothesized that social learning is negatively correlated with social network distance. That is, we expected that pupils are most strongly influenced by their nearest peers (i.e., friends), followed by friends of friends, etc. However, previous research showed that the subjective perception of relationships is at least as important for social learning (Harris, 2012; Kalkstein et al., 2016). Indeed, in a previous study using the same experimental social learning task, participants who felt more strongly related to the observed peers, also exhibited higher levels of learning (Molleman, Kurvers, & van den Bos, 2019). Based on these findings, we hypothesized that effects of network distance on social learning are mediated by the subjective closeness (i.e., how strongly a pupil feels socially connected to a peer). We therefore measured how close the learner felt to the observed peer, with the widely used and validated Inclusion of the Other in the Self scale (IOS; Aron et al., 1992; Gächter et al., 2015).

Second, we examined how social learning is impacted by the social status of the peer within the network. Prestige biases in social learning are well established (Brand et al., 2020; Henrich & Gil-White, 2001), and preferentially learning from high-status peers can help increase one's own social status in, or belonging to, a group (LaFontana & Cillessen, 2010; Ojanen et al., 2005). This evidence is consistent with the theoretical framework of Social Learning Theory, which states that learning happens through the observation of others (Bandura & Walters, 1963): high-status peers draw more attention than others and are therefore more observable than lower status peers (Shi & Xie, 2012). These motivations might be particularly pronounced in adolescence, during which social status and a sense of belonging are important drivers of behavior (Crone & Dahl, 2012; Yeager et al., 2018). Individuals with high social status also occupy key positions in social networks. Accordingly, social status is reflected in network centrality metrics such as "eigenvector centrality" (having many friends who have themselves many friends) and "betweenness centrality" (connecting different clusters in the network), each of which has been associated with more traditional notions of popularity (Rawlings et al., 2017; van den Bos et al., 2018). Taken together, we expected that a peer's centrality in the social network is positively associated with social information use by the learner.

Third and finally, we analyzed how social learning is impacted by perceived achievement of the peer. Copying successful others is a commonly studied social learning strategy, documented across species and behavioral domains (Kendal et al., 2018). Already from an early age, children pay particular attention to those individuals who are proficient in the task at hand (Wilks et al., 2015), and model their own behavior after them (Wood et al., 2013, 2015). In the context of our study, success is defined as being skilled at the task relevant to the learner. Although information about

achievement or skill on a specific task is not always available, pupils tend to have quite accurate impressions of the academic potential of their classmates, which is generally associated with their “smartness” (Gest et al., 2008). For this reason, to measure perceived academic achievement, we asked pupils to nominate peers who they perceived as “smart.” Based on the above-mentioned evidence, we expected that pupils who are perceived as smart will have more impact on learners, despite their potentially lower social status.

Some cultures depict “smart” kids as socially isolated and barely influential, and in adolescents’ studies, popularity and academic achievement are often independent from one another (Boyatzis et al., 1998; Vaillancourt et al., 2003), if not anticorrelated (Hopmeyer Gorman et al., 2002). However, depending on the context and the prevailing social norms, different sociometric profiles (i.e., “popular” pupils, students who excel academically) can exert social influence (Laninga-Wijnen et al., 2018). Here, our definition of being successful encompasses the idea of solving problems better than others. Importantly, it implies that pupils might benefit from particularly heeding social information provided by classmates who are perceived as smart.

We took a combined social network and experimental approach to test if the core elements of social learning contribute to peer learning in the classroom environment. We examined how high school pupils learn from different peers in their network, using a validated and incentivized judgment task (Molleman, Kurvers, & van den Bos, 2019). This task provides a controlled method to quantify the extent to which individuals use social information provided by their peers. Based on social network data, we experimentally varied the social distance (e.g., friends vs. non-friends) between a pupil (learner) and the peer who provided the social information (the demonstrator). This network data was also used to evaluate demonstrators’ social status (eigenvector and betweenness centrality). Finally, we collected peer nominations of smartness and popularity. Our combined approach allowed us to ask novel questions about social relations, peer status, and peer learning.

Based on the evidence presented above, we formulated the following main hypotheses:

1. Social learning is negatively correlated with social distance between the learner and the demonstrator and this effect is mediated by the learner’s subjective closeness to the demonstrator.
2. Social learning is positively correlated with the social status of the demonstrator.
3. Social learning is positively correlated with the perceived academic achievement of the demonstrator.

Next to the main hypotheses, we conducted an exploratory analysis on whether participants’ own social status and perceived academic achievement influenced their social learning behavior. Since our study was not explicitly designed to address this question, we did not formulate any specific hypothesis for this analysis (but see Sijtsma & Lindenberg, 2018; Wang et al., 2020 for examples of how own social status can be related to social influence). We show that consideration of social relationships in the classroom opens fruitful ways forward in developing novel and potentially more effective forms of peer learning. Our findings are thus a first step toward applying insights from the broader social learning literature to the school context. In the

discussion we will relate these findings to existing interventions focused on school culture and classroom cohesion.

Materials and Methods

General Procedures

We recruited participants from two Dutch high schools, for a total of 10 classrooms and 249 potential participants. 192 participants from these classes expressed their interest to participate in the study (77%). Data was collected in two Waves with a 2-week interval. Between Waves, an additional 16 participants dropped out, resulting in a final sample of 176 participants (see Supplemental Table S5; Supplemental Materials Section 3.2 for details on the Dutch school system and sample composition across classrooms). Each Wave started with brief oral instructions, followed by an opportunity to ask questions. After that, participants completed a peer nomination questionnaire and three tasks on tablet computers. In total, these activities lasted 40–50 min. Here we report results from the questionnaire and one of the tasks. The sessions were planned during schooling hours. If students were finished before the end of the hour, they were instructed to remain seated and to not disturb their classmates. Prior to the study we obtained consent from the participants. For participants younger than 16, additional consent was obtained from their parents or caretakers. The study was approved by the Ethics Review Board of the University of Amsterdam (case number 2019-DP-10269).

Monetary Incentives

In each Wave, schools received five euros for each participating pupil. In addition, one participant per class could win a 40 Euro web shop voucher through a lottery. The lottery was structured as follows. Students were informed at the beginning of Wave 1 that they would complete three tasks in which they could earn points, and each point was worth a lottery ticket. At the end of Wave 2, a 40 Euro voucher card would be awarded to the participants with the winning ticket. Students were told that collecting as many tickets as possible would result in the best chance to win, as in a normal lottery. Points were distributed across the three tasks. In the task described here, points were awarded based on the accuracy of the response in a randomly selected round (see Experimental Task sections for details). Participants could earn points in each task in both Waves. The total number of points that could be won in each task was calibrated on task duration. Total points won by each participant were communicated at the end of Wave 2, as to not influence the behavior of participants in the tasks based on their current score.

Stimuli

Questionnaire for Obtaining Peer Nominations

In Wave 1, participants completed a questionnaire about their relationship with their classmates (Van den Bos et al., 2018). We included questions to measure friendships (“Which classmates are your friends?”), perceived popularity (“Which classmates are the most popular?”), and perceived smartness (“Which classmates are smart?”; see Supplemental Table S1 for all questionnaire items). For each question, participants made nominations by selecting names from a list comprising all classmates, with no limits on the number of

nominations. In our statistical models, we only included reciprocal friendship nominations (see Social Network Analyses section).

We used peer nominations of smartness as a proxy for perceived academic achievement. Participants were asked to nominate all their classmates who they considered smart. We standardized total numbers of nominations at the classroom level by dividing the number of received nominations by the number of possible nominations. In addition to peer nominations of smartness, we collected traditional peer nominations of popularity for exploratory analyses of social status (see Supplemental Table S2).

Experimental Task Measuring Social Information Use

Our measure of social information use is based on a validated judgment task called the Berlin Estimate Adjustment Task (BEAST; Figure 1A; Molleman, Kurvers, & van den Bos, 2019). The BEAST is a behavioral task designed to capture individuals' propensity for social information use, a most basic aspect of social learning. The task has been proven effective with adult and developmental populations (Molleman et al., 2020; Molleman, Kanngiesser, & van den Bos, 2019). The BEAST has been shown to have a range of desirable psychometric properties. Specifically, previous studies reported that participants were consistent in the use of social information both within task rounds, and when they were retested after a 2 weeks and 9 months interval (Molleman, Kurvers, & van den Bos, 2019). Additionally, social information use in the

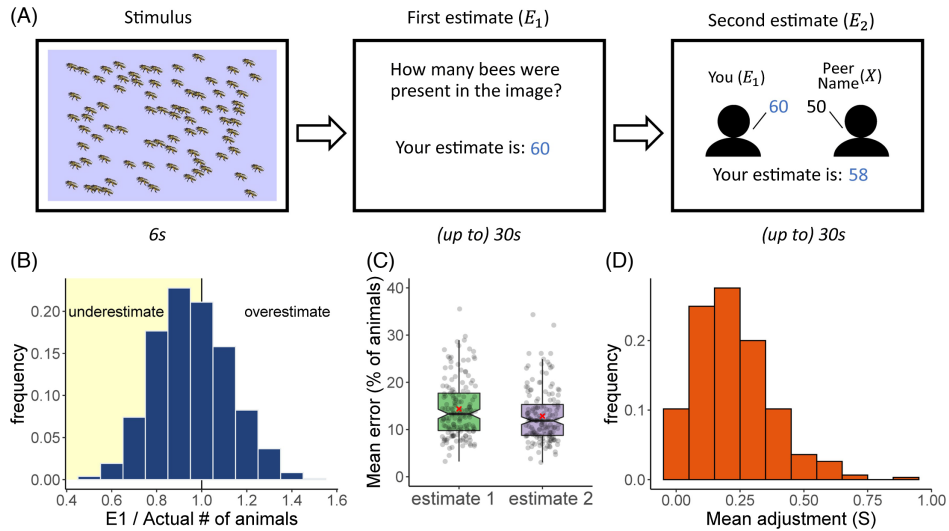
BEAST positively correlates with social information use in other established decision-making tasks, such as the Moving Dots Task and two-alternative forced-choice tasks (Molleman, Kurvers, & van den Bos, 2019).

In our version of the BEAST, participants had to estimate the number of animals in a series of five images, each image showing a different animal species (see Supplemental Materials Section 4 for screenshots). In Wave 1, participants completed the series three times without social information, so that we obtained three estimates for each participant for each image. We used these estimates as social information in Wave 2 (see below).

In Wave 2, participants completed two blocks of five rounds of the BEAST, in counterbalanced order. Again, they estimated the numbers of animals in the images, but after submitting their first estimate (E_1), they observed the estimate of a classmate (social information; X) and then submitted a second estimate (E_2). We experimentally manipulated the network distance of the classmate by using the social network data. In one block, this classmate was a peer with minimal distance to the participant (i.e., a friend), and in the other block, this was a classmate with maximal distance to the participant (i.e., a non-friend; see Figure S1 for distribution of network distances in experimental blocks). We controlled the source of social information to maximize variation in the key variable of interest (network distance), while minimizing variation in other external factors that might affect social information use. To do so, peers were always gender-matched, we kept constant the distance

Figure 1

Experimental Design and Basic Results



Note. (A) Task measuring social information use. Participants observed an image with a group of animals for 6 s. After the image disappeared, they had to enter their estimate. After confirming their first estimate (E_1), participants observed the name and the estimate of a classmate, or demonstrator, who saw the same image. Based on this social information (X), participants could make a second estimate (E_2). We used participants' relative adjustments to quantify their social information use (See Behavioral Data Analysis in the main text). (B) Distribution of errors in first estimates, indicating that participants on average underestimated the correct number with 10%. (C) Boxplots of participants' mean errors in first and second estimates. Second estimates were more accurate, indicating that social information improved performance. Black bars indicates the median, boxes includes the interquartile ranges. (D) The distribution of individuals' average adjustments across all trials. The average of .22 indicates that participants tended to assign substantially more weight to their own estimates than to social information. See the online article for the color version of this figure.

between first and second estimate (~20%), and when possible, we selected social information pointing toward the correct number of animals.

To avoid the possibility that participants could learn about their own skill or the accuracy of their peers, they did not receive feedback about their performance during the task. Participants were rewarded for accuracy. At the end of each Wave the computer randomly selected one of the participant's estimates. If that estimate was exactly correct, the participant earned 100 points. For each animal off, we subtracted five points, and the number of points could not become negative. In this way, participants were incentivized to respond as accurately as they could in all the rounds, as they did not know which estimate would be selected for payment. Points were summed at the end of Wave 2, and participants received one lottery ticket for each point earned. Participants were thus incentivized to adjust their estimates only if they believed that it would actually improve their chances of winning tickets.

Subjective Closeness

After the experimental task all participants filled in a short visual questionnaire to measure the participants' subjective closeness to the peers they had observed in the experimental task. We used the IOS scale, in which participants characterized their relationship with each of both peers on a scale from 1 (*very distant*) to 7 (*very close*; Aron et al., 1992; see Supplemental Materials Section 4). The IOS scale has been shown to have excellent alternate-form reliability, very good test-retest reliability and good convergent validity. It has also been shown to have as good or better predictive validity compared to other, similar scales (Aron et al., 1992; Gächter et al., 2015).

The score on the IOS scale provides a subjective account of the relationship between the participant and the peers who provided social information in the two experimental blocks (yielding two values for each participant: IOS_{friend} , $IOS_{nonfriend}$), thus complementing the social network measures derived from the social network.

Data Analysis

Unless indicated otherwise, all data analyses were performed using the *R* software (R Core Team, 2020), with the *RStudio* IDE (RStudio Team, 2020).

Social Network Analyses

Social network analyses were performed with the *R* package *igraph* (Csardi & Nepusz, 2006). We constructed undirected unweighted friendship networks, drawing an edge (friendship connection) between two nodes (participants) only if they nominated each other as friends (Figure 2A). For each dyad in a network, we calculated network distance as the shortest path between the two nodes. In addition, we calculated eigenvector centrality and betweenness centrality for each node in the network. These measures account for different dimensions of social status. Eigenvector centrality indicates a node's influence in the network due to the number of its connections, and the number of connections those connections have themselves (Newman, 2010). Betweenness centrality highlights which nodes are in a strategic position between (otherwise distant) subgroups in the network, giving access to

information from divergent sources. Betweenness centrality of a specific node is based on the number of shortest paths between dyads passing through it (Newman, 2010). To ensure that our main network measures are not compromised by participant dropout, we included a number of robustness checks based on third-party friendship nominations (see Supplemental Materials Section 3.3 for details).

Behavioral Data Analysis

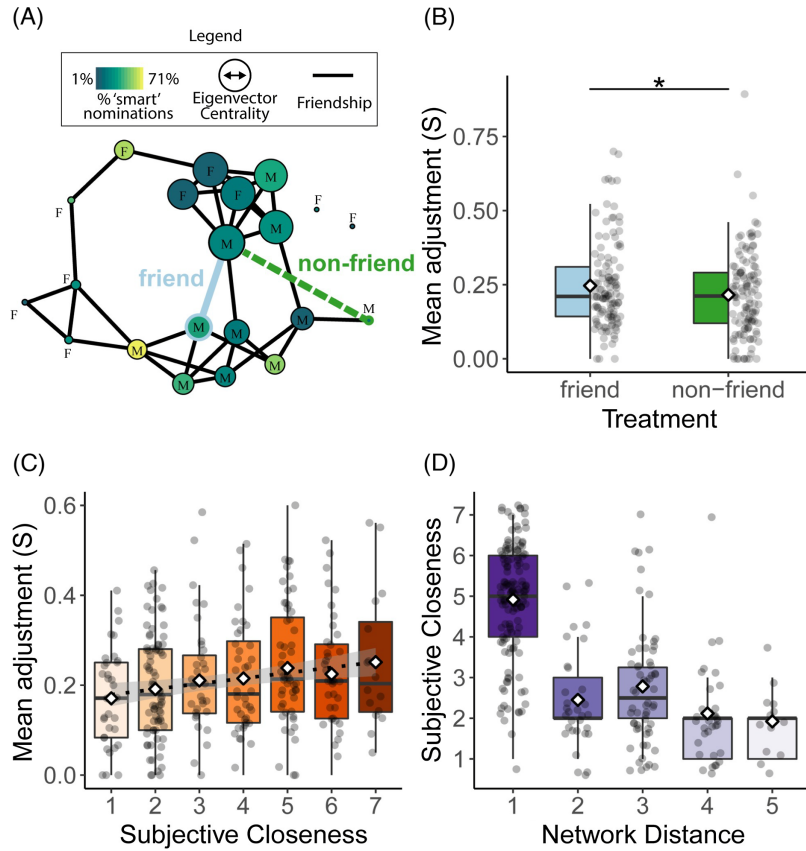
Measure of Social Information Use (S). For each round of the BEAST, we calculated participant's social information use (s) as the relative distance they moved toward the social information: $s = (E_2 - E_1) / (X - E_1)$. Note that a value of $s = 0$ indicates ignoring social information and keeping one's first estimate, $s = .5$ indicates assigning equal weight to one's own estimate and social information, and $s = 1$ indicates copying the peer's estimate. For each block, we averaged the values of s to obtain an overall measure of social information use. This measure, denoted S , is the key behavioral outcome variable quantifying social learning (Molleman, Kurvers, & van den Bos, 2019). Each participant was characterized with two values of S : one when the source of social information was a friend (S_{friend}) and one when its source was a non-friend ($S_{nonfriend}$).

Exclusion Criteria. In the analyses of the experimental task, we only included rounds in which the second estimate was a weighted average of participants' own first estimate and social information (so, meeting the condition $0 \leq s \leq 1$), and we excluded participants for whom $0 < s$ or $s > 1$ in more than three rounds per treatment (each treatment had five rounds). Participants for whom the two experimental treatments could not be properly defined (i.e., no combination of a same-gender friend and a same-gender non-friend existed in the classroom social network) were also excluded from the analyses.

Mediation Analysis. We used linear multilevel regression models to examine the mediation effect of subjective closeness on the relationship between friendship (network distance = 1 versus network distance >1) and social information use (S). In a subsequent step, we constructed a more fine-grained mediation model where the binary independent variable "friendship" was replaced by network distance between the peer and the learner (range: 1–5, friends, friends of friends, etc.). We used the *MLmed* macro in SPSS (Hayes & Rockwood, 2020) with random intercepts for participants (including random slope models fail to converge). Effects were estimated by Monte Carlo simulations generating 95% confidence intervals (CIs) using 10,000 resamples. We report unstandardized betas. After analyzing the mediation models with friendship (Model 1) and network distance as independent variables (Model 2), we extended Model 2 to include the covariates for the social network centrality (eigenvector centrality and betweenness centrality) and perceived smartness of the demonstrator (Model 3).

Exploratory Analyses. In our main analysis we included social status and perceived smartness of a peer as covariates in the mediation model. However, peer learning is a complex and interactive process, and also individual characteristics of the learner might have a role in social information use. Since our study was not designed to test such hypotheses, we exploratively tested whether adding characteristics of the learner to the mediation model would better predict learning patterns. Specifically, we added eigenvector

Figure 2
Social Learning From Peers Across Network Distances



Note. (A) Social network from one of the sampled classes illustrating the key predictors in our analysis. Each node represents a participant. Lines (edges) between nodes indicate that both participants nominated each other as friends. Thick lines show examples of the experimental treatments, administered in counterbalanced blocks in which participants observed estimates from either a friend (solid line) or a non-friend (dashed line). Node size indicates eigenvector centrality. Node colors reflect percentages of classmates nominating the participant as “smart.” (B) Boxplot showing that participants learn more from friends than from non-friends. Black bars indicates the median, boxes includes the interquartile ranges. Mean adjustment (white diamonds) was $S = .24$ for friends, and $S = .21$ for non-friends. Gray dots indicate individual participants’ data points. (C) Social learning increases with perceived subjective closeness (1 = *very distant*, 7 = *very close*) to the demonstrator, as measured by the Inclusion of the Other in the Self (IOS) questionnaire. High ratings indicate that participants identify closely with the demonstrator. Format of boxplot as in (B). (D) Participants’ ratings of subjective closeness (1 = *very distant*, 7 = *very close*) are the highest for friends (network distance = 1), and sharply decrease for peers farther away in the social network. Format of boxplot as in (B). See the online article for the color version of this figure.

and betweenness centrality scores, and smartness nominations received by the learner (Model 4) to the most complete mediation model (Model 3).

Results

Sample and Social Network Questionnaires Descriptive Statistics

176 pupils from 10 classes (52% female; $M_{\text{age}} = 15.07$, $SD = 1.61$) took part in the social network questionnaire and both Waves

of the study (for a breakdown of the demographics at the classroom level, see Supplemental Table S5). In the questionnaire, pupils were asked to nominate their friends, the most popular peers and peers who they considered smart. We observed large variability both in smartness ($M = 7.50$, $SD = 5.62$) and in popularity ($M = 3.74$, $SD = 5.03$) nominations, whereas friendship nominations were more similar between students ($M = 5.84$, $SD = 2.79$; see Table 1 for an overview of descriptive statistics).

Out of the 176 pupils who completed both Waves, the requirements for a successful experimental manipulation in the behavioral task (one gender-matched friend and one gender-matched non-friend) were

Table 1*Means, Standard Deviations, and Correlations With Confidence Intervals of Received Nominations and Network Variables*

Variable	<i>M</i>	<i>SD</i>	1	2	3	4
1. Smartness nominations	7.50	5.62				
2. Popularity nominations	3.74	5.03	-.26** [-.39, -.12]			
3. Friendship nominations	5.84	2.79	.17* [.02, .31]	.30** [.16, .43]		
4. Eigenvector centrality	0.41	0.38	-.07 [-.21, .08]	.34** [.20, .47]	.53** [.42, .63]	
5. Betweenness	0.05	0.09	.00 [-.15, .15]	.02 [-.13, .16]	.17* [.02, .31]	.15 [-.00, .29]

Note. *M* and *SD* are used to represent mean and standard deviation, respectively. Values in square brackets indicate the 95% confidence interval for each correlation.

* $p < .05$. ** $p < .01$.

met by a subsample of 139 peers. This was due to multiple factors: in some classes the majority of the participants were of one gender and finding two gender-matched peers for the minority gender was not possible. In other classes, some pupils' friendship nominations were not reciprocated, so no network connections could not be identified. An additional four pupils were excluded due since they had values of s outside the expected range of 0–1 in more than three rounds of a block, resulting in a final sample of 135 pupils. Overall, pupils were excluded from the sample for heterogeneous reasons, and we did not identify meaningful patterns (Supplemental Materials Section 3.2).

Basic Behavioral Results

In line with previous results obtained using the BEAST paradigm (Molleman, Kanngiesser, & van den Bos, 2019; Molleman, Kurvers, & van den Bos, 2019), participants tended to initially underestimate the number of animals, with the mean of the first estimate being 10.0% lower than the actual number of animals (Figure 1B). Observing social information improved accuracy: revised estimates were significantly closer to the actual numbers of animals in the images (Figure 1C; Supplemental Table S4; linear mixed model with participant as random effect; $p < .001$). Adjustments in individual rounds were overwhelmingly in the expected range of $0 \leq s \leq 1$ (98.1% of rounds; Figure S3), indicating that participant's second estimates were typically weighted averages of their own first estimate and social information. Overall, these results suggest that participants understood the task and used social information to improve their performance.

Mean adjustments across all rounds of both task blocks varied strongly between individuals (Figure 1D). Some participants never revised their first estimates, ignoring social information ($S = 0$). Most participants were characterized by a value around $S = .22$ and values of $S > .5$ were rare, indicating that they did integrate social information, but on average assigned substantially less weight to it than to their own first estimate. This “egocentric discounting” is an often-observed phenomenon in the literature on social information use in (Molleman, Kurvers, & van den Bos, 2019; Morin et al., 2021; Moussaïd et al., 2013). In the next sections we examine how participants' social information use (S) depends on network distance, the peer's social status, and achievement.

Friendship and Social Information Use

As expected, participants adjusted more when observing a friend than when observing a non-friend, Figure 2B; M (SD) $S_{friend} = .244$ (.149); $S_{nonfriend} = .211$ (.141); paired t -test: $t = 2.446$, $df = 135$,

$p = .016$, Cohen's $d = .23$. Reported subjective closeness was substantially higher for friends than for non-friends, M (SD) $IOS_{friend} = 4.952$ (1.350); $IOS_{nonfriend} = 2.516$ (1.230); t -test: $t = 15.833$, $df = 135$, $p < .001$. These results indicate that the experimental treatments and the IOS questionnaire meaningfully capture the hypothesized differences between friends and non-friends. Furthermore, subjective closeness was positively correlated with mean adjustment: on average pupils adjusted their initial estimate by 25% when matched with their closest peers but this further decreased to 17% with increasing social distance (Figure 2C; Pearson's $r = .176$, 95% CI [.065, .283], $p = .002$). This result is consistent with the hypothesis that the effect of friendship on social information use is mediated by subjective closeness.

We constructed linear multilevel regression models to test the mediating effect of subjective closeness on the relationship between friendship (network distance = 1 vs. network distance > 1) and social information use. Supporting our hypothesis, the mediation analysis reveals that the indirect effect from friendship to social information through subjective closeness is significant ($\beta = .036$, $p = .009$, Table 2, Model 1; Figure 3), while the direct effect of friendship is no longer significant when controlling for subjective closeness ($\beta = -.008$, $p = .646$, Table 2, Model 1). The latter suggest the effect of friendship is fully mediated by subjective closeness.

Network Distance and Social Information Use

More fine-grained analyses based on the network distance between the participant and the demonstrator revealed a negative correlation between network distance (friends, friends of friends, etc.) and subjective closeness (IOS; Figure 2D; Pearson's $r = -.463$, 95% CI [-.545, -.371], $p < .001$). Specifically, participants' ratings of subjective closeness were the highest for friends (network distance 1), and sharply decreased for peers farther away in the social network. In addition, the mediation analysis using network distance instead of binary friendship as an independent variable also yields a significant indirect effect ($\beta = -.01$, $p = .008$; Table 2, Model 2; and Figure 3). This confirms the role of subjective closeness as a mediator for social learning. In addition, it suggests that non-friends who are relatively close in the network may still have influence on their peers, but this influence tends to decrease with social distance.

Social Status and Achievement Shape Social Learning

We subsequently extended our “core” mediation model with measures of peers' social status (eigenvector centrality or betweenness centrality) and achievement (perceived smartness; Table 2, Model 3). We observed that participants adjusted their estimates more when

Table 2
Determinants of Social Information Use

Variable	Model 1		Model 2		Model 3		Model 4	
	Friendship (no/yes)		Network distance		Network distance		Network distance	
	Estimate (SE)	p	Estimate (SE)	p	Estimate (SE)	p	Estimate (SE)	p
Paths								
a	2.470 (.165)	<.001	-.927 (.084)	<.001	-.780 (.079)	<.001	-.778 (.079)	<.001
b	.014 (.005)	.008	.013 (.006)	.007	.010 (.005)	.041	.010 (.005)	.042
c'	-.008 (.017)	.646	.006 (.006)	.706	.002 (.007)	.839	.001 (.007)	.890
Indirect	.036 (.014)	.009	-.012 (.005)	.008	-.008 (.004)	.04	-.009 (.004)	.038
Covariates demonstrator								
Eigenvector centrality					.051 (.020)	.014	.051 (.021)	.015
Betweenness centrality					-.064 (.056)	.234	-.066 (.056)	.245
Smartness					.070 (.025)	.005	.070 (.025)	.006
Covariates learner								
Eigenvector centrality							-.009 (.029)	.756
Betweenness centrality							.167 (.110)	.130
Smartness							-.029 (.039)	.449
Intercept	.212 (.012)	<.001	.225 (.010)	<.001	.158 (.030)	<.001	.188 (.015)	<.001
BIC	75.346		751.689		728.260		734.256	

Note. Estimates of linear mixed mediation models fitted to mean adjustment (*S*), with “participant” as random intercept. Coefficients are unstandardized across models. *a* indicates the pathway from the independent variable to the mediating variable. *b* indicates the pathway from the mediating variable to the dependent variable (*S*). *c'* indicates the direct pathway from the independent variable to the dependent variable after accounting for the mediating variable. Indirect refers to the pathway from the independent variable to the dependent variable, passing through the mediator. In Model 1 Friendship [0, 1] is used as the independent variable. In Models 2, 3, and 4 Network Distance, which varied from 1 to 5, is used as independent variable. Subjective Closeness is the mediator between Friendship/Network Distance and mean adjustment (*S*; for a schematic representation, see Figure 3). BIC = Bayesian information criterion.

observing peers who occupy central positions in the classroom network (eigenvector centrality, $\beta = .051$, $p = .012$). However, this effect was not observed for betweenness centrality ($\beta = -.064$, $p = .254$).

Peers who are often nominated as being smart by their classmates did induce an increased use of social information ($\beta = .076$, $p = .018$), despite that perceived smartness did not predict accuracy in the task (Figure S2). Including the status and perceived smartness of

the demonstrator in the model increased the model fit, quantified as Bayesian information criterion (BIC). More importantly, the direct and indirect effects of network distance and subjective closeness remained qualitatively unchanged. These results indicate that beyond subjective closeness, both demonstrator status and demonstrator achievement influence social information use.

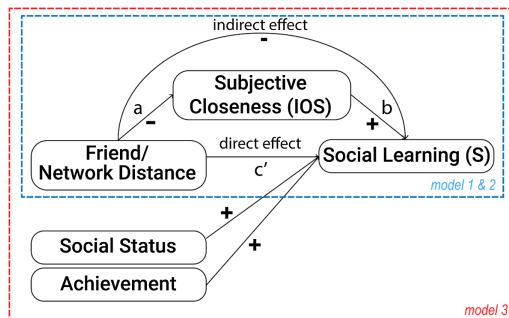
Exploratory Analyses

Finally, we ran an additional mediation model in which we also included characteristics of the learner as covariates (Table 2, Model 4). Specifically, we added eigenvector and betweenness centrality scores, and smartness nominations received by the learner. None of these covariates was significant, indicating that participants' behavior in the task did not depend on their own social status, or smartness nominations. Contrary to what previous studies suggested (Shi & Xie, 2012; Sijtsma & Lindenberg, 2018; Wang et al., 2020), learner social status or perceived achievement did not affect their social information use (Table 3, Model 4). Additionally, including these covariates led to a poorer model fit (higher BIC compared to Model 3). In the Supplemental Materials we include further robustness checks with alternative operationalization of social status and ways to structure the social network, none of which affect the conclusions from main models reported here (Supplemental Materials Section 3.1, Supplemental Tables S2 and S3).

Discussion

In the past decades, researchers have identified ways of structuring social learning in the school context to make it more effective. However, there has been little focus on how relationships between peers in a classroom impact social learning. Here we leveraged social network analyses and an experimental approach typical of the

Figure 3
Structure of the Main Mediation Models Examining Determinants of Social Learning



Note. The baseline model tested the hypothesis that social learning is shaped by friendship (Model 1) or network distance (Model 2), mediated by subjective closeness. The extended model (Model 3) also included social status (Eigenvector centrality and Betweenness centrality) and perceived academic achievement (smartness nominations) of the demonstrator. Model 4 is not included here. Signs (+ and -) in the scheme represent the direction of the statistically significant effects. The direction of the effects was identical in all three models, but the coefficient estimates slightly varied between models. Exact coefficients for each model are reported in Table 2. See the online article for the color version of this figure.

broad literature on social learning to identify three key factors of social relations that contribute to social information use in the classroom. First, social information use among pupils decreases with increasing network distance between demonstrator and learner, and this relationship between social information use and social distance was mediated by subjective closeness. Second, social information use increases with the centrality of the demonstrator. Finally, above and beyond these network-based effects, peers who are considered “smart” have a larger impact on pupils’ decisions. Below we discuss our results and their potential implications for structured peer learning and the broader school context.

Our first key result is that social information has the most impact when it is provided by a friend, and this impact decreases with increasing network distance between the demonstrator and the learner. For instance, the difference in learning between friends and non-friends was quantifiable as a 12% decrease in social information use. Note, that this may appear to be a small effect, but it reflects the impact of only a single interaction. In the school context these interactions would be repeated over multiple occasions, and the compounding effect of smaller effects may lead to large learning benefits.

As expected, the effect of network distance on social information use was mediated by subjective closeness and holds when controlling for social status (eigenvector centrality) and perceived academic achievement (smartness nominations; Table 2). One explanation for the relationship between network distance and subjective closeness may be based on homophily: already from a young age, people show a preference to interact and bond with individuals who are similar to them (McPherson et al., 2001). This preference may extend to epistemic trust, that is, learners may trust that those close to them are not only knowledgeable or skilled, but also willing to communicate reliable information. Strong bonds become therefore important for teachers to promote and cultivate, as having close friends in the classroom may increase pupils’ motivation to attend school and engage in group work, ultimately improving their performance.

Our second key result is that the social status of the demonstrator has a unique impact on pupils’ social information use (Table 2; Figure 3). Previous studies hypothesized that social status may be used as an indirect cue for achievement, based on the assumption that successful individuals tend to gain higher social status in groups (Henrich & Gil-White, 2001). However, in the classroom setting, social status is often not a reliable cue for achievement as it is not typically correlated with academic achievement (Boyatzis et al., 1998; Mihaly, 2009; Vaillancourt et al., 2003). Indeed, in our sample, perceived smartness was not correlated with social status (neither eigenvector nor betweenness centrality) and was negatively correlated with popularity (Table 1). It is thus more likely that the increased learning from high-status individuals reflects motivations related to gaining status or a sense of belonging. Such motivations are believed to peak in adolescence (Dijkstra et al., 2010; Yeager et al., 2018) and numerous studies show that in this period high-status individuals have a disproportionate influence on their peers’ behavior (Dijkstra et al., 2008), particularly in domains such as risk-taking (Rambaran et al., 2013), health behavior, and substance abuse (Helms et al., 2014). Our results show that these social motives also affect learning in the classroom context by increasing the willingness to revise previous decisions, thus implying that they could also be harnessed to promote more efficient transfer of information.

Our third key result is that the perceived smartness of the demonstrator contributed to social information use of the learner. This is in line with numerous studies on social learning showing that skilled individuals are more likely to be copied, followed, and learned from (Henrich & Gil-White, 2001; Kendal et al., 2018; Wood et al., 2013). Academic achievement has been one of the prime selection criteria in structured peer tutoring (Alegre et al., 2019) and it is interesting to see that even when confronted with a novel task in which skill plays only a minimal role, being seen as smart increases social influence.

Implications for School Psychology

To date, the finding that social information use is affected by social distance has been established in several studies with adults (e.g., Kalkstein et al., 2016; Molleman, Kurvers, & van den Bos, 2019), but, to our knowledge, it has never been tested in adolescents, nor in real social networks or in classroom settings. Our experimental approach allowed us to examine how specific properties of the relationship between classmates shapes social learning. This information is relevant for models of PAL, and specifically peer tutoring (Alegre et al., 2019). In contrast to collaborative learning, peer tutoring involves the specifically assigned roles of tutor and tutee. The tutor is often selected based on superior skill or knowledge, from the same (same-age tutoring) or different grades (cross-age tutoring). Beyond age or skill, not many grouping recommendations have been offered to teachers (Topping et al., 2017). Our data, however, suggest that the social distance between tutor and tutee may be key to the effectiveness of peer tutoring. It may also help explain why same-grade tutors may be more effective than different grade tutors (see for instance Alegre et al., 2019, for meta-analyses of math tutoring): despite that tutors from higher grades may have superior skills, they are socially more distant.

Although individuals might generally benefit from following competent others, the social motives for social learning may not always be beneficial in the classroom context. As pointed out above, a skilled person may have a reduced impact on a learner when they are separated by a large network distance. Conversely, a friend who is close and central in the social network, may have a significant impact, even if he or she is not skilled at the task and thus likely to worsen rather than improve the learner’s performance. Overall, our results lay bare network-based mechanisms that may weaken, or strengthen, the potential impact of the tutors in social learning in the classroom.

Taken together, these results lead to two complementary practical recommendations building on social network metrics. First, teachers can promote peer learning by recognizing when a prospective tutor is too socially distant from the tutee to have a meaningful effect, independently of how skilled they are. In such cases, more efficient learning might be achieved by selecting a less skilled, but socially closer individual. Second, one could focus on building and maintaining social cohesion in the classroom. With increasing social cohesion, the number of direct connections within the classroom is increased, reducing overall social distance between peers (cf. Van den Bos et al., 2018) which may in turn facilitate peer learning (Patrick et al., 2007). Indeed, it has been shown that when pupils do not have access to peers who are willing to provide help, levels of achievement in the classroom decrease (van Rijsewijk et al., 2018). Interestingly, there is some evidence that suggests that peer learning

itself may indirectly contribute to the development of positive social behavior (Bowman-Perrott et al., 2014). As such, peer learning, and specifically the selection of dyads for PAL, can be integrated in multitiered system of support (MTSS) programs that also focus on increasing social cohesion and positive school culture. For instance, the network analyses can reveal which dyads could potentially improve network cohesion by connecting disconnected parts of the network. The network cohesion and/or missing links can easily be established by using existing free or commercial software (e.g., <http://www.sometics.com> or <https://beyondluna.com/>).

In sum, as a first low-cost (both in time and money) step toward incorporating our results into everyday teaching activities, teachers could start collecting sociometric information about their pupils, and map classroom social networks across several dimensions (e.g., friendship, popularity, smartness). This data provides a better grasp of the social relationships between their students and could be used to identify efficient dyads for peer learning to contribute on learning outcomes. Furthermore, network data could be integrated with existing screenings and interventions aimed at supporting students, such as MTSS. This would allow teachers to tackle academic needs with a holistic approach that also considers pupils' integration in their peer group.

Limitations and Future Directions

Our study demonstrates social information use in an ecologically relevant context, with real decisions by real peers, and real stakes. Our experimental approach using a simple task allowed us to quantify pupils' social information use with high levels of control in a naturalistic setting. In contrast, field observations are often noisy; one cannot control for prior knowledge or skill of the peers, and other external factors that simultaneously affect social learning, leading to a cascade of confounding effects. However, in our case, simplicity is also a limiting factor. Before extrapolating these results to everyday teaching activities, the effects would need to be evaluated by substituting our abstract social learning task with more concrete assignments or tutoring exercises. Indeed, experimental work suggests that both complexity (Dickerson et al., 2013) and the level of abstraction (Kalkstein et al., 2016) of the task may interact with the type of demonstrator a learner prefers. Importantly, our experimental setup could be readily adapted to more complex tasks that are closer to the school curriculum (e.g., learning math or grammar) and more extensive forms of interaction that capture essential features of tutoring and collaborative learning, while keeping the same experimental social network mold. Fostering our understanding of how social relations impact social learning will provide critical advances for developing more efficient structured peer learning in the classroom.

Finally, we offer some considerations on the demographic aspects in our study. First, the age distribution of our sample is relatively broad, but not powered to test for age differences. Future research should also focus on age differences in social learning strategies (Molleman et al., 2020; van Leeuwen et al., 2018), as research from other fields suggest that social information use in general, and sensitivity to social status in particular, may be stronger in early adolescence (Badaly et al., 2012; da Silva Pinho et al., 2021). Second, the large majority (9 classes out of 10) of adolescents in our sample were recruited from the pre-university level of high school. Therefore, the conclusions presented above may be readily generalizable to

pupils with average to above average IQ, and would need to be replicated for students attending pre-vocational education.

Conclusion

The current findings provide a promising starting point for further studying the relation of social network embeddedness and social learning in the classroom. We observed that the network closeness to the demonstrator as well as the demonstrator's social status have a positive impact on social information use by the learner, above and beyond the demonstrator's perceived smartness. These results highlight that tutor-tutee pairs based only on skill may be suboptimal, and they should also take into account social relationships between individuals, who have specific social ties and positions within their social network. Furthermore, investing in the social bonds between students, may help to raise the overall performance of the classroom.

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