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Patterns of social interaction in the educational experience analized through a computational social sciences perspective

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Table of Contents

List of Figures

List of Tables

Resumen

Esta investigación explora cómo las interacciones sociales en contextos educativos influyen en los resultados académicos, la cooperación y la dinámica grupal en aulas de educación primaria. A través de métodos de Ciencias Sociales Computacionales y Sistemas Complejos, se integran tres enfoques clave: la ciencia de redes para medir la estructura social y la posición de los estudiantes, la recolección de datos comportamentales mediante experimentos de campo basados en teoría de juegos aplicados en el aula y el análisis econométrico para aproximar efectos causales.

El primer estudio examina cómo la reciprocidad en las relaciones sociales dentro del aula favorece el rendimiento académico, mostrando que los estudiantes que participan en interacciones recíprocas obtienen mejores resultados. El segundo estudio investiga cómo la amistad modula las relaciones jerárquicas en escuelas públicas, revelando que el estatus social influye en las dinámicas de cooperación, aunque las amistades pueden mitigar las asimetrías jerárquicas. El tercer estudio se enfoca en las interacciones sociales de niños con Trastorno del Espectro Autista (TEA) en aulas que incorporan tanto a estudiantes con como sin necesidades educativas especiales, mostrando que estos estudiantes tienden a ocupar posiciones periféricas en las redes sociales y participan con menos frecuencia en relaciones recíprocas.

Los hallazgos de este proyecto profundizan nuestra comprensión de las relaciones sociales en el ámbito educativo y tienen importantes implicaciones para la gestión de la dinámica escolar, tanto dentro de las aulas así como para el diseño de políticas que promuevan una mayor convivencia e integración social.

Abstract

This research explores how social interactions in educational settings influence academic outcomes, cooperation, and group dynamics in primary school classrooms. By applying methods from Computational Social Sciences and Complex Systems, this work integrates three key approaches: network science to measure social structure and student positioning, the collection of behavioral data through field experiments based on game theory applied in the classroom, and econometric analysis to approximate causal effects.

The first study examines how reciprocity in social relationships within the classroom enhances academic performance, showing that students who engage in reciprocal interactions achieve better results. The second study investigates how friendship modulates hierarchical relations in public schools, finding that cooperation dynamics among peers are strongly influenced by social status, but friendships can mitigate these hierarchies. The third study focuses on the social interactions of children with Autism Spectrum Disorder (ASD) within classrooms that incorporate both students with and without special educational needs, showing that these students tend to occupy peripheral positions in social networks and engage less frequently in reciprocal relationships.

The findings of this project provide a deeper understanding of social relationships in educational contexts, with significant implications for managing classroom dynamics and designing educational policies aimed at improving school coexistence and social inclusion.

Introduction

Human learning presupposes a specific social nature and a process by which children grow into the intellectual life of those around them.

LEV S. VYGOTSKY

School is one of the key experiences of childhood, a nearly universal part of growing up. From an early age, children are organized into groups to be instructed in various subjects. In classrooms, hallways, and playgrounds, peer groups interact constantly. Every day, children study together, form friendships, cooperate, and navigate social dynamics. The formal education system is not just a place for academic instruction—it is where social interactions shape each student's educational journey and development.

At its core, education is a collective endeavor. Learning does not occur in isolation but is deeply embedded within social relationships [1]. As children engage with their peers, they develop essential interpersonal skills alongside academic knowledge. These social bonds enable collaboration and mutual support, which are crucial for success both within and beyond school.

While the importance of social relationships in education is well-recognized, the impact of peer interactions on academic performance, cooperation, an ad social inclusion—particularly among younger students—remains less explored. Research has shown the influence of social networks on learning outcomes in high school and higher education [2, 3], yet elementary school settings have received less attention. Capturing social dynamics in younger children is challenging, as survey-based methods are often less effective due to cognitive limitations and biases such as social desirability, where respondents tend to answer questions in ways that they believe will be viewed favorably by others [4]. These challenges are even more pronounced for students with special educational needs (SEN), such as those with Autism Spectrum Disorder (ASD), who face additional barriers to social integration [5, 6, 7].

Through three interconnected studies—presented as chapters—this research applies a Computational Social Science framework that integrates network science, experimental game theory, and regression analysis to examine key aspects of social interactions in elementary classrooms. The first study explores how reciprocity influences academic performance, the second investigates the role of social hierarchies and friendships in shaping cooperation, and the third examines the integration of students with SEN, particularly those with Autism.

Our findings highlight the key role of peer relationships in shaping both academic success and social outcomes. We found that reciprocity fosters academic achievement, while friendship mitigates inequalities within social hierarchies. However, the integration of students with SEN remains a challenge, requiring targeted interventions to support their social inclusion.

These insights emphasize the need for educational strategies that promote cooperation, social support, and inclusive practices. By fostering reciprocal relationships and friendships, educators can create more inclusive environments, which is particularly crucial for students who may struggle with integration. Beyond theoretical contributions, this research provides practical tools for measuring and monitoring peer interactions in the classroom. By leveraging computational approaches, this thesis offers data-driven strategies to assess and support social relationships, ultimately contributing to the development of more inclusive and cooperative learning environments.

The remainder of this introduction section provides an overview of the three studies, outlining their research questions, key findings, and contributions. This is followed by a discussion of the methodological framework, explaining how experimental game theory, network science, and econometric analysis are integrated to examine social interactions in the classroom.

Studies Overview

The first study, ***Reciprocity Heightens Academic Performance in Elementary School Students***[1], examines the role of mutual cooperation on academic outcomes. Using a social dilemma game to observe cooperative behaviors, this study analyzes the reciprocity patterns of 946 children, aged 9 to 11, across 45 classrooms in 14 public schools in Chile. The findings reveal that students who engage more frequently in reciprocal interactions tend to perform better academically, suggesting the importance of mutual support in fostering effective learning environments.

Building on this foundation, the second study, ***Friendship Modulates Hierarchical Relations in Public Elementary Schools***, explores how social hierarchies and friendships shape cooperation among the same group of students. While higher-status students typically receive more resources from their peers, the study shows that friendships can disrupt these hierarchical patterns, promoting more balanced and egalitarian interactions. This research highlights how social dynamics can reinforce or mitigate social inequalities, with friendship playing a vital role in fostering a more equitable social environment.

The third study, ***Autism Shapes Social Integration and Reciprocity in Elementary Classrooms***, focuses on the social integration of children with ASD within neurodiverse classrooms. This study includes 625 students, aged 6 to 9, from 21 classrooms across six public schools in Chile. By analyzing how children with ASD navigate peer net-

[1] This study was published in 2022 in the journal *Heliyon*, available at 10.1016/j.heliyon.2022.e11916

works—particularly their centrality and reciprocity within these networks—the study reveals that these children often occupy peripheral positions and engage less in reciprocal relationships. These findings highlight the social challenges that students with SEN, especially those with ASD, face in school environments.

Methodological Framework

This thesis employs a **Computational Social Science framework** to analyze social interactions in elementary school classrooms. By integrating **experimental game theory, network science, and econometric analysis**, this approach allows for a multi-layered investigation into how reciprocity, social hierarchies, and peer relationships shape cooperation, academic success, and social inclusion.

Each method plays a distinct yet complementary role:

- **Experimental game theory** allows us to observe cooperative behaviors in controlled yet ecologically valid settings.
- **Network science** provides tools to map and quantify the structure of peer relationships.
- **Econometric analysis** helps to approximate causal relationships between social interactions and key educational outcomes.

By combining these methods, this thesis present a comprehensive framework that integrates behavioral, structural, and statistical perspectives on classroom social dynamics.

1. Experimental Game Theory: Observing cooperation in Action

Game theory provides a structured framework to **study strategic interactions**, where an individual's choices influence not only their own outcomes but also those of others. Developed in the mid-20th century by John von Neumann and Oskar Morgenstern, game theory has been widely applied in economics, politics, psychology, and social sciences.

One of the most well-known models illustrating strategic decision-making and cooperation dilemmas is the **Prisoner's Dilemma**, originally formulated by Albert Tucker. In this scenario, two individuals arrested for a minor crime but suspected of a more serious offense are interrogated separately. Each must choose whether to confess (defect) or remain silent (cooperate). If both remain silent, they receive a minimal sentence, whereas if both defect, they receive a moderate one. However, if one defects while the other cooperates, the defector goes free, leaving the cooperator with the harshest punishment [8].

Although cooperating by remaining silent yields the best collective outcome, the theoretical prediction—known as the Nash equilibrium [9]—is that rational individuals will choose to defect, prioritizing self-interest even when mutual cooperation would be more beneficial. This paradox makes the Prisoner's Dilemma a powerful model for real-world interactions, from economic negotiations to social cooperation, where individuals must constantly balance personal gain against the collective good.

The experimental application of game theory brings theoretical insights into real-world settings, allowing researchers to observe actual decision-making in controlled environments [10]. Unlike self-reported measures—which are prone to social desirability bias [11] or limited by children's cognitive development [4]—experimental games capture real behaviors through observable choices [12]. Prior research has also demonstrated that cooperative actions in these games correlate with real-world behaviors [13, 14].

However, empirical studies show that individuals often deviate from Nash equilibrium predictions; their behavior is shaped not only by incentives but also by the social context and existing relationships. In this study, we explore how reciprocity, friendship, social hierarchies, and developmental stage may influence cooperative decisions. To investigate these dynamics, we brought experimental methods into real-world settings.

Games in the classroom

We implemented two interactive digital games to examine cooperation and social preferences among elementary school students. These games simulate real-life decision-making while maintaining experimental control and were conducted over a single school day to ensure a natural yet consistent environment.

- The **Token Game** (Studies 1 and 2) assessed reciprocity and cooperation through a structured social dilemma inspired by the Prisoner's Dilemma.
- The **Stars Game** (Study 3) measured social preferences and hierarchical structures through peer selection and resource allocation.

A key feature of both games was their non-anonymous design. Unlike traditional game settings where pairings are typically anonymous, students saw the names and/or photos of their classmates, allowing us to assess how existing relationships—friendships, social status, and cooperative history—shaped decision-making. After playing, students completed a peer nomination survey, identifying friends, classmates they wanted or did not want to spend time with, and (in the Token Game) those they considered most and least liked and popular.

The **Token Game** was structured in rounds, with each student playing one round paired with every classmate. In each round, students received 10 tokens and decided how many to send to their assigned peer. Any tokens received were doubled in value, creating a social dilemma where cooperation maximized a pair benefits, but defection could yield higher individual gains. This design allowed us to examine reciprocity, cooperation strategies, and the role of social relationships in decision-making.

In contrast, the **Stars Game** focused on peer selection and resource distribution. Students first selected 10 classmates, prioritizing certain social ties. They then distributed 15 stars among them, forcing unequal allocations. This design revealed favoritism, inclusion, exclusion, and how different developmental trajectories—such as Autism Spectrum Disorder (ASD)—shaped resource sharing decisions. Designed for younger students (ages 6–9), the game included audio instructions to enhance accessibility for children with special educational needs (SEN).

Together, These games provided granular behavioral data on cooperation, reciprocity, and resource distribution, serving as key inputs for network analysis and econometric modeling.

2. Network Science: Mapping Classroom Social Structures

While game theory captures individual decision-making, network science enables the study of peer interactions and underlying social structures that are often difficult to assess through traditional methods. By analyzing classroom relationships as structured networks, we can quantify how students are embedded in social groups and how these connections influence cooperation, academic performance, and inclusion.

Each classroom is conceptualized as a social network, where students are nodes, and their interactions—friendships, cooperation in games, and shared activities—form edges. This approach allows us to map complex social structures that shape student interactions and provide a more systematic analysis of group dynamics.

Using network science, we can:

- **Visualize** peer group structures, identifying patterns of inclusion and exclusion.
- **Identify influential students** by analyzing centrality—how well-connected a student is within the classroom (e.g., PageRank [15]).
- **Analyze reciprocity**—whether social ties are mutual or one-sided.
- **Assess social status** by examining hierarchical structures within the network.

This network-based approach reveals hidden social patterns that may not be immediately visible through traditional observational methods. For example, students with high centrality may have greater influence over classroom dynamics, while those with low reciprocity may struggle with social integration.

By integrating network analysis with experimental game data, we can quantify the structure of social groups and systematically examine how cooperative behaviors relate to broader classroom dynamics.

3. Econometric Analysis

To quantify the impact of social interactions on academic and social outcomes, we employ econometric models that allow us to isolate the effects of reciprocity, social status, and network structure on cooperation and learning. By incorporating statistical controls and leveraging variation in social behaviors, these models help approximate causal relationships from mere associations.

Our analysis applies the following key econometric techniques:

- **Fixed effects models** – Account for unobserved classroom-level and individual characteristics that may influence outcomes but remain stable. By controlling for these factors, fixed effects models ensure that our estimates reflect within-student and within-classroom variations, reducing potential biases.

- **Difference-in-differences (DiD)** - Used in Study 1 to assess the impact of reciprocated cooperation on academic performance. This method compares GPA changes over time across students with different levels of cooperation, controlling for pre-existing differences and external influences.

These models ensure that findings are statistically robust, allowing us to move beyond correlations. By integrating experimental game data, social network analysis, and econometric modeling, this research presents a comprehensive framework to measure and understand how classroom social dynamics shape both academic performance and peer relationships.

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Chapter 1

Reciprocity Heightens Academic Performance in Elementary School Students

Lean on me, when you're not strong, and I'll be your friend, I'll help you carry on

BILL WITHERS

Abstract

Social relationships are pivotal for human beings. Yet, we still lack a complete understanding of the types and conditions of social relationships that facilitate learning among children. Here, we present the results of a study involving 946 elementary school children from 14 different public schools in Chile designed to understand their social learning strategies in classrooms. We mapped students' social relationships using a behavioral experiment –a non-anonymous social dilemma– that allows us to measure cooperation and infer reciprocal and asymmetrical relationships between peers. We implemented the experiment synchronously in each classroom using networked tablets and a friendly user interface to mitigate cognitive barriers and boost students' engagement. Using linear models and a difference in difference identification strategy, we found that reciprocity heightens academic performance by comparing two consecutive academic semesters. After controlling for class attendance, sex, parents' education, and fixed effects per class group, this result holds. We expect this study to motivate elementary education teachers worldwide to promote reciprocity among students, thus empowering both educators and learners to be more effective in their endeavors.

1.1 Introduction

"No significant learning can occur without a significant relationship," in this statement from a lecture given at the Education Service Center in Houston, Texas in 1995, Dr. James Comer, from Yale University, clearly expresses the critical role of social relationships between students and their peers, teachers, friends, and family for learning. Certainly, this sentence does not mean that we cannot learn from people with no direct relationships; in fact, we can learn from unrelated people, books, and even from online forums. Yet, knowledge and experiences acquired from meaningful relationships are remembered and applied more than others. Dr. Comer's quote also suggests a direction: social relationships come first, and learning will follow. Here, we will take this insight and provide quantitative evidence on how reciprocity in social relationships is beneficial for learning in elementary school students.

In recent decades, several studies have shown a significant association between students' position in their social networks and their academic performance at all ages [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 11]. Academic performance correlates positively with social capital–the individuals' network of connections and tacit cooperation [13]–among college students in online degree programs [4], and with the flow of online and offline communication among undergraduates [8]. Yet, we still lack a complete understanding of the connection between social networks and learning, particularly among elementary school children.

Long-term returns to education depend mostly on early learning outcomes [14, 15, 16]; thus motivating the study of factors that contribute to the learning in elementary school students at both the individual and group levels. At the individual level, academic achievement has been shown to improve with parental education [17] and the involvement of parents in school activities [18]. Student time management [19], sleep quality and duration [20], physical activity [21] and, internet use [22], also contribute positively to learning. Here we attempt to shed light on how social relations within the classroom influence learning outcomes.

At the group level, positive externalities –peer effects– are known to be pivotal for social learning [23, 24, 25, 26, 27] and play a key role in academic outcomes [8, 5, 28, 29, 30]. Indeed, how people capture the effects of their social relationships within a particular social environment largely depends on the teaching strategy [10] and the social structure of their cooperative relationships [31]. For instance, at the dyadic level, social learning can be understood as a natural form of pedagogy, where cognitive mechanisms enable the transmission of cultural knowledge through imitation and communication [32]. What distinguishes this natural pedagogy from other types of social learning, e.g., prestige-biased social learning [33, 34], is that it not only requires the disposition to learn from the "student-role subject," but the willingness of the "teacher-role subject" to share their knowledge [32]. Thus, from a game-theoretical perspective, a pedagogic act between peers [35], qualifies as an act of cooperation in a standard social dilemma, a scenario in which individual and collective interests collide because there are incentives to maximize individuals' payoffs that generates a sub-optimal collective performance [36].

Capturing cooperative dispositions between individuals is challenging and often requires multidimensional instruments to uncover social relationships. Efforts to capture social networks date back to Jacob Moreno's sociograms [37]. Under Moreno's approach, the social network is obtained through surveys that ask students to state both who they like or dislike to spend time with and who their friends are [38, 39, 40, 41, 6]. Traditionally, relational studies are conducted through surveys. However, for primary school students, survey-based social network mapping may not be sufficient because of the exacerbation of different types of biases [42] such as the social desirability bias [43] (over-reporting of socially desirable behavior); cognitive barriers (difficult to establish that subjects fully understand the questions) [44]; and lack of engagement (length or unfriendliness of instruments generate poor answers) [45, 46, 47, 48] associated with the implementation of self-report based instruments

To tackle these biases, we implemented a game-theory-based experiment in which all the students of a given class play a dyadic social dilemma with each classmate. The game is played in a set of networked tablets using a friendly drag and drop interface. This methodological approach facilitates the behavioral mapping of cooperative relationships by settling elementary school students in a familiar and ecological interactive environment. The advantage of using game theory to map the social network is twofold: first, due to the non-anonymous character of the game, it allows us to capture in a more comprehensive way the nature of cooperative relationships among students who, in most cases, have been together in the same class group for more than three years [49]; and second, the interactive nature of the game in which different actions lead to different payoffs mitigates the biases related to survey-based instruments [50].

Here, we focus on the effect of children's position in their classroom cooperative network on their academic performance. We mapped the cooperative networks of 946 children aged 9 to 11 from 45 different classrooms in 14 Chilean public schools using a behavioral measure based on a non-anonymous dyadic social dilemma. We use these data to study the following question: Do students that participate in more mutually cooperative relationships increase their GPAs more than other students? In the next section, we explain in more detail the game-theoretical experiment and its interface, data, and methods used. We then show the results and the econometric strategy to establish outcomes, and finally, we discuss the conclusions, limitations, and future work.

Network Theory and Social Capital

Studies have found a positive relationship between the degree centrality and measures of individual social capital and the number of alters who may provide social support [51]. Egocentric network density moves beyond a simple count of the number of members in the network to consider the extent to which alters know one another. Thus, a respondent provides information on the relationships between the alters in their network. For a general account of network-based measures of social capital, see [52].

An alternative approach to measuring the resources provided by a particular link is to focus on the tie's strength following sociologists' early work on social networks. In his seminal paper, Granovetter states that tie strength is a "... (probably linear) combination of the amount of time, the emotional intensity, the intimacy (mutual confiding), and the reciprocal services which characterize the tie" [53](p. 1361). Standard measures of tie strength include frequency and duration of contact, whether the tie is emotionally supportive, and whether it is multidimensional [54].

Most of these studies rely on the survey-based elicitation of social networks. This approach in the context of school communities riddles back to the studies by Jacob Moreno [37]. Indeed, his 1934 book Who Shall Survive? contains some of the earliest graphical depictions of social networks (sociograms). Since then, social network analysis has been upgraded by techniques coming from graph theory such as alternative measures of centrality [55], and community detecting algorithms [56]. However, survey-based methods still prevail in current approaches that study the relationship between the topology of the social structure of the class and its link with individual academic performance [5].

Experimental Game Theory and Cooperation

The implementation of social dilemmas that are characterized by the tension between individual and social incentives, such as trust games [57], public goods game [58], or common-pool resource games [59], provided empirical evidence for behavioral anomalies concerning the prediction of the homo economicus model (individuals' perfect rationality), understood as a simplified version of Stuart Mil's original abstraction. These deviations from the standard model have been interpreted as the result of other-regarding preferences [60] such as altruism, reciprocity, or inequity aversion [61].

The first wave of experimental studies mainly used Graduate students as experimental subjects, referred to by Henrich et al. [62] as WEIRD (Western, Educated, Industrialized, Rich, and Democratic) subjects and involved anonymous interaction. Then, the experimental literature has slowly moved to study natural populations [63] and involve games implemented in the field which stylistically represent social dilemmas that agents face in real-life [64, 65]. The new body of literature that studies the external validity of game-theoretic experiments states that cooperative social norms that are prevalent in the real world can penetrate laboratory behavior [66]. Individuals who are more cooperative in the real world also behave more cooperatively in the lab [67, 68]; and groups who achieve higher levels of cooperation in the real world also achieve higher levels of aggregate cooperation when playing a social dilemma in the lab [69, 70, 71]. The social domain of all of these experimental studies ranges from the fishers of Toyama Bay [69] through the exploitation of benthic resources in the Chilean coast [72], to the Wikipedians studied by Algan Et al. [68]. These results suggest that individual contribution to social capital and group social capital in the real world can be measured in the lab using game-theoretic social dilemmas that reproduce the tension between individual interest and social efficiency that agents face in real life.

To the extent that one of the major threats to the external validity of economic experiments as argued by Levitt Et al. [73, 74] refers to the anonymous character of interaction within the lab, we should expect more significant levels of external validity in our experiment. Moreover, a recent study that shows that non-anonymous interaction increases cooperation in contrast with anonymous interaction suggests that pre-existing social connections do affect laboratory behavior [49].

Network-based Measures of Social Capital and Experimental Game Theory

In the study of cooperation between humans, experimental game theory has contributed to understanding mechanisms that explain phenomena such as cooperation in collective action problems or the dynamics of reciprocal exchange [75]. Traditional research has mainly focused on anonymous interaction. However, group and dyadic social dilemmas in real life are often played between known subjects with previous and future history embedded in a social network structure. A school classroom provides an ideal environment for controlled social dilemma experiments whose results can be contrasted against real-life indicators of school life.

The possible outcomes for any dyadic game—reciprocal mutual gains, indifference (or negative reciprocity), or abuse (where one party benefits at the expense of the other)—are used as proxies for the nature of real-life relationships between students. Given that learning is a collective enterprise [23], and that peer effects have been shown to significantly impact school performance (for a review, see [28]), we hypothesize that a student's position within their social network and the strength of their ties can modulate their ability to capture learning externalities—that is, the indirect academic benefits a student may gain from being surrounded by high-performing or cooperative peers. Since these externalities emerge from peer activities during the learning process, academic performance should be positively affected, as suggested by previous theoretical work [31].

1.2 Methods

1.2.1 Sample

We collected data from 946 students (between the 3rd and 5th grade) with an average age of 10.16 ± 1.18 (57.5% were females). Data was collected in 14 different public schools and a total of 45 classrooms (see Supplementary Methods 1 for a descriptive table for each classroom). We also collected administrative records for each student, including classroom attendance, gender, educational level of student's parent or guardian, and GPA. Most of the students in the sample have been members of the same classroom for more than three years, spending together around eight hours each school day. Finally, we also collect data on a peer-nomination survey of friends in which they nominate from 2 to 5 classmates as their closest friends.

Our data collection methods and experimental protocol was approved on May 4, 2016 by the human subjects review board of Universidad del Desarrollo (IT15I10079).

1.2.2 The Game

To measure relational cooperation, we implement a modified Prisoner's Dilemma using a friendly user interface in tablet computers (Fig. 1–1 A). Our design involves two modifications concerning the standard experimental design. First, the interaction is non-anonymous. In each round, students know who their counterparts are. Under standard game-theoretic experimental protocols, which involve anonymous interaction, networks elicited in the lab emerge from scratch, mainly through assortative interaction between anonymous players [76]. However, in order to capture the nature of pre-existing relationships we departed from the standard protocol and consider non-anonymous interactions.

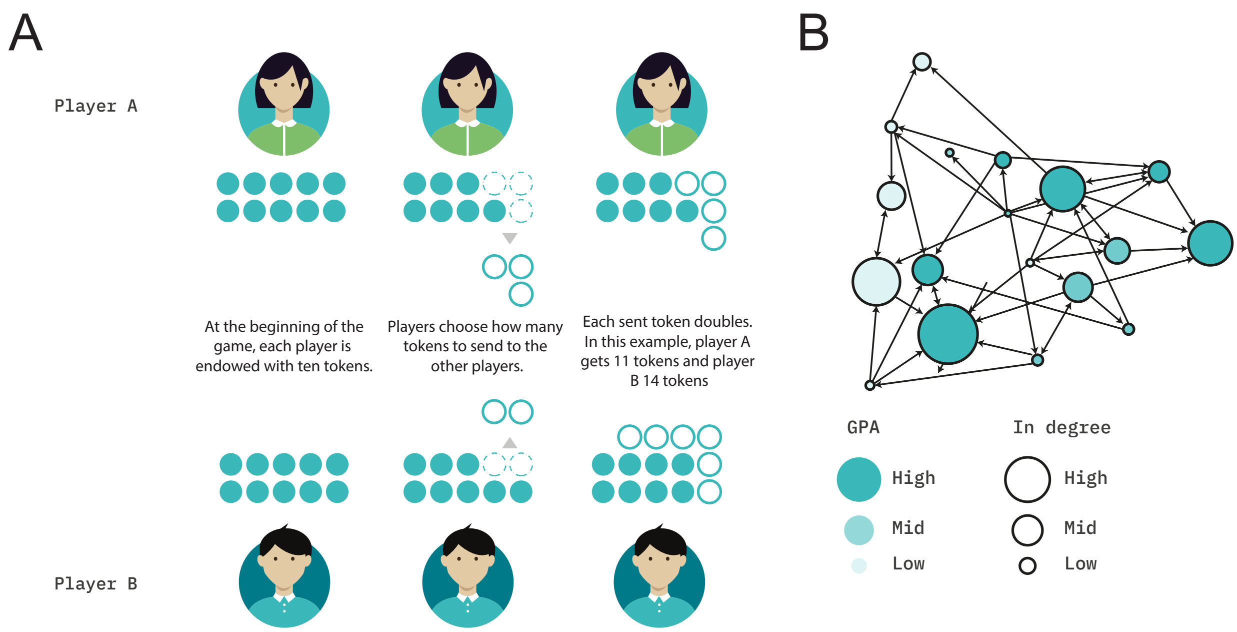

Figure 1–1 Experimental game. A) Students play a social dilemma; example of a dyadic interaction: i) Both players are endowed with 10 (ten) tokens. ii) Simultaneously, player A decides to send 3 (three) tokens, and player B decides to send 2 (two) tokens. iii) Sent tokens are doubled. iv) Player A receives 4 (four) tokens and player B receives 6 (six) tokens. B) A students' network for a single classroom. For the sake of visualization, edges correspond only to fully cooperative interactions, sending all tokens.

Thereby, their choices when playing again each other are not only the result of prosocial dispositions (or their absence), but also the result of their history and the perceptions they have about each other [49]

Second, rather than deciding whether to cooperate, students can implement different levels of cooperation by sending a positive amount of tokens or choosing not to cooperate and keep all of their tokens. In each dyadic interaction, both students are endowed with ten tokens. Then, each student decides simultaneously how many tokens to give to the other students. Every received token doubles, so students get the tokens they keep plus twice the tokens they receive. Thus, we created a social dilemma where individuals' incentives (keep all tokens) face social incentives (give tokens to their peers with whom their share a history and common past).

The experiment ends once every student has played with all their classmates. We use these cooperative interactions to map students' networks. For instance, Figure 1–1 B shows a classroom network in which nodes represent students, and directed links indicate fully cooperative interactions (a student giving ten tokens to another student).

1.2.3 Network Measures

We quantified individuals' cooperation and reciprocity in their classrooms using network measures. We define a weighted adjacency matrix for each classroom w_{ij}, representing the number of sent tokens from student i to student j. Table 1–1 shows the network metrics used in this study.

Network measure	Social Capital	Formula
Average in-degree	Average received cooperation	$r_i = \frac{1}{N}\sum_{j\neq i} w_{ji}$
Average out-degree	Average sent cooperation	$s_i = \frac{1}{N}\sum_{j\neq i} w_{ij}$
Reciprocated weight	Reciprocated cooperation	$R_i = \frac{1}{N}\sum_{j\neq i} min[w_{ji}, w_{ij}]$
Page-Rank	Social ranking	$Rank_i = \frac{1-d}{N} + d\sum_{j=1}^{n} \frac{w_{ij} Rank_j}{\sum_{k=1}^{n} w_{kj}}$

Table 1–1 Network measures. w_{ij} is the number of tokens sent from i to j, d represents a dumping factor ($d = 0.85$ following [77]), and N is the number of students in each classroom

Average received cooperation, r_i, measures the average cooperation received by ego (i). Average sent cooperation, s_i, measures the average sent cooperation. Reciprocated weight, R_i, measures the average level of reciprocity for each ego (i). $Rank_i$, calculated using Page-Rank [77], measures the relative social ranking of students based on the network of cooperation. See Supplementary Figure A–2 for a correlation plot of all variables.

1.3 Results

Figure 1–2 shows the emerging patterns of token sendings among students, where the total number of sending combinations among classmates is $18,334$. Panel A shows the bivariate distribution of sent and received tokens. Peer interactions concentrate close to the corners. In fact, more than 15% of the exchanges are fully cooperative (Figure 1–2 A I), while 22.1% of interactions are highly defective, and involve both students sending two or fewer tokens to each other (Figure 1–2 B II). Asymmetric interactions are also visible in the behavioral game. About 12% of interactions involve a student sending ten tokens and getting two or fewer tokens in return (Figure 1–2 B III). Also, we observed that each student sent tokens across the entire range of values (Supplementary Figures 3.2), suggesting that the previous history of interactions among a pair of students matters for their decision-making process [49] beyond pure strategies such as always cooperate or always defect.

Figure 1–2B depicts a histogram summarizing the amount of sent tokens. Although the experimental design allowed students to send any amount between zero and ten tokens, the distribution reveals a polarized pattern: students tend to adopt either fully cooperative strategies—sending ten tokens—or clearly non-cooperative ones—sending zero tokens, which has a distinct mass in the distribution. In our analysis, we expand the definition of low cooperation to include sendings of fewer than two tokens, considering that children often exhibit aversion to inequity[**?**] and may avoid sending minimal amounts that would create strongly unequal outcomes.

Now, we ask, do students who participate in a high number of mutually cooperative relationships increase their GPAs more than other students? We investigate if reciprocity, defined in each exchange as the minimum amount between sent and receiving tokens (See Table 1–1), plays a role in academic performance. Here, the ideal situation to correctly identify the reciprocity's causal effect in academic performance would be to exploit an exogenous variation in reciprocity. Still, it is impossible to create such a variation in this type of experimental design due to the intricacies between reciprocity and peer interactions. Instead, we rely on statistical tools [78] to estimate the individual future GPA as a function of the individual-level average reciprocated cooperation, controlling for different confounders. Omitted variables simultaneously determining reciprocated cooperation and GPA improvement or reverse causality could provide biased point estimations. Remarkable possible omitted variables affecting both academic performance and reciprocity are intelligence, illness, and socioeconomic background (See Supplementary Notes 1.1 for more detail); therefore, we provide proxy variables for them (prior academic performance, attendance, and guardian's education, respectively). However, we acknowledge that other unconsidered omitted variables could play a role in the identification process. Yet, our statistical tools help us unveil a cleaner effect of reciprocity on future GPA.

We rely on a two-fold identification strategy: first, refining the statistical model with relevant controls and a fixed effect controlling for average classroom characteristics. Second, we implement a complementary treatment intensity difference-in-differences estimation [79] to address some concerns related to time-invariant unobserved confounders.

We define the base statistical model (eq. 1.1) by estimating the individual future GPA as a function of the individual average reciprocated cooperation (See methods section, Table 1–2). We also include confounding variables, such as gender (G_i), percentage of class attendance (A_i), level of education of the guardian ($TESC_i = 1$ if the guardian completed secondary school, 0 otherwise), and the number of students in each classroom (CS_i).

Table 1–2 displays the estimation for the model defined by Equation 1.1, with a few variations in control variables and fixed effects. Column 1 is the base estimation without any network-related variables. From column 2 to column 4, we control for the classrooms' average unobserved differences using fixed effects θ_i. In column 3, we observe the effect of the individual average reciprocated cooperation R_i (presented as z-score in the whole sample for interpretability). Finally, model 4 includes three new elements: i) Individual average sent cooperation, s_i. ii) Individual-level social ranking, $Rank_i$ [77, 80] (see the Methods section, Table 1–2), and iii) Previous semester's GPA, GPA_{i0}, which quantifies

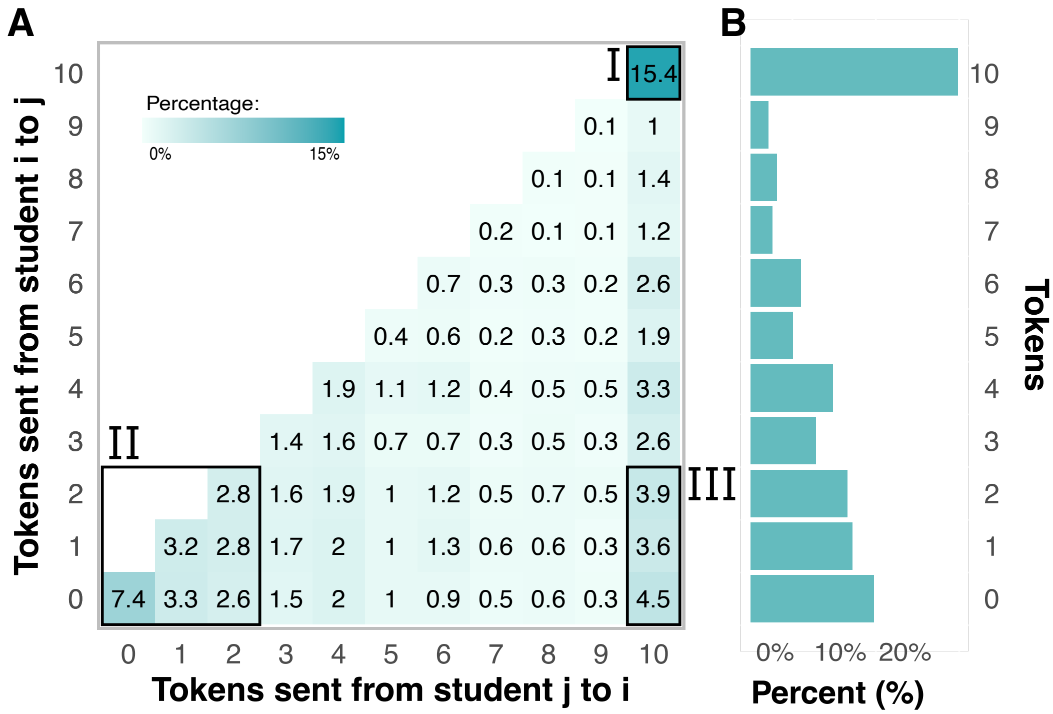

Figure 1–2 Patterns of sent and received tokens across all peer interactions. A) Bivariate distribution of sent tokens. We observe three peaks describing the most commonly used strategies: I) Social optimum (top-right). II) Nash equilibrium (bottom-left). III) Asymmetric exchange (bottom-right). B) Univariate distribution for sent tokens.

individual previous accomplishment. Prior individual GPA provides a proxy for individual talent and controls by several time-invariant confounding variables that correlates with GPA, such as household income, practicing sports, among others. These three elements are presented as z-scores over the whole sample for interpretation. Our specification is the following:

$$GPA_{i1} = \beta_1 R_i + \beta_2 s_i + \beta_3 Rank_i + \beta_4 GPA_{i0} + \beta_5 G_i + \beta_6 A_i + \beta_7 TESC_i + \beta_8 CS_i + \theta_c + e_i, \quad (1.1)$$

where, GPA_{i1} represents the GPA of the student i and e_i is the error term.

We find a positive and significant effect of reciprocated cooperation on GPA. More pre-

	Dependent variable:			
	GPA (after measuring)			
	(1)	(2)	(3)	(4)
Reciprocated cooperation			0.050***	0.088***
(z-score)			(0.015)	(0.033)
Sent cooperation				−0.057**
(z-score)				(0.026)
Rank				0.065**
(z-score)				(0.026)
Grades	0.720***	0.746***	0.732***	0.699***
(before measuring)	(0.024)	(0.023)	(0.024)	(0.025)
Class attendance	0.001	−0.0004	−0.001	−0.0001
(%)	(0.001)	(0.001)	(0.001)	(0.001)
Tutor comp. sec. school	0.038	0.028	0.027	0.024
(yes)	(0.026)	(0.024)	(0.024)	(0.024)
Gender	−0.089***	−0.063**	−0.056**	−0.053**
(Male)	(0.026)	(0.027)	(0.027)	(0.026)
Class size	0.0002			
	(0.002)			
Constant	1.448***			
	(0.162)			
Fixed effects	Pooling	Class	Class	Class
Observations	769	769	769	769
R^2	0.613	0.636	0.641	0.652
Adjusted R^2	0.610	0.612	0.617	0.627
F Statistic	241.733***	314.478***	257.097***	191.879***
	(df = 5; 763)	(df = 4; 720)	(df = 5; 719)	(df = 7; 717)
Note:			*p<0.1; **p<0.05; ***p<0.01	

Table 1–2 OLS regressions for students' GPA after measuring cooperation.

cisely, we find that an increase of one standard deviation in reciprocated cooperation is associated with an increase of 0.088 units in future GPA. We note that GPA in Chile goes from 1.00 to 7.00, and the average GPA of the first and the second semester of 2017 are 5.87 and 5.77, respectively. Therefore, the average variation between both semesters is $\Delta_{GPA} \approx -0.100$. Thus, the reciprocated cooperation effect size (0.088) and the average decrease of GPA between the two periods (0.100) are comparable. Indeed, the effect size is 88% of the average variation (See Supplementary Figure A–4 for a predicted v/s observed values plot for model 4 using both future GPA and difference of GPA as dependent variables).

Yet, some meaningful challenges could be affecting our results. For instance, changes in the classroom configuration, including new teachers, new students, or increasing/decreasing the school income. Also, changes at the individual level, such as a new job for the student's guardian or a house move, would impact household income and social capital outside of the classroom, respectively. Besides, other individual changes, such as a student's illness, a long trip, failing a school year, or family issues, would impact school engagement, among others. However, we assume that most of these unobserved variables are time-invariant within our study period (see Supplementary Notes A.1.1).

Finally, to overcome all of the potential issues related to time-invariant unobserved confounders and provide evidence on the magnitude of the relationship between reciprocated cooperation and GPA improvement, we use a treatment intensity difference-in-difference framework [79]. Here, our treatment intensity variable is individual average reciprocated cooperation (R_i), a continuous variable, which induces variation at the individual level. Our specification is the following:

$$GPA_{it} = \beta_1 + \beta_2 T + \beta_3 R_i + \beta_4 A_{it} + \beta_5 X_i + \delta T \times R_i + \varepsilon_i + e_{it}, \tag{1.2}$$

where ε_i represents individual-level fixed effects (we note that individual-level fixed effects absorb classroom level fixed effects) and e_{it} is the error term. GPA_{it} is the GPA of student i in period t, T represents the semester and it takes values 0 (before measuring, $t = 0$) and 1 (after measuring, $t = 1$), R_i is the treatment intensity (reciprocated cooperation), A_{it} is the class attendance for both time periods, X_i is a vector of time-invariant individual controls, and finally, the diff-in-diff estimator is represented by δ.

Table 1–3 shows five variations of the specification showed in eq. 1.2 and model 6 shows the equivalent first difference strategy. In models 1-5, we observe that our diff-in-diff estimator is robust under different sub-specifications of eq. 1.2, even after controlling by

	Dependent variable:					
	GPA (Diff-in-Diff)					
	(1)	(2)	(3)	(4)	(5)	(6)
Reciprocity * Time	0.047* (0.027)	0.043* (0.026)	0.043* (0.025)	0.044* (0.023)	0.039*** (0.012)	
Dummy reciprocity * Time						0.084*** (0.027)
Reciprocated cooperation (z-score)	0.096*** (0.019)	0.061*** (0.018)	0.139*** (0.025)	0.265*** (0.034)		
Time	−0.083*** (0.026)	−0.108*** (0.025)	−0.107*** (0.024)	−0.106*** (0.022)	−0.092*** (0.012)	−0.113*** (0.013)
Sent cooperation (z-score)			−0.128*** (0.020)	−0.206*** (0.025)		
Rank (z-score)			0.107*** (0.020)	0.106*** (0.027)		
Class attendance (%)		0.020*** (0.001)	0.019*** (0.001)	0.018*** (0.001)	0.006*** (0.001)	0.006*** (0.001)
Tutor comp. sec. school (yes)		0.145*** (0.025)	0.130*** (0.024)	0.121*** (0.024)		
Gender (Male)		−0.213*** (0.025)	−0.224*** (0.025)	−0.129*** (0.026)		
Class size		0.001 (0.002)	0.011*** (0.003)			
Constant	5.908*** (0.018)	4.074*** (0.131)	3.983*** (0.131)			
Fixed effects	Pooling	Pooling	Pooling	Class	Individual	Individual
R^2	0.048	0.216	0.259	0.338	0.905	0.904
Adjusted R^2	0.047	0.213	0.255	0.326	0.828	0.827
Observations	1,866	1,676	1,676	1,676	1,676	1,676
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 1–3 Difference-in-difference estimation of GPA. Models one (1) to five (5) differ in control variables and fixed effects. In model 6, we built a dummy variable for reciprocated cooperation. It takes value 1 if the reciprocated cooperation level for individual i is in the top quartile, and it takes value 0 otherwise.

individual fixed effects (model 5). We note that fixed effects in model 5 absorb all the individual and classroom level controls. Both remaining coefficients, the time and the interaction between reciprocated cooperation and time are quite consistent across all the models. In model 6, we set a dummy variable for the treatment as 1 for all individuals in the top quartile of reciprocated cooperation and 0 otherwise. Given the nature of dummy variables, we observe a small increase in the parameters; however, the errors also increase.

In fact, there is an error overlapping between model 6 and all the previous models.

Therefore, we argue that our diff-in-diff estimator is consistent and robust across all the models (Table 1–3 models 1-6). Particularly interesting, is model 5 on Table 1–2. The diff-in-diff estimator is positive (0.039) and significant (p-value< 0.01), even after controlling by all the unobserved time-invariant individual characteristics, which is approximately a half of the associative effect presented in Table 1–2 model 4. The average GPA difference between $t = 0$ and $t = 1$ for controls and counterfactual are 0.100 GPA units.

1.4 Discussion

Individuals' position in their social networks is associated with educational outcomes at all ages. Moreover, the literature on social learning states a positive relationship between a student's social network position and academic performance. There are two possible and non-exclusive explanations in this context: i) Central students get better GPAs through positive learning externalities from their social connections; or ii) Higher GPA leads to a higher status, resulting in more central students in their social networks. Here, we provide evidence on the former by studying cooperative patterns in elementary school students using a video game based on game theory and a difference in difference identification strategy. Studying educational outcomes in elementary school is challenging because of the potential biases in surveys measurement instruments. Therefore, we implemented a lab in the field approach to map students' social relationships in their classrooms. Students played a non-anonymous social dilemma in interconnected tablet computers through a friendly user interface where they had to choose how many tokens to share with their peers (Fig. 1–1 A). Thus, we mapped the entire student's cooperative network in their classroom (Fig. 1–1 B).

We found that students mainly engage in three types of cooperative relationship: fully cooperative(Fig. 1–2, I), non-cooperative (Fig. 1–2, II), and relationships in which the co-operation is asymmetric (Fig. 1–2, III). Then, we define reciprocated cooperation as the minimum between sent and received cooperation and found it improves elementary school student's GPA. We provided evidence on the positive and significant effect of reciprocated cooperation and GPA used both linear models (Table 1–2) and a difference-in-difference identification strategy (Table 1–3) exploiting an endogenous treatment intensity variable [79]. In the former, we show that the effect of received, sent, and reciprocated tokens survives even after controlling by confounding variables, such as previous GPA, sex, class attendance, and the educational level of the student's guardian. We find evidence supporting reciprocated cooperation as a predictor of future GPA. In the latter, the central assumption is that both control and treatment groups follow parallel trends in the absence of our treatment intensity variable, the reciprocated cooperation. Changes in GPA follow the same trend in the absence of reciprocated cooperation for all students. Some limitations exist here. Any change within the time interval studied in a confounding variable that affects both GPA and reciprocated cooperation could hinder our results. For instance, a change in family income may impact reciprocity through the popularity of a student. Also, it may affect GPA through getting a private professor or changes in the access to the internet [22]. Also, practicing sports may impact reciprocated cooperation through popularity, and also it may affect GPA [21, 81] at getting healthy. Thus, any change between the first and second semester of the academic year in which the experiment was implemented in the level of a guardian's student income or the student started to practice a sport could have impacted reciprocated cooperation and GPA. These changes would make the parallel trend assumption for our difference in difference specification unfulfilled because we cannot control nor measure any of these changes. It is always impossible to ensure that parallel trends assumption is wholly fulfilled. Yet, we provide robust and consistent evidence of a directional effect from reciprocated cooperation to GPA improving, under the premise of parallel trend is fulfilled (see Supp. Notes A.1.1). We consider this work to contribute to our understanding of the link between social networks and learning outcomes and how novel methodologies such as experimental game theory can help us in this endeavor.

From a methodological perspective, our results open new avenues for the role of game-theoretical and network-based tools to leverage relational information in elementary education [52, 82] bypassing the common biases of survey instruments. We contribute to the external validity of game-theoretic experiments in school context producing a measure of the individual's social capital embodied directly in the student's relationships and indirectly by the configuration of the network as a whole [82]. Using this approach we are able to map a representative social network for young people with a common history [49].

Finally, literature states that the ability to recognize friendship ties, and their directionality, limits people's ability to engage in cooperative arrangements [83]. Thus, from a policy perspective, the natural question to ask is what kind of intervention might improve students' academic performance by optimizing the potential benefits of cooperation. Our results, together with the lack of GPA homophily (see Supplementary Notes, Fig. A–1 and Table A–1), suggest that encouraging friendships through, for instance, interventions of the spatial arrangement of the class [84] or an instructional design that promotes the formation of social ties in the classroom [34, 35, 85, 86, 87, 88, 89, 10, 90] are potentially fruitful alternatives to explore. Thus, we open the possibility for intervention by promoting relationships within the classroom that might significantly affect the academic achievements of vulnerable students.

References for Chapter 1

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Chapter 2

Friendship Modulates Hierarchical Relations in Public Elementary Schools

I get by with a little help from my friends.

THE BEATLES

Abstract

Social relations are not just a backdrop for education but a key component that shapes students' experiences. Among these, cooperation is crucial for academic and social development making it essential to understand which classroom environments can foster it. Yet, little is known about how relational cooperation intersect with social hierarchies and friendship among young children in public elementary schools. Here, we investigate these dynamics among 859 children aged 9 to 12 in Santiago, Chile, using a social dilemma game that reflects real-life tensions between individual benefits and collective gains.

We found significant gaps in peer exchanges in the game linked to status differences, measured by the PageRank of popularity nominations, where higher-status students received more from their peers than they gave in return. This reveals a social stratification in cooperative behavior related to status, where children of lower status exhibit deference to higher-status peers. However, this hierarchy dissolves within the boundaries of friendship, suggesting that friendship can transcend status disparities and be a powerful force to foster school cooperation. Additionally, we propose an alternative measure for social status based on in-game behavior that replicates all findings, highlighting our game-based framework as a tool to assess and understand classroom social dynamics.

2.1 Introduction

Beyond its fundamental role in knowledge acquisition, schooling involves a complex system in which social relations shape the performance, satisfaction, and overall well-being of each student [1, 2, 3, 4, 5, 6, 7]. Indeed, cooperation is key for promoting positive social interactions, teamwork [8], and enhancing students' quality of life [9, 10]. Therefore, understanding which classroom environments can foster cooperation is crucial. This is especially important in elementary education, where foundational social skills are developed with lifelong consequences [11, 12].

Picture a typical elementary school with its own social order, where some kids are seen as more popular and influential than others. This *pecking order* is frequently present in activities inside and outside the classroom, driving group formations, and conflicts. Literature and film often portray this universal experience, from Golding's classic *Lord of the Flies* (1954) to the influential *Mean Girls* (2004). While the role of social status in human societies is well-documented [13, 14, 15, 16, 17, 18, 19], little is known about how social hierarchies, cooperation, and friendship intersect among young children in public elementary schools. Can friendship mitigate these hierarchical dynamics?

Social hierarchies have been present since the ancestry of our species [13, 14] and their influence extends to all spheres of society, including education. Social rank, considered as an individual's position within a group [16, 15, 17, 18, 19], affects interpersonal relations [20, 21, 22], decision making [23, 24, 22, 17, 25], group effectiveness [26, 27, 28], and many day-to-day interactions. Power over others provides material and social advantages [29]. It grants significant influence over group decisions and the behavior of others [30, 31, 32]. High status is related to better fitness, well-being, and happiness [33, 34, 35, 36, 37].

Humans are driven to seek for status [33, 38]. This pursuit can be achieved through dominance, marked by coercion and aggressive displays of power [39, 40, 41] or through prestige, which is earned by demonstrating valuable skills that inspire others to follow voluntarily [16, 42]. Both forms of status confer social and material advantages [29, 25] where lower-status individuals offer resources or compliance [43], either by dominance-based force or prestige-based voluntary deference. Thus, higher-status individuals receive more in social interactions, as status differences guide benefits their way.

As a reflection of larger society, school environments tend to mirror social structures such as hierarchy. From an early age, children recognize hierarchies [44, 45, 46] and align with those of higher rank [47, 48]. During adolescence, there is an increased awareness of one's social standing, separate from their parents status [49]. This awareness is expressed through acceptance, dominance, or perceived popularity [50, 51], shaping interpersonal relationships in school [52, 53].

Social status in school contexts is often studied and measured with popular or liking relationships [51, 54, 55] or alternatively, with friendship nominations [56, 57, 58, 59, 60]. These measures implies that being well liked or receiving many friendship nominations indicates higher status. However, recent studies show that friendship and status, while related, are distinct, with only a moderate correlation between friendship nominations and status attributions [61, 62]. This evidence emphasize the intersectional and dynamic interrelations between friendship and various status attribution networks, cautioning against solely inferring status from friendship ties [63, 64, 65, 66, 67].

Considering friendship as an additional dimension of social relationships raises the question: What role does it play in hierarchical relations? Although kinship and reciprocity drive cooperation, they do not fully explain human prosociality, especially among non-relatives [68]. Friendship, although there is no one concept of friendship [69] and can be applied from very close to more distant relations [70, 71] It could be defined as a voluntary bond marked by trust, support, and emotional connection [72, 73, 74] that involves reciprocity and cooperation beyond transactional interactions [75]. This bond suggests that friendship could counterbalance hierarchical structures, adding a nuanced dimension to social interactions within the school environment.

Given the importance of status in shaping social dynamics and the goal of promoting cooperation in education, we analyze the less explored relation between social status and cooperation for different types of friendship. We hypothesized that cooperative interactions would reflect existing social hierarchies, with lower-ranked individuals deferring more to those of higher status. However, we anticipate that friendship, rooted in mutual reciprocity, can disrupt this dynamic, guiding cooperation toward greater equality despite existing rank disparities. To test this, we conducted a large-scale experiment involving 859 children from 14 elementary schools in Santiago, Chile, using a social dilemma game to map cooperative patterns in 45 classmate groups.

Using interconnected tablets, each participating classroom engaged in a two-part interface: they start solving a social dilemma game to measure relational cooperation, followed by a nomination section to capture friendship and liking relationships. The Chilean school system, where students typically remain with the same peer group throughout their primary and secondary education, allowed us to observe naturally evolving social relationships. Most of the participants had the same classmates for more than three years, spending approximately eight hours together each school day. This setup provided an opportunity to observe long-term social structures and peer interactions.

In the social dilemma game, a student distributed ten tokens between herself and a classmate using a drag-and-drop interface that displayed her peer's name and photo. Structured in rounds, the game ensured interactions with all classmates. The game mimics a real-life social dilemma by doubling the value of tokens received from peers, creating tension between individual and social incentives that mirrors the prisoner's dilemma. If both students sent all their tokens, each received 20 tokens; if no tokens were sent, each kept their initial 10 tokens. However, if one student sent all their tokens and received nothing in return, they ended up with zero tokens while the other student gained 30 tokens. Our game presents two key differences from traditional prisoner dilemma: First, it allows students to choose any cooperation amount between 0 and 10 tokens, providing granular data on cooperative behavior, beyond the three cases presented in the example; Second, it is non-anonymous allowing us to observe how students navigate cooperation within their peer groups, capturing the influence of pre-existing relationships on their choices.

The presence of social desirability bias [76], cognitive challenges [77], and reduced engagement [78, 79, 80, 81] make it difficult to capture cooperative dispositions, especially in younger populations. To address these issues, we combined nomination instruments with experimental game theory via an interactive video game interface. Evidence suggests that lab-observed cooperative behavior often correlates with real-life cooperation [82, 83]. Building on prior research [84, 85], this experimental setting offered an engaging and age-appropriate format for students to naturally express their cooperative tendencies and social interactions through their token distributions [86, 87, 88]. After completing the social dilemma section, the students nominated up to five classmates they liked the most, liked the least, considered friends, and were regarded as the most and least popular, providing comprehensive data on their social preferences.

We mapped each peer group's social structure using a network based on students' game actions, quantifying their status through the PageRank [89] of popularity nominations. This score reflects a student's relative importance within their peer group by considering both the number and significance of nominations received. We then calculated a *social rank gap* to compare the social status between pairs of students and a *cooperation gap* to measure differences in observed cooperation. Using fixed-effects regression models, we analyzed the relationship between cooperation and social rank gaps, grouping participants into three categories: non-friends, mutual friends, and those with unreciprocated friendship nominations, to provide an in-depth mapping of social structures and cooperative dynamics within each classroom.

Our findings reveal that cooperation tends to follow a hierarchical pattern, where individuals with higher social status receive more than they give in pair interactions. However, this pattern vanishes among mutual friends, suggesting that friendship has an equalizing quality that challenges established social status dynamics.

For pairs in which only one student identified the other as a friend, we noticed that their behavior was influenced by the relative status of those who acknowledged the friendship. When the higher-status individual made the nomination, the pair behaved like mutual friends. In contrast, when the lower-status individual made the nomination, the pair exhibited hierarchical patterns similar to non friends, suggesting a *aspirational friendship*.

Finally, we proposed an alternative measure of social rank based solely on in-game behavior, calculating individual status through the PageRank algorithm derived from token exchanges. This *Behavioral Social Rank* quantifies the social position without relying on popularity nominations. It was strongly correlated with the status measure from popularity nominations and replicated all observed hierarchical patterns in cooperation and their relation to friendship. These findings highlight the significant role of friendship in the moderating of classroom cooperation and demonstrate the potential of our game-based framework as a practical tool to assess classroom social dynamics.

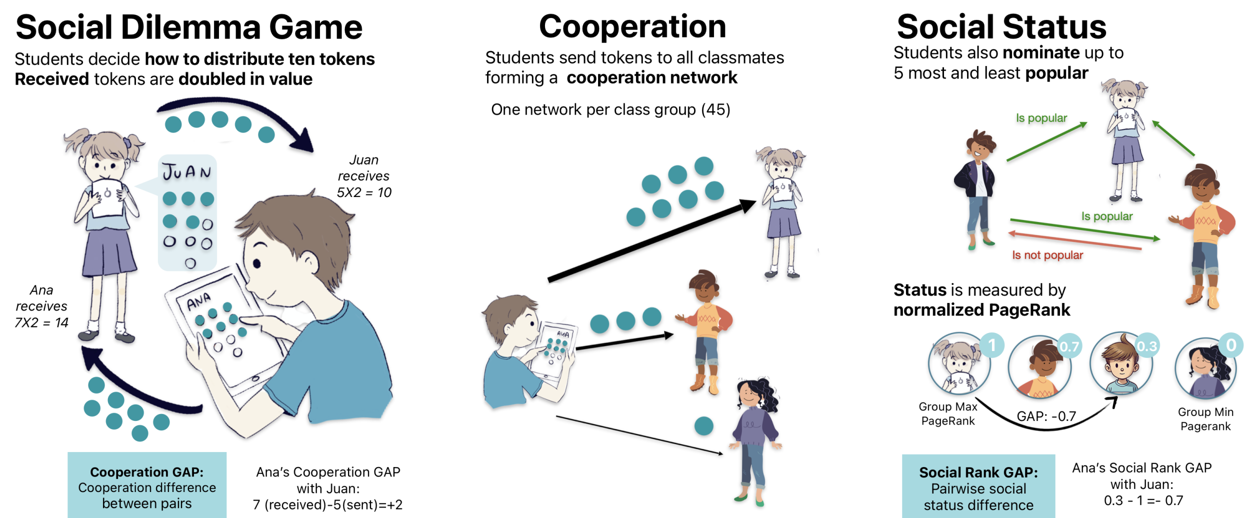

Figure 2–1 Experiment Overview and Main Measures. Students interacted with a tablet interface for the games. Popularity nominations were collected to calculate each student's social rank using the PageRank algorithm. Relative rank differences were assessed through a PageRank gap, while cooperation dynamics were measured by observing token exchanges and calculating cooperation gaps.

2.2 Methods

2.2.1 Participants

The study included 859 children aged 9 to 12 years from 14 different elementary schools in Santiago, Chile. The participants had an average age of 10.16 (s.d. 1.18) years, and 57.5% were female (detailed demographic statistics are available in the supplementary materials).

The students were grouped into 45 classroom due to the Chilean institutional setting. In this system, students are typically assigned to a specific classroom group at the beginning of their education and remain with the same peer cohort until graduation unless they leave the school, their guardians request a change, or they fail the school year. Each classroom is the main setting for most academic and social activities, with students spending around eight hours together daily. This institutional arrangement fosters a stable and consistent peer environment, with most of the students in our sample being part of their respective groups for at least three years.

2.2.2 Experimental Data Collection Process

Data was collected in the student's regular classroom environment over a single school day using a network setup of tablet computers. Each student participated through a drag-and-drop game interface on a tablet. They first played a social dilemma game designed to measure relational cooperation. Next, students completed a nomination section on a game interface to indicate up to five friends, most popular, most liked, and disliked classmates. Additionally, we collected individual administrative records, including classroom attendance, gender, parent or guardian's educational level, and GPA.

The study received ethical approval from the Institutional Research Ethics Committee of the Universidad del Desarrollo (IT15I10079) and was conducted with the informed consent of all guardians of the participating students. The experiment was carried out between July and August 2017, at the beginning of the second school term. Students could opt out of the data collection process at any time.

2.2.3 Social dilemma game for measuring relational cooperation

We implemented a social dilemma game to experimentally capture classroom-wise relational cooperation. In a series of rounds, students were randomly paired and tasked to distribute ten tokens between themselves and their peers using a drag-and-drop interface displaying their peers' names and photos. This setup facilitated capturing a total of 17,804 pairwise interactions.

To resemble a real-life social dilemma, all received tokens doubled in value, generating tension between social and individual incentives. This payoff structure establishes a direct trade-off between reaping the benefits of cooperation and the risk of being exploited by non-reciprocators. For example, in a fully cooperative interaction in which both players send all of their tokens, each player would receive twenty tokens. However, if their peer decides to keep all their tokens, they may end up with nothing. In contrast, a fully non-cooperative interaction in which both players decide to keep all their tokens results in each one ending up with their initially endowed ten tokens.

The incentives of our game are rooted in the traditional *Prisoner's Dilemma*, where the theoretical prediction by Nash (1951) suggests that participants should keep all their tokens due to the risk of explotation by others defection [90]. However, our experimental design deviates from the standard game in two key aspects: interactions are non-anonymous and students' ability for partial cooperation. Considering that students were aware of their counterparts' identities in each round, their cooperative decisions should be influenced not only by prosocial tendencies but also by their past interactions and expectations [87, 88]. Additionally, instead of a binary choice to cooperate or not, participants can send any amount of tokens between zero and ten. This flexibility in cooperation levels enables us to fine-tune their relationships, moving beyond simple cooperation or defection to explore a spectrum of interactive behaviors. These features allow us to experimentally elicit finally-grained cooperation patterns among known peers.

2.2.4 Map of relational cooperation and cooperation GAPS

We constructed a cooperation network from the interactions observed during the social dilemma game to understand the social dynamics and hierarchies of the peer group in their classroom. Each student is represented as a node, with directed edges between pairs indicating the tokens exchanged, where zero tokens represent non-cooperation. This network mapping reflects the relational cooperation within each classroom by analyzing how participants distribute tokens. The network structure not only captures individual behaviors but also reveals the collective dynamics of resource distribution and social relationships.

Particularly, by focusing on pairwise interactions, we can characterize the relationships between students by distinguishing between reciprocated and non-reciprocated tokens [91]. We define a 'cooperation gap' as the difference in the number of tokens sent and received. The balance of tokens exchanged, what one student sends to another versus what they receive, can reveal much about the nature of their relationship. A zero gap, indicating equal exchange, points to a balanced relationship. In contrast, a non-zero gap suggests a one-sided dynamic, where one individual gives more than they receive. These cooperation gaps provide insight into students' interactions and relationships, reflecting the social structure within the classroom. The presence of gaps, particularly when theoretical incentives should lead to reciprocal exchanges, such as sending zero tokens, can indicate underlying advantages or hierarchical deference between individuals.

Algorithm for Filtering Trivial Token Exchanges

To focus on meaningful exchange patterns, we applied a shuffling algorithm that preserves each participant's distribution of sent tokens. This approach maintains the out-degree (number of tokens sent) while reshuffling exchanges to remove correlations from random distributions. Given the meaning of zero-token exchanges, this shuffling method was preferred over random assignment based on average sendings. Interactions falling within a 95% confidence interval—indicating they could occur by chance—were filtered out to keep only non-trivial exchanges. Detailed steps and the algorithm's implementation are provided in the supplementary materials 1.

2.2.5 Individual Social Rank

We measured individual social rank based on the popularity peer nominations. The students nominated up to five classmates who were the most popular and well-known and the least popular and well-known. To calculate individual social rank within the classroom, we aggregated popularity nominations as directed weighted links in a network and applied the PageRank centrality algorithm [89], considering who ranks whom.

Each popularity nomination is a positive link, each non-popularity nomination is a negative link, and a non nomination is a neutral stance. To facilitate the calculation of metrics for a standard weighted network, we translate the scale considering as 0 is negative, 1 is neutral, and 2 is positive.

Then, the PagerRank centrality algorithm assigns a score to each node in the network based on the weight of the edges connecting it to other nodes as described in equation 2.1. This score represents the relative importance of a student in the network that considers the number of connections, their importance, and their exclusivity. We argue that the heterogeneity of this measure captures the social hierarchy of the classroom.

The PageRank centrality is defined as:

$$PRank_i = \frac{1-d}{N} + d\sum_{j=1}^{n} \frac{w_{ij} PRank_j}{\sum_{k=1}^{n} w_{kj}} \tag{2.1}$$

Here, d is the damping factor (set to 0.85 following [89]), and N is the total number of students in the classroom. L(i) represents the set of students who sent tokens to student i, and w(j) is the total number of outgoing links (i.e., tokens sent) from student j. In this context, the first term accounts for a baseline probability of receiving a link (random jump), while the second term distributes influence based on the amount of tokens received from others in the network. The weight w_{ij} reflects the number of tokens sent from student j to student i, reinforcing the role of directed, weighted interactions in shaping each student's social position.

Then, we normalize this PageRank to proxy individual social standing within a given classroom. The resulting score ranges from 0 to 1, where 0 indicates the lowest-ranked individual in a given class group and 1 is the highest-ranked one, which serves as a measure of individual social status.

2.2.6 Relational Social Rank and Social Rank GAP

After measuring individual rank, we qualify the relational hierarchical standing between a pair of individuals in the game as the difference of their normalized PageRanks [92], or Rank GAP.

$$RankGAP_{ij} = PageRank_i - PageRank_j \tag{2.2}$$

Therefore, a rank gap indicates the difference in rank between a pair of students. It has a value between -1 and 1: negative values indicate the sender has a higher rank, positive values indicate the receiver has a higher rank, and zero indicates equal rank within the class.

2.2.7 Peer Cooperation and Friendship Regression Modeling

We used regression methods to study the relationship between differences in cooperation (cooperation gap) and status relation (social rank gap) between pairs of students. We analyzed all individuals and grouped participants according to their declared friendships from the nomination survey, including fixed effects for the class group.

The base model for a student i interacting with student j is:

$$(w_{ij} - w_{ji}) = \alpha + \beta * (PageRank_i - PageRank_j) + u_{ij} \tag{2.3}$$

or

$$\text{Coop Gap}_{ij} = \alpha + \beta * \text{Rank Gap}_{ij} + u_{ij} \tag{2.4}$$

where w_{ij} is the number of tokens sent from the student i to j, and PageRank$_i$ is the student i' PageRank measure of status. The estimated coefficient β represents the change in the cooperation gap related to an increment of 1 in the rank difference.

Given that students are nested in class groups and we observe the complete interaction network, we implement fixed effects at the individual and class group level that capture both the average generosity of the individual, as well as the features of the class group. Therefore, incorporate a sender fixed effect (η_i) and a class-level fixed effect (c_ij) to account for individual-level idiosyncrasies that are constant between interactions.

$$\text{Coop Gap}_{ij} = \alpha + \beta * \text{Rank Gap}_{ij} + \eta_i + c_{ij} + u_{ij} \tag{2.5}$$

To incorporate friendship, we allowed for different intercepts and slopes with an indicator (MF) variable for mutual friendship relations, comparing to the non friends case.

$$\text{Coop Gap}_{ij} = \alpha + \beta * \text{Rank Gap}_{ij} + \gamma_1 * \text{I(MF=1)}_{ij} + \theta_1 * \text{Rank Gap}_{ij} * \text{I(MF=1)}_{ij} + \eta_i + c_{ij} + u_{ij} \tag{2.6}$$

2.3 Results

2.3.1 How does friendship shape cooperation and reciprocity in the game?

We begin by analyzing pairwise interactions in the social dilemma game, which reflect how students navigate the tension between self-interest and cooperation in dyadic exchanges. In each round, participants allocated ten tokens between themselves and a known peer, with the received tokens being doubled in value. While classic game theory predicts purely self-interested behavior in such settings [90], our findings reveal a more nuanced reality: asymmetric reciprocation was the most common pattern, followed by fully cooperative and low-cooperation exchanges. This suggests that decisions were not solely strategic but likely shaped by the identity of the peer and the social context, including past interactions and personal preferences [87].

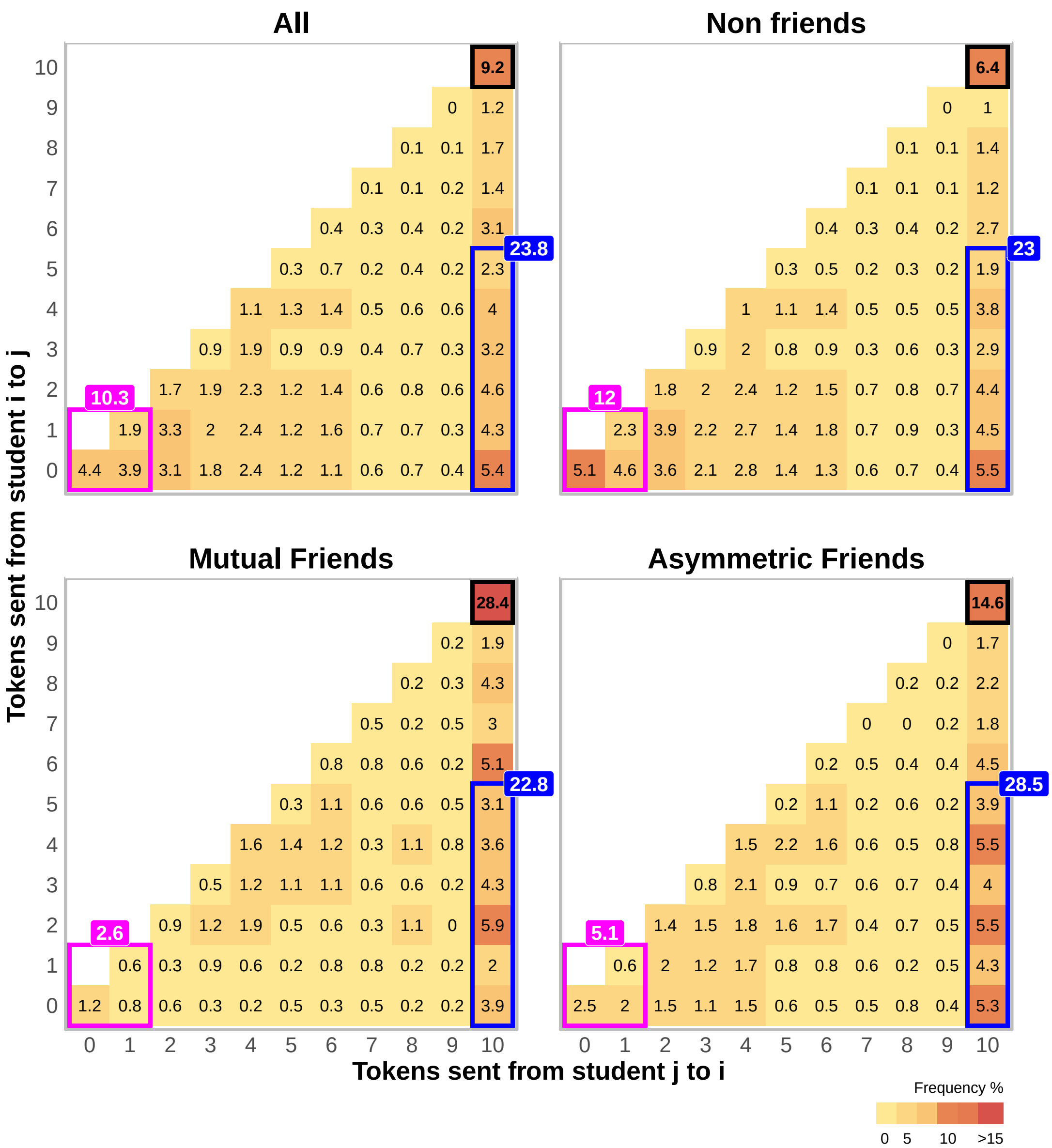

Figure 2–2 Interacted tokens by declared friendship classification. Each matrix entry is the percentage of student pairs exchanging specific token combinations in the *Social Dilemma game*. These percentages are calculated within distinct categories: Panel "All" considers all 17,804 interactions; "Non friends" includes pairs without mutual friendship nominations, accounting for 78.2% of interactions; "Mutual friends" are pairs with mutual friendship nominations (7.2%); and "Asymmetrical Friends" include pairs where only one student has declared the other as friends (14.6%). Key areas highlighted are: i) non-cooperative or marginally cooperative exchanges in the lower left corner (magenta), ii) full cooperation with an exchange of all 10 tokens in the upper right corner (black), and iii) substantial imbalances where one student benefits by at least five additional tokens, in the lower right corner (blue).

Among all interactions, 9.2% showed full cooperation (both students sending all tokens), while 10.2% were non- or low-cooperative, involving the exchange of one or fewer tokens. The majority of exchanges were asymmetrical, with 23.8% being highly unbalanced—cases where a student sent all ten tokens but received five or fewer in return—indicating substantial inequality in reciprocation (Figure 2–2 - Panel All).

To better understand these patterns, we examined how cooperation varied with friendship ties. Among non-friends—students without reciprocal friendship nominations, representing 78.2% of all dyads—non-cooperation rose to 12%, and full cooperation dropped to 6.4%, suggesting a greater tendency toward self-interest in the absence of social bonds (Figure 2–2 - Panel Non Friends).

In contrast, those pairs that acknowledged each other as mutual friends (7.2% of interactions) displayed significantly more cooperation: 28.4% of their exchanges were fully cooperative, and only 2.6% were non-cooperative. Still, 22.8% of these interactions remained highly asymmetrical, suggesting that even among close peers, inequalities persist (Figure 2–2 - Panel Mutual Friends).

The last group of asymmetric friends, where only one student declared the other a friend (14.6% of interactions)—showed intermediate levels of full cooperation (14.6%) and the highest rate of asymmetrical reciprocation (24.6%), pointing to the nuanced dynamics shaped by unreciprocated social perceptions (Figure 2–2 - Panel Asymmetric Friends).

Overall, these results highlight the diverse range of interaction strategies among students, encompassing both cooperative and non-cooperative behaviors. The presence of asymmetric reciprocation in different friendship contexts suggests complex social dynamics at play. These persistent cooperation gaps in all groups may suggest a possible underlying social hierarchy, rather than being purely random. Furthermore, the marked trend towards cooperation among mutual friends highlights the potential of friendship to act as a leveling factor in social interactions, counterbalancing asymmetries.

2.3.2 Does social status shape cooperation among non-friends?

Given the prevalence of asymmetric outcomes in the social dilemma game, we hypothesized that these patterns might reflect an underlying social hierarchy. To test this, we analyzed how differences in social status influence cooperation, especially the cooperation gaps between students. We utilized regression methods to analyze cooperation differences as a function of status relations, revealing distinct hierarchical patterns based on social status differences.

Focusing on interactions among non-friends, we observed that token exchanges were more non-cooperative and asymmetric. Status relation between a pair of students was measured by their *Rank Gap*, indicating the difference in their normalized PageRank between sender and receiver. A rank gap of -1 means that the lowest-ranked individual is sending tokens to the highest-ranked one, 0 indicates equal rank, and 1 signifies that the highest-ranked individual is sending to the lowest-ranked one.

Our results show that exchanges among non friends are influenced by differences in social status, favoring higher-status individuals. Higher-status individuals tend to send fewer tokens to lower-status peers and receive more in return. Specifically, the number of tokens sent by lower-ranked individuals decreases as the status difference increases, while the number of tokens received by higher-ranked individuals increases (Figure 2–3 - left).

To ensure the validity of these nontrivial cooperative relations, we employed out-degree-preserving randomization, filtering out tokens that could be explained by random distributions. This process generated a network maintaining the same out-degree (sent tokens) for each node but with rewired edges, preserving the observed network structure while removing trivial correlations. The detailed algorithm is described in the sup. materials.

We found that for this group social status differences significantly correlate with cooperation levels. As the *Rank Gap* widens, the cooperation gap increasingly favors higher-status individuals, as illustrated by the positively sloped trend line in Figure 2–3 - right panel. A one-unit increase in social rank gap is linked to a significant rise in cooperation gap by 2.6 and 3.1 tokens for observed and filtered data, respectively (P<0.001). This pattern persists even after controlling for classroom and individual fixed effects (Table B–3).

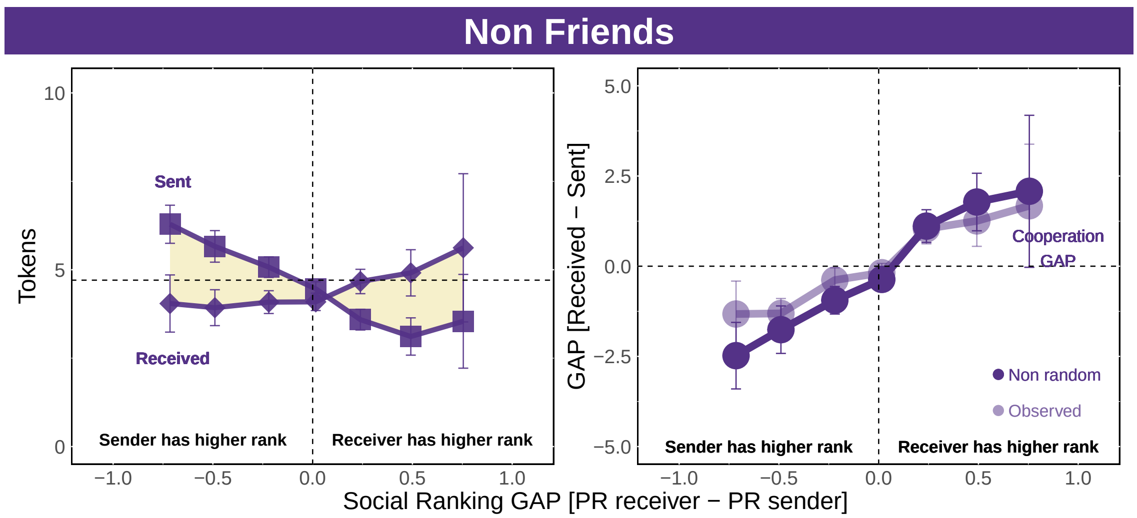

Figure 2–3 Cooperation Gaps Favor Higher-Status Individuals in Non-Friend Interactions. Shows interactions among pairs without friendship nominations, focusing on the relationship between social rank and cooperation. Higher-ranked individuals tend to send fewer tokens and receive more from lower-status peers, leading to a positive cooperation gap that widens with increasing rank differences. **Right:** Correlation between social rank gap and cooperation gap, where larger status differences result in larger gaps. The darker line represents filtered interactions (excluding those explained by chance), while the lighter line shows observed data. **Left:** Relationship between social rank gap and sent (squares) and received (diamonds) filtered tokens. The mean of interacted tokens (4.8) is indicated as a reference point.

2.3.3 Do mutual friendships override hierarchical patterns of cooperation?

Having examined the hierarchical patterns among non friends, we now turn our attention to the dynamics within mutual friendships. In this context —where both individuals acknowledge the friendship with a nomination— we observe that there is no association between social status and cooperation. Statistical analysis showed no significant correlation between social rank gap and the gap in exchanged tokens, sharply contrasting with the dynamics among non-friends, where a clear status-related pattern is observed (Fig. 2–3 - right).

This absence of hierarchy results from more balanced exchanges between friends, leading to a zero cooperation gap. In these interactions, mutual friends send and receive similar numbers of tokens, regardless of their relative social status (Fig. 2–4 - left).

Interestingly, even though both sent and received tokens are higher than the overall average, the balance in these exchanges ensures that there is no significant cooperation gap, regardless of status differences (Fig. 2–4 - right). This suggests that mutual friendship has a strong equalizing effect on cooperative behavior, which overrides the typical influence of social hierarchy.

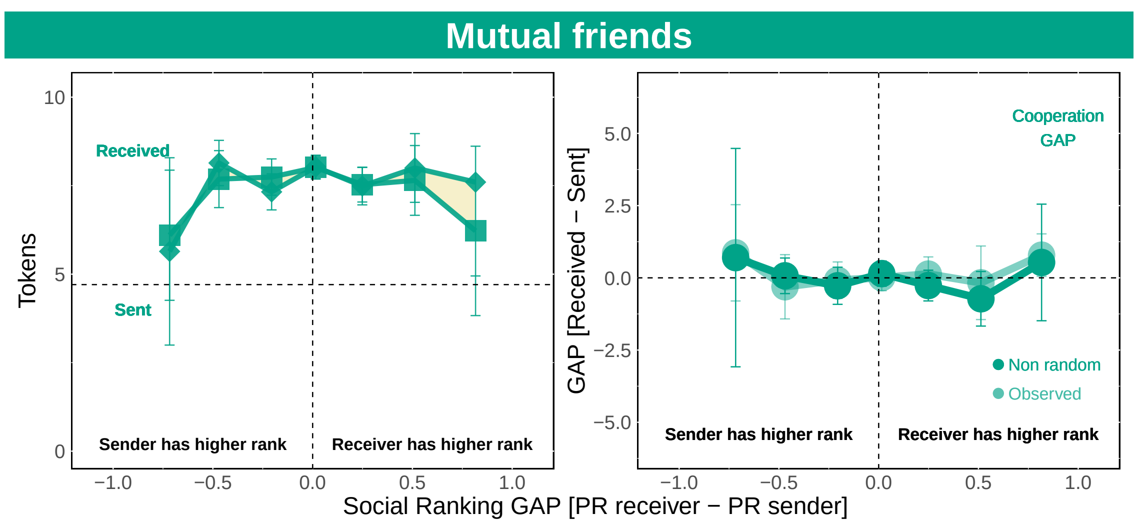

Figure 2–4 Between friends, cooperation GAPS disappears. Displays interactions between friends, showing no cooperation gaps as both sent and received tokens are higher than the overall average, with high reciprocity regardless of status differences. **Right:** Correlation between social rank gap and cooperation gap. Larger status differences correlate with greater cooperation gaps. **Left:** Relationship between social rank gap and sent (squares) and received (diamonds) tokens, where a social ranking gap of -1 means the lowest-status individual sends tokens to the highest-status individual. The mean number of tokens interacted (4.8) is marked as a reference.

2.3.4 How does social status shape cooperation in asymmetric friendships?

As a final focus, we examine the dynamics within asymmetrical friendships, where only one individual in each pair declared the other as a friend. This group showed higher full cooperation rates than the overall sample but lower than mutual friends, along with more non-cooperative behavior than mutual friends, yet less than non-friends. Also, they displayed the highest level of asymmetric reciprocation.

Our analysis revealed a dual pattern in exchange dynamics—egalitarian or hierarchical—depending on the status of the friendship nominator (Figure 2–5). When the higher-status individual nominated the friendship, interactions resembled those of mutual friends, with similar exchanges of sent and received tokens, leading to a small or zero cooperation gap, even in the context of status disparities.

Conversely, when the lower-status individual initiated the friendship, the interaction followed a hierarchical structure similar to non-friends. In these cases, the higher-status student, who did not reciprocate the friendship, sent fewer tokens and received more. These cooperation gaps were directly related to social status differences, highlighting a hierarchy-favoring dynamic in these asymmetric friendships, potentially reflecting an aspirational motive of the lower-status nominators.

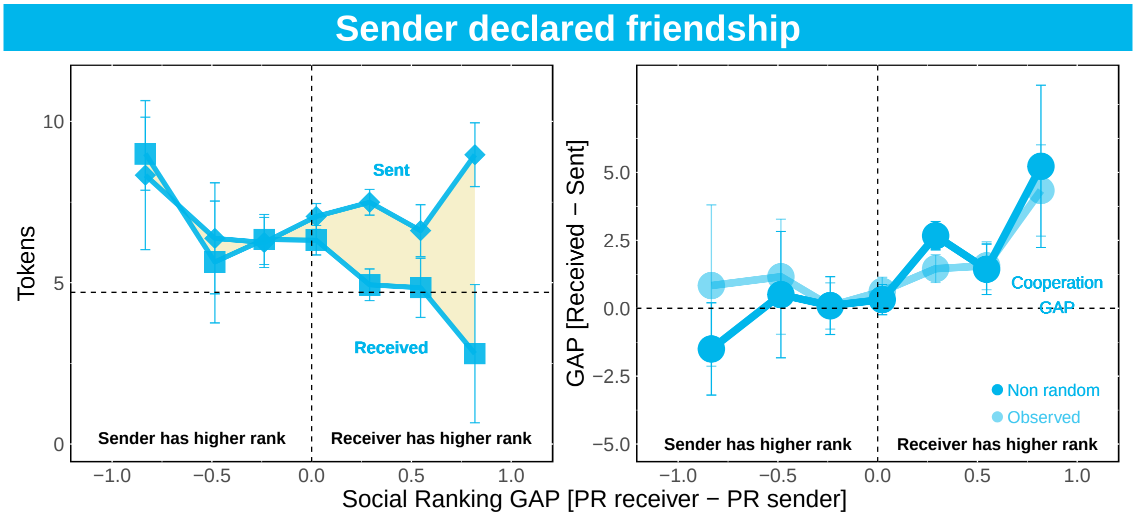

Figure 2–5 Cooperation Patterns in Asymmetrical Friendship Nominations. This figure illustrates interactions within pairs where the token sender also made a one-sided friendship declaration. It shows that the pattern of sent and received tokens aligns with the hierarchical status of the friendship nominator. Two distinct patterns emerge: when the nominator has higher status, interactions are reciprocal (similar sent and received tokens); when the nominator has lower status, a hierarchical pattern appears, with higher-status individuals sending less and receiving more. **Left:** Relation between tokens sent (squares) and received (diamonds) and the social rank gap. A gap of -1 indicates the lowest-status individual sends to the highest-status one, 0 indicates equal rank, and 1 indicates the highest-status individual sends to the lowest-ranked. The mean number of tokens (4.8) is marked as a reference. **Right:** Relation between the social rank gap and the cooperation gap (difference between sent and received tokens). A larger social rank difference corresponds to a larger cooperation gap.

2.3.5 Game-based behavior alternative measure for social rank

Given that evidence that relational cooperation reflects underlying class hierarchies, we explored whether the social dilemma game alone could serve as a reliable proxy for social status within peer groups. Specifically, our goal was to determine whether the game-based data could replicate the patterns observed with the popularity nominations.

First, we used the game interactions to map each classroom's cooperative network and estimated individual social status using the PageRank algorithm, which was based on the number of tokens received and the rank of the senders. This game-based PageRank measure strongly correlated with the traditional popularity-based measure (Pearson Corr.

0.842, Spearman Corr. 0.849, both significant at $p < 0.001$), suggesting that in-game behavior effectively captures classroom social hierarchies (Figure 2–7 - A).

Next, we replicated all key findings using this game-based measure, observing the same hierarchical cooperation patterns related to status gaps, the absence of such patterns among friends, and the varied behaviors in non-friend interactions. Higher-status individuals received more and sent fewer tokens, mutual friends exhibited balanced exchanges, and asymmetric friendships mirrored the traditional patterns depending on the hierarchical relationship of the nominator (Figure 2–6).

To ensure these findings were not due to random chance, we used the tokens filtered after the out-degree-preserving randomization to filter out trivial interactions. This process generated a network with preserved structure but rewired edges, validating that our results reflected social dynamics rather than statistical anomalies.

In summary, our analysis demonstrates that in peer interactions, higher-status individuals receive more and send fewer tokens, while mutual friends maintain balanced exchanges. In asymmetric friendships, the pattern depends on the nominator's status—mirroring our previous results obtained using the social rank based on popularity.

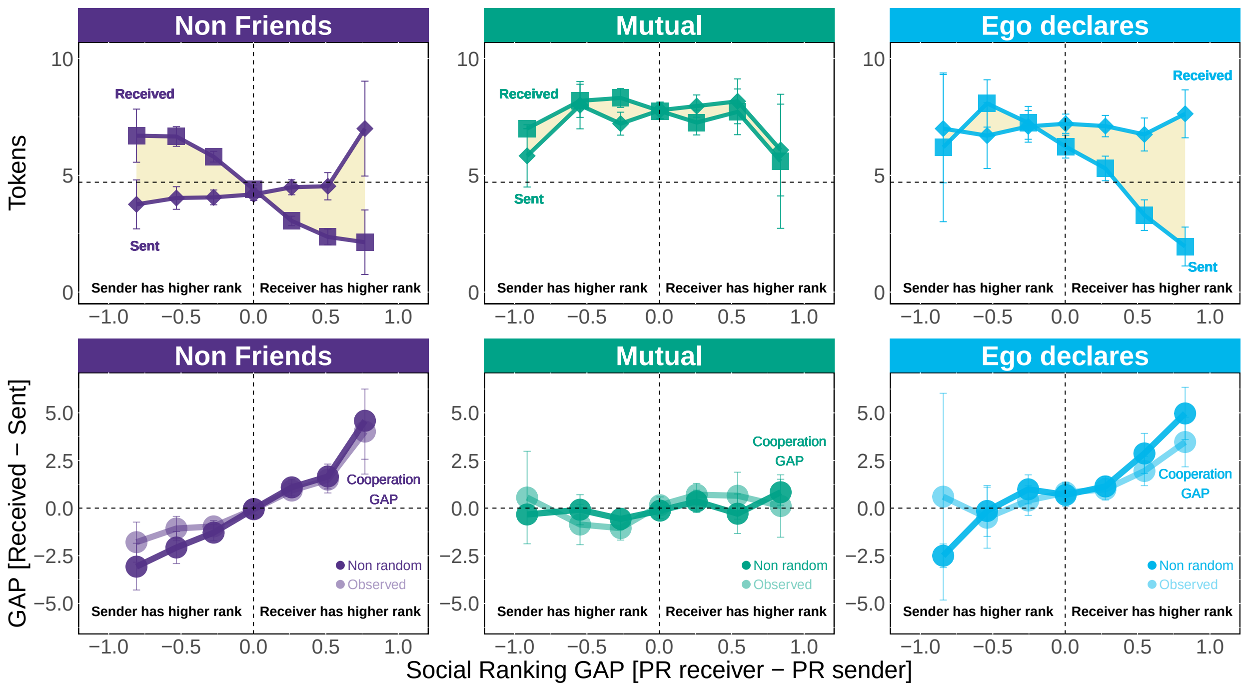

Figure 2–6 Relational cooperation and Behavioral Social Rank, for different friendship groups. This figure illustrates the relationship between peer cooperation and peer rank, as determined by the Behavioral Social Rank (normalized PageRank based on the cooperation network). The **first row** displays token exchanges—sent (squares) and received (diamonds)—for filtered tokens. The **second row** highlights Cooperation Gap patterns for observed (light line) and filtered (dark line) tokens. A notable Cooperation Gap favoring higher-status individuals is evident in non-friend relationships. This gap disappears in mutual friendships but reappears in asymmetrical friendships when the alter has a higher rank, mirroring previous social status measures.

This alternative game-based Behavioral Social Rank measure also correlated strongly with traditional questionnaire-based status measures and observable variables, further validating our findings (Fig. 2–7). The first row of the figure shows a high correlation between the Behavioral Social Rank and the initial social rank derived from popularity nominations. Additionally, there is a positive (but weaker) correlation with friendship nominations (Pearson correlation 0.49), which aligns with the literature where friendship is also used to assess social status. The Behavioral Social Rank also correlates positively with observable indicators of student engagement, such as attendance and GPA.

We then focuses on comparing with peer nomination data. Here, the Behavioral Social

Rank correlates positively with being liked ($R = 0.51$, $p < 2.2e-16$) and being perceived as popular ($R = 0.46$, $p < 2.2e-16$). Conversely, it shows a negative correlation with being disliked ($R = -0.40$, $p < 2.2e-16$) and a weaker negative correlation with an aggression score derived from questionnaire responses ($R = -0.15$, $p = 1.4e-05$), further proposing the Behavioral Social Rank as a robust tool for understanding and assessing classroom social structures.

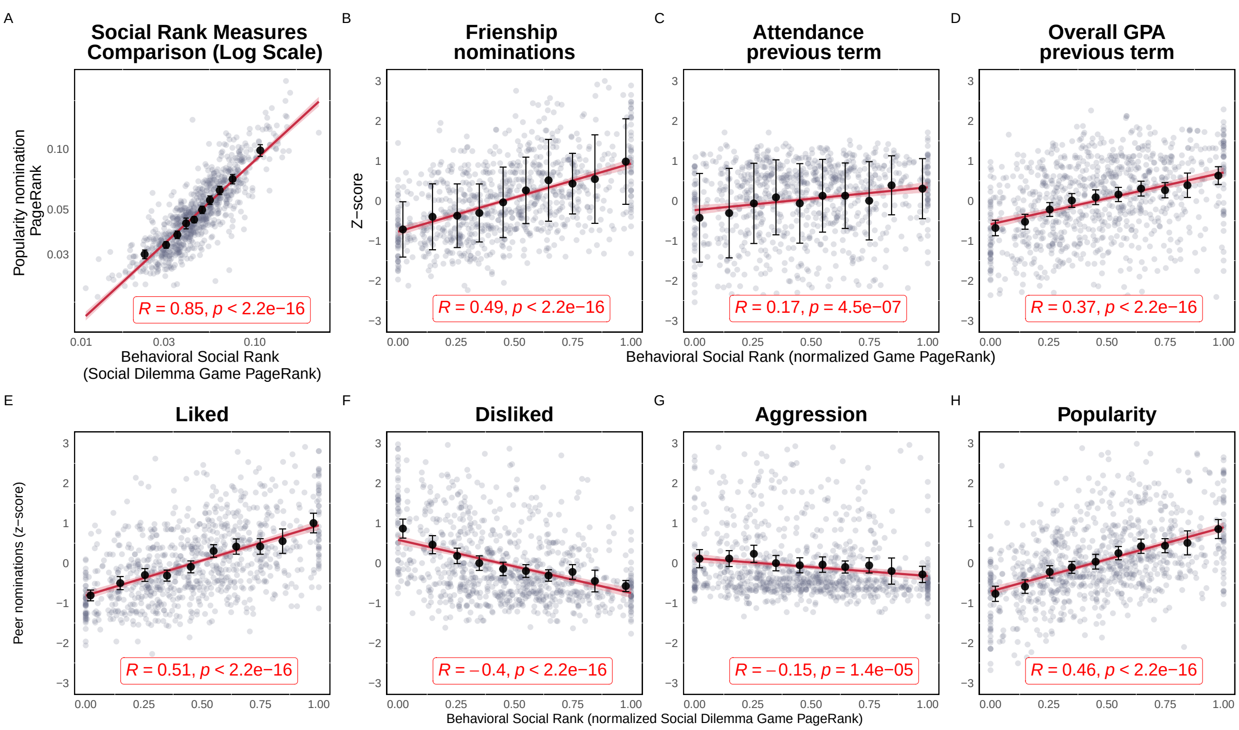

Figure 2–7 Behavioral Social Rank and Student Characteristics. These plots illustrate the correlation between the Behavioral Social Rank (calculated as the PageRank from the social dilemma game's cooperation network) and various student characteristics. In red is highlighted a linear model, and the Pearson correlation coefficient. **First Row:** The first panel compares this Behavioral Social Rank with the initial social rank measure based on popularity nominations (displayed on a log scale). Subsequent panels show correlations with the number of friendship nominations, attendance, and overall GPA from the previous academic term. **Second Row:** The panels depict correlations between the Behavioral Social Rank and peer nominations for popularity, likability, dislikability, and aggression scores.

2.4 Conclusion and Discussion

In this study we contribute to the understanding of the intersection between cooperation, social hierarchies, and friendships among elementary school children in Chile, revealing how the dynamics of cooperative behaviors can be significantly influenced by these social structures. We found that in the absence of friendship, children's interactions largely adhere to hierarchical norms, with lower-ranked individuals typically deferring to those with higher status. However, the presence of mutual friendships disrupts this pattern, fostering more egalitarian interactions that defy the conventional hierarchy.

These findings align with and extend existing research in educational psychology, which has shown the importance of social structures in influencing student interactions. By showing that friendships can counteract the effects of hierarchical structures, our study adds a new dimension to our understanding of social interactions within educational settings. This insight is crucial for developing educational strategies that promote more inclusive and supportive environments.

Many studies have measured social status through friendship networks, implying that having many friends or being well-liked correlates with higher social status [93, 58, 59, 94, 95]

However, recent work, such as [61, 62], suggests that while friendship and status are related, they are distinct dimensions. Our study supports this distinction, showing that friendship not only represents a separate social dimension but also moderates the influence of status, reducing hierarchical disparities in interactions among friends.

Overall, our findings highlight an influential role of social status differences on asymmetries in children's cooperation, with friendship ties serving as a balancing force. We show that cooperative interactions are not distributed randomly but follow identifiable patterns shaped by social rank and relational closeness. In particular, mutual friendships override status-based hierarchies, while asymmetric friendships reflect aspirational dynamics from lower-status individuals. These insights suggest that fostering reciprocal social bonds—such as encouraging inclusive group work, shared activities, and recognizing unilateral social efforts—may help reduce social asymmetries and promote cooperation in the classroom.

Additionally, we introduce an innovative experimental framework for assessing children's social standing and cooperative interactions, with potential applications extending beyond academic research. By capturing the subtleties of social dynamics, this framework offers teachers and policymakers a powerful tool to monitor relational inequality, identify socially isolated students, and design targeted interventions to foster more equitable and supportive classroom environments.

Our findings resonate with the broader literature on social influence and peer relations, which often explores how status and informal social ties affect behaviors such as substance use, academic performance, and psychological well-being [96, 97, 98, 63]. By illustrating that friendships can alter the hierarchical dynamics of cooperation, our findings contribute to a deeper understanding of how social processes within schools shape individual outcomes and broader social structures.

Our methodological approach of integrating sociogram techniques with experimental game theory has proven particularly effective in capturing these subtle dynamics. This approach allows us to observe genuine behaviors in a controlled setting, overcoming some of the biases inherent in survey methods. The use of a video game interface not only engaged the children, but also provided a familiar context for them to express their natural social behaviors. We also provided evidence that is not necessary to directly ask students for any type of popularity or other nominations to measure underlying social standing from the observed cooperative behaviors.

While our results provide insights into the interplay between social status, cooperation, and friendship among elementary school children, it is important to recognize its limitations. First, the lack of exogenous variation in status within our experimental design limits our ability to estimate the causal effect of status on cooperative behavior. Furthermore, the specificity of our sample may not fully represent the diverse range of social dynamics present in different cultural or age groups. These concerns question the internal and external validity of our findings and their applicability to other social settings.

Looking forward, this research opens several branches for further investigation. Future studies could explore how these dynamics play out in different cultural contexts and educational stages, potentially through longitudinal studies to track these interactions over time. Such research would deepen our understanding of the long-term effects of these social dynamics on children's development and educational outcomes. In addition, exploring interventions designed to foster friendship and cooperation could provide practical strategies to improve social cohesion and equity in educational settings.

In conclusion, our study highlights the powerful role of friendships in the moderating of social hierarchies among young learners. By showing how personal relationships can lead to more equitable interactions, our findings offer practical approaches for educators to create environments that nurture positive social interactions. The ability of friendships to balance social hierarchies enriches both theoretical understanding and practical efforts to improve the social environment in schools.

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Chapter 3

Autism Shapes Social Integration and Reciprocity in Elementary Classrooms.

We're one, but we're not the same. We get to carry each other, carry each other

U2

Abstract

During childhood, schools are a crucial environment for social interactions, making them ideal for evaluating the inclusion of children with special educational needs (SEN). Children with Autism Spectrum Disorder (ASD) often face challenges in peer relationships, yet how this condition impacts specific social dynamics and school coexistence is not well understood. To address this issue, we examined social relationships and dynamics within elementary schools. We hypothesized that, compared to their peers without ASD, children with ASD: (i) are more peripheral within social networks, reflecting a low degree of centrality, and (ii) engage less in reciprocal relationships, indicating diminished social reciprocity. To test these hypotheses, we introduced a novel ecological approach, using game theory to quantify social integration and reciprocity among children with ASD in elementary schools. Social networks were constructed for each classroom based on the children's peer selections during a distributive game in which they had to send tokens to their peers. After analyzing the measures of network centrality and reciprocity, we found that children with ASD were significantly less central and less involved in reciprocal peer relationships compared to their peers without ASD or with other SEN conditions. These results highlight the relevance of interventions that promote social inclusion and open new avenues for future research to explore the intersection of neurodevelopmental conditions and social dynamics. This exploration has the potential to inform policies and practices contributing to how educational systems accommodate diverse learning needs.

3.1 Introduction

Schools are a critical environment during childhood, where all kinds of social interactions occur. Knowing how to live with others who are different is crucial for satisfactory social relationships [1]. From the perspective of individual development, evidence has shown that a variety of affective and cognitive processes can influence how children develop their social behaviors and integrate into peer groups. Certainly, the maturation of these processes is not homogeneous among children, as it is influenced not only by neurodevelopmental variables but also by family dynamics, local contexts, and cultural meanings [2]. From an inclusive perspective, studying social interactions in schools becomes relevant, considering that the educational context serves as a space for encounter and coexistence in diversity [3]. In this setting, some children who could face different learning barriers participate alongside their peers in formative activities [2, 3]. Understanding how children with special educational needs (SEN) manage these social dynamics is crucial, especially considering neurodevelopmental conditions such as autism, which evidence has consistently shown to be associated with social difficulties and challenges in social interactions.

Autism Spectrum Disorder (ASD) is a neurodevelopmental condition characterized by persistent difficulties in social communication and social interaction in various contexts, along with the presence of repetitive and restrictive patterns of behavior, interests, or activities. Concerning these challenges in social functioning, research has revealed that from early in life, infants at high risk of developing ASD and children with ASD show alterations in attention to social stimuli [4, 5, 6, 7]. Furthermore, evidence has also described that difficulties in understanding others' emotions and in the ability to comprehend the perceptions and experiences of others, known as the theory of mind or mentalization, correlates with ASD symptoms [8]. Children with ASD have also been described to show inappropriate communication initiation, stereotyped language, context use, and non-verbal communication[9], tend to persevere more, and initiate and respond less during a conversation[10]. Taking into account these types of difficulty is crucial to understanding what the challenges children with ASD face when it comes to fitting into peer groups and how they are perceived by others. Evidence has shown that higher levels of autistic traits predicted lower peer acceptance and higher peer rejection [11]. Moreover, children and adolescents with ASD are at an elevated risk of experiencing bullying victimization compared to students without SEN and students with other neurodevelopmental conditions or disabilities[12, 13, 14, 15]. Symptoms such as making naive and embarrassing remarks, difficulties in knowing how to cooperate in a team, and having involuntary facial or body movements were statistically significantly associated with being victimized[12].

Not only difficulties in social interaction and communication have been reported as associated with victimization, challenges with peer acceptance, and high levels of rejection in students with ASD, but also internalizing and externalizing behaviors [15, 11]. Internalizing behavior is defined as focused on the own self encompassing aspects such as withdrawal, anxiety, depression, and emotional problems. Externalizing behaviors are described as related to an interaction with the social environment including traits like aggression, impulsivity, deviance, or hyperactivity [16]. These two kinds of behaviors are present in ASD [17]. Internalizing symptoms are related to higher victimization among students with ASD [17], while externalizing symptoms are related to higher perpetration [15]. Importantly, evidence has shown that bullying perpetration in children with ASD are more likely influenced by ASD-related behavioral issues and communication difficulties, and the presence of comorbid psychopathology such as intellectual disability, conduct disorder or oppositional defiant disorder [18, 19, 20]. These variables are crucial for fully understanding the phenomenon of bullying perpetration among children with ASD, considering that one of the criteria for defining bullying is intentionality (Olweus, 2013). In this respect, the challenges described in individuals with ASD regarding the recognition and response to the mental states of others make it difficult to determine whether aggressive behavior is based on the child's externalizing or aggressive behaviors rather than the child's intention [21, 22, 23, 24, 19].

In addition, in cases of bullying victimization, difficulties with theory of mind raise concerns that children with ASD may struggle to acknowledge or communicate bullying behaviors [19]. In this context, studying children who face social challenges, such as children with ASD, can contribute to understanding how social interaction networks form in school environments. Measuring social networks during childhood requires tailored instruments that ensure inclusivity and avoid the stigmatization of children as 'different' or 'atypical' [25, 26].

Considering this evidence, we tested two hypotheses: compared to children without ASD, children with ASD (i) occupy more peripheral positions within social networks, reflecting a low degree of centrality, and (ii) engage less in reciprocal relationships, indicating diminished social reciprocity. We address these aspects by designing a game that is played on a user-friendly interface, which enables the identification of participants' 'revealed preferences' regarding social interactions, and thus elicits the collaborative social network within each classroom [27, 28].

Social networks were constructed for each classroom based on the children's selections, and we analyzed measures of centrality and reciprocity. Our findings indicated that children with ASD received significantly fewer selections and preferences compared to their peers without ASD or those with other SEN. Furthermore, when compared to students without SEN, children with ASD exhibited significantly lower levels of engagement in reciprocal relationships. By analyzing the social dynamics and interactions of children with diverse neurodevelopmental trajectories, we aim to better understand the unique social challenges faced by children with ASD in educational environments and to contribute to the planning of effective inclusive school coexistence policies.

3.2 Methods

3.2.1 Ethics statement

All methods and the experimental protocol were approved by the Universidad del Desarrollo Ethics Committee and adhered to the principles of the Declaration of Helsinki and the Local Ethical Guidelines for Research Involving Human Subjects. The study considered obtaining both an informed consent from the students' parents/legal guardian and the children for their voluntary participation. Children's responses were kept completely confidential and their names were replaced with alphanumeric codes. Participating schools received a written report on the results of their students' participation, and a special education teacher designed strategies aimed at promoting inclusion. Additionally, a verbal feedback session was conducted with the responsible researcher, the project coordinator, and the special educator to clarify the results and proposed strategies as necessary.

3.2.2 Sample

Our sample consisted of children in the first fourth grades attending schools located in urban areas of Chile (see the Participants section for more details). This research was conducted from July 2021 to May 2022. Due to the COVID-19 pandemic, throughout the year 2020, schools in our country experienced 'lockdown' restrictions, transitioning to in-person classes intermittently in 2021 [29]. In 2022, the 'lockdown' restrictions were lifted. All the students who participated in this study experienced periods of confinement and were part of a 'virtual classroom' at some point in their academic life. This also carried over to participation in the experimental game. Of the 26 classrooms that participated in our study, 11 participated in the activities online, while the remaining 15 participated in person. We included this aspect in our analysis. In the specific case of the classrooms that participated in our study, none of them were separated before playing the game. Given that our sample included children from 1st to 4th grade, it was a requirement that the majority of students had been together either at the beginning of the year (for those who participated at the end of the academic year) or for at least one year prior (for those who participated at the beginning of the academic year).

3.2.3 Participants

A total of six elementary schools enrolled in the Chilean National Program of School Integration (in Spanish PIE, "Programa de integración Escolar") participated in this research. Schools in this program receive support to implement an inclusive strategy aimed at contributing to the continuous improvement of the quality of education provided in the educational institution, promoting presence in the classroom, participation and achievement of learning objectives for each and every student, especially those with SEN [30]. The program defines general guidelines, but each school board manages implementation details. Four of the participant schools were municipal schools and two were privately subsidized institutions. Municipal schools are funded through state subsidies, while privately subsidized schools receive funding through a shared financing model, which consists of state resources and payments made by each family [31].

A total of 26 classrooms from 1st to 4th grade participated in the study. The average number of students per classroom was 27.12, with a median of 27 (ranging from 16 to 39). Therefore, from a total of 705 enrolled students, 625 parents (88.7%) consented to their children (between 6 and 11 years old) to participate. Of those who consented, 161 were children with SEN (25.8%; 18 children with ASD) (Table 3–1). Grades and attendance records were provided by the schools (for details, see Supplementary Table

C–1). All participants were Spanish speakers.

Grade	Enrolled students	Students with consent (% of enrolled)	'Active players' (% with consent)	SEN Students with consent (% of with consent)	'Active players' with SEN (% of SEN students with consent)
First	196	183 (93.4%)	154 (84.2%)	42 (23%)	34 (80.9%)
Second	170	151 (88.8%)	124 (82.1%)	40 (26.5%)	28 (70%)
Third	183	161 (87.9%)	140 (87%)	42 (26.1%)	33 (78.6%)
Fourth	156	130 (83.3%)	112 (86.1%)	37 (28.5%)	31 (83.8%)
TOTAL	**705**	**625 (88.7%)**	**530 (84.8%)**	**161 (25.8%)**	**126 (78.2%)**

Table 3–1 Sample description. The study population included all students whose parents provided informed consent. Consequently, the estimates for 'Active Players' (students who were both senders and receivers in the game) and 'Students with SEN with parental informed consent' were derived from the total number of students with parental informed consent. There were no significant differences among grade levels in any of these groups, as indicated by the ANOVA test (F = 0.228, p = 0.876).

In order to conduct the game session in each classroom, a headshot photograph of each participant was required to be integrated into the game interface. Therefore, when parents (or legal guardians) provided their informed consent for the students, they were requested to submit a headshot of their child to the school. It is important to note that some students did not participate in the game despite having their parents' informed consent due to various reasons (e.g., illness, loss of interest, difficulties with internet connection, etc.). As a result, the final sample of participants included two categories of 'game players': i) 'Active players,' referring to children who played the game, and ii) 'Non-active players,' referring to children who were unable to play the game for any reason, but their headshots were present in the game interface to be selected and receive stars.

3.2.4 The *Stars Game*

Based on experimental game theory [27, 28], a computational distribution game was developed. This game enables the identification of participants' 'revealed preferences' regarding social interactions, and thus elicits the collaborative social network within each classroom. The game is self-contained, lasting 5 - 7 minutes, with written and audio instructions. It can be played at home or in the classroom, accessible from any internet-connected device. The game ensures the anonymity of responses and operates as a platform online rather than as a standalone application. Before the game started, a video containing all the instructions was displayed to explain the rules to the children regardless of their level of reading. All subsequent instructions were presented in both text and audio formats to maintain this accessibility measure. Children provided their informed consent through the game interface by answering the question, “Do you want to play?”. The game comprises four stages:

1. **Real Effort task:** The game starts with a real effort task to earn 15 stars, requiring children to pop 15 moving bubbles to earn stars. The rationale for including this stage was to captivate the child’s interest in the game by providing an interactive experience and allowing them to actively participate in acquiring something, establishing a sense of ownership of what would be shared with another person [27, 28].

2. **Choice of classmates:** After completing the effort task, a screen displaying individual headshots of each classmate appeared. To ensure accessibility and equal opportunity for all participants, regardless of their technology proficiency, the scrolling through the classmates’ headshots occurred automatically at first, showcasing all classmates. Children were then instructed to manually scroll through the screen to choose 10 classmates to play with (Figure 3–1-A).

3. **Stars allocations:** After selecting their 10 classmates, children were instructed to allocate the 15 stars earned in the “effort task” stage to the chosen classmates (Figure 3–1 - B). The interface prominently displays the headshots of selected classmates, ensuring all are visible for thoughtful decision-making during star distribution. This setup facilitates recognition, recall, and evaluation of social preferences within their network.

4. **Peers' nomination:** Once the game was finished, three additional screens were presented to the children to answer: Which of these classmates are you willing to hang out with? Which of these classmates do you not want to hang out with? Which of these classmates are your friends? These screens used a similar interface to the choice of classmates' stage. None of these three questions had a limit on the number of classmates that could be nominated. Children had the option to choose some of their classmates, none of them, or all of them. This instruction was explicitly stated to the children in each case.

After the child completed the game, a coloring book with star motifs was given to them as a thank-you gift for their participation.

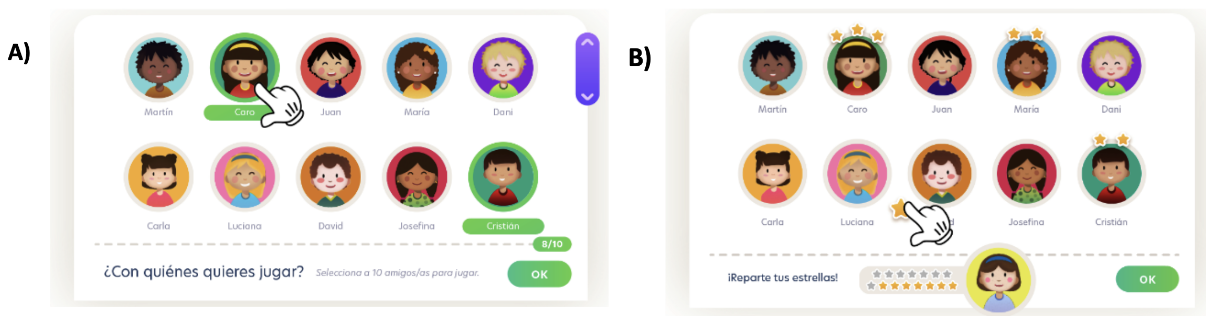


Figure 3–1 Example of the "Stars Game" interface. Boxes depict the A) selection of classmates' stage, and B) stars allocation stage. Avatars are used for illustrative purposes only. During gameplay, children had access to pictures of their classmates in order to ensure that the selection and preferences were correctly allocated. Image reproductions are used with permissions from https://www.nieblagames.com/ and https://invadelab.cl/.

3.2.5 Game Restrictions and Incentives

The game was designed with two key restrictions to compel students to make meaningful choices, regarding partner selection and star allocation. First, in the stage of choosing classmates, children must select 10 partners from among all their peers to progress to the next stage. This mandatory selection was conducted independently of any prior actions, nudging students to form a social group of 10 peers.

Second, during the star allocation stage, children must distribute 15 stars among 10 chosen classmates. They had total freedom in their allocations, with the option to give any number of stars, from none to all, to any peer. The challenge was to distribute an odd number (15) among 10 recipients, requiring unequal distribution. To distribute equally, at least 5 classmates would receive an additional star. This arrangement challenged children's tendencies toward fairness and equality [32, 33, 34]. Furthermore, the choice of 10 peers allows for the inclusion of both close connections and broader interactions within their peer group [35, 36]. The non-anonymous nature of the game mirrors real-life social interactions, where decisions are influenced by existing relationships and past interactions [37, 38]. By allowing a range of preference levels (0 to 15 stars), the game captures a nuanced spectrum of social interactions. This setup, grounded in game theory principles and previous research [39, 40], offers an age-appropriate format for students to express their social preference tendencies. Observing how students navigate resource allocation within their peer groups provides insights into the influence of pre-existing relationships on their choices and the overall social dynamics in classrooms.

3.2.6 Social Network Measures

To analyze student interactions within each classroom, we constructed networks in which students are represented as nodes linked based on their behavior in the game. In particular, each network consist of two layers: The first, the 'player choice network,' consists of non-weighted directed links (c_{ab}) from student a to student b, indicating peer selection. The second, the 'stars allocation network,' includes weighted directed links (s_{ab}) representing the number of stars sent from student a to student b after selection (Figure 3–2).

From this network structure, we analyze two main components: students' positions in the network based on centrality and their reciprocity behavior, as detailed below:

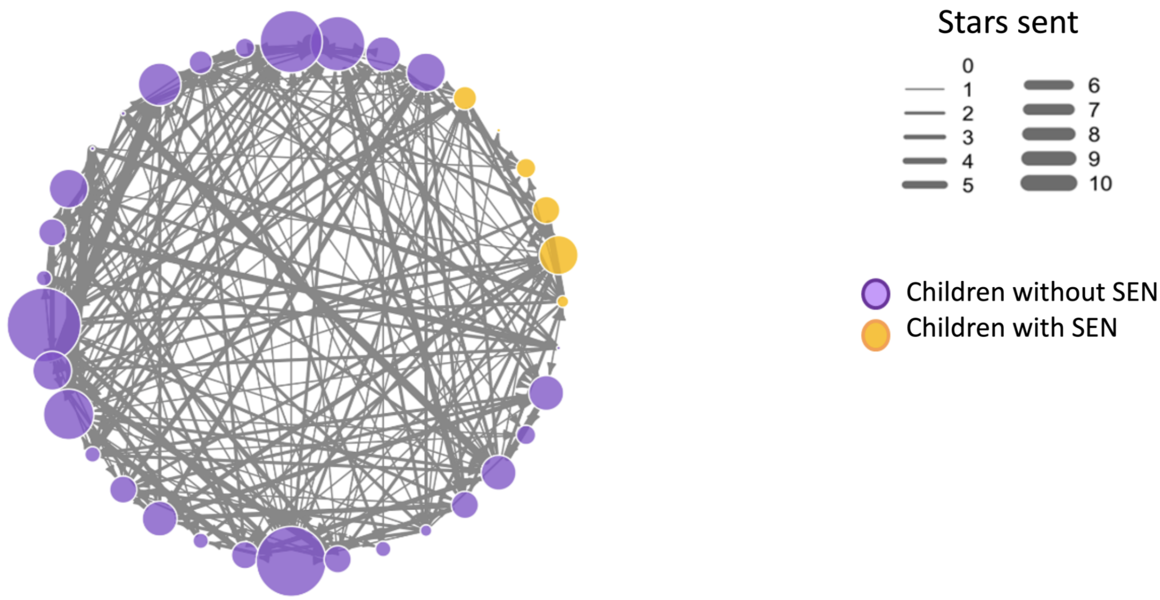


Figure 3–2 Example of a 3rd-grade classroom social network. Each circle represents an individual student in the classroom. Purple depict children without SEN, while yellow represent children with SEN without distinguishing specific diagnoses. The lines show the specific interaction between two students, with the thickness reflecting the number of stars received in that particular interaction. The size of each circle corresponds to the total number of stars received.

Centrality Measures

Centrality quantifies a student's position within the class network, reflecting their peers' preferences based on the choices and resource allocations they receive. We analyzed centrality in both the 'player choice network' and the 'stars allocation network', as follows:

Choice Network Centrality Considering that, in the stage of choice of classmates, each student must choose 10 classmates, the centrality measure in the choice network answers the question: if children are required to choose 10 peers, how often is a particular student included in these groups? In order to answer this question, we defined a Choice Average In-Degree centrality. This metric measures the number of times a student was chosen by peers within their classroom (line thickness in Figure 2). It serves as an extensive measure of centrality since all students are potential recipients of choices. This metric captures the popularity or social acceptance of each student within the classroom. It is averaged to allow comparisons across different classes, by the following equation:

$$C_a = \frac{1}{n} \sum_{a \neq b} c_{ab} \tag{1}$$

Stars Network Centrality Considering that, in the stars allocation stage of the game, the students can freely distribute 15 stars among the 10 chosen classmates, this network provides a granular measure of relationships. This network is a subset conditional on selection, where stars sent are considered weighted directed links. Therefore, we defined a Stars Average Weighted In-Degree Centrality (In-Strength). This metric measures the total number of stars received by each student, calculated as the sum of the weights of incoming edges on average (size of each circle in Figure 2). It reflects the intensity of peer preference. This metric highlights how resources are distributed among the chosen peers and indicates the degree of preference or importance attributed to each student by their classmates. This metric is determined by the following equation:

$$S_a = \frac{1}{n} \sum_{a \neq b} s_{ab} \tag{2}$$

Combining these centrality measures provides a nuanced understanding of both the overall position (based on constrained choices) and the intensity of preference (based on star allocations) for each student. This comprehensive approach allowed us to assess how integrated a student was within their peer group and the strength and quality of their interactions.

In addition to these metrics, we also considered three specific centrality measures to further understand the characteristics of students with ASD in detail. The additional metrics were defined as follows:

PageRank Centrality This measure was calculated using the PageRank algorithm, which assigns a ranking to each node based on the number and quality of incoming links, accounting for the broader network structure (Lawrence Page, R. M., 1998). It can be considered as a proxy for social rank in the group (Ball & Newman, 2013). This metric was defined by the following equation:

$$PR_a = \frac{1-\alpha}{n} + \alpha \sum_{b \in M(a)} \frac{PR(b)}{\text{out inks}(b)} \tag{3}$$

where α represents a damping factor of 0.85, and $M(a)$ represents the subset of all individuals linked to a.

Betweenness Betweenness Centrality measures the extent to which a student lies on the shortest paths between other students. It represents the role of the student as a bridge or intermediary within the network, indicating their importance in facilitating communication and information flow between different parts of the network. This metric was defined as the sum of the proportion of shortest paths passing through the student individual a, considering all nodes that are not a and include two other peers (m, l).

$$\text{Betweenness}_a = \sum_{m \neq a \neq l} \frac{\sigma_{ml}(a)}{\sigma_{ml}} \tag{4}$$

where σ_{ml} is the total number of shortest paths from node m to node l and $\sigma_{ml}(a)$ is the number of those paths that pass through student a.

Closeness Closeness Centrality reflects how close a student is to all other students in the network, based on the shortest path distances. A high closeness centrality indicates that a student can quickly interact with all other students, suggesting a central position in terms of communication efficiency. It was defined by the following equation:

$$\text{Closeness}_a = \frac{1}{\sum_{b \neq a} d(a, b)} \tag{5}$$

where $d(a, b)$ is the shortest path distance between nodes. This measure ranges from 0 to 1, with 1 indicating that the node is maximally close to all other nodes in the network. It is important to note that closeness centrality is undefined for unconnected nodes. In these cases, we assign it a value of 0, indicating the lowest possible centrality.

Reciprocity Measures

Reciprocity examines mutual interactions within the network, focusing on whether students choose each other or send similar amounts of stars. This analysis was limited to students who were present on the day of the game and actively participated, as only these students had the opportunity to reciprocate interactions.

We defined two reciprocity scores for each student, one for the choosing stage and one for the stars stage. These scores, ranging from 0 to 1, quantify the overall proportion of reciprocated interactions a student was involved in.

Additionally, we analyzed reciprocity at the dyadic level by examining the probability of mutual selection between two students using regression models. This approach provides a more granular understanding of the likelihood of reciprocal choices (see Equation (16) in the next section for more details).

Reciprocated Choice Score The reciprocated choice score measures the proportion of mutual selections a student receives during the choosing stage. To calculate this score we identified pairs of students who select each other, forming bidirectional links. The reciprocated choice score RC_a for student a was calculated as follows:

$$RC_a = \frac{2\sum_{a \neq b} \min[c_{ab}, c_{ba}]}{\text{degree}(a)} \tag{6}$$

Here, c_{ab} takes the value 1 if student a chose student b, and 0 otherwise. The factor of 2 accounts for each bidirectional link having one in-link and one out-link. The degree of a student is the total number of in and out links they have, representing all their interactions. This score ranges from 0 to 1, where 1 represents the case in which all interactions are reciprocal, and 0 indicates no reciprocal interactions.

Reciprocated Stars (Weight) Score This metric measures the proportion of mutual exchange of stars for each student within the game. If a student, classified as an active player, does not get selected by classmates, their star value defaults to 0. By aggregating the minimum number of stars exchanged with each peer (Squartini et al., 2013), we calculated the reciprocated weight score RS_a for student a as follows:

$$RS_a = \frac{2\sum_{a \neq b} \min[s_{ab}, s_{ba}]}{\text{weighted degree}(a)} \tag{7}$$

Here, s_{ab} is the number of stars sent from student a to b, and weighted degree(a) is the total number of stars a student interacts with, including both sent and received stars. The factor of 2 accounts for bidirectional exchanges having both an in-link and an out-link. This metric provides insights into the depth of reciprocal interactions within the classroom by reflecting the degree of mutual investment in relationships.

Network measure	**Social Capital**	**Network layer**	**Mathematical Formulation**
Choice Average In-Degree Centrality	Constrained social choice	Choice of classmates	$C_a = \frac{1}{n}\sum_{a\neq b} c_{ab}$
Star Average Weighted In-Degree Centrality (In-Strength)	Resources allocation	Stars allocation	$S_a = \frac{1}{n}\sum_{a\neq b} s_{ab}$
Reciprocated choice	Constrained social reciprocity	Choice of classmates	$RC_a = \frac{2\sum_{a\neq b}\min[c_{ab},c_{ba}]}{\text{degree}(a)}$
Reciprocated Stars weight	Unconstrained social reciprocity	Stars + choice	$RS_a = \frac{2\sum_{a\neq b}\min[s_{ab},s_{ba}]}{\text{weighted degree}(a)}$
PageRank Centrality	Social rank	Stars + choice	$PR_a = \frac{1-\delta}{n} + \delta\sum_{b\in M(a)}\frac{PR(b)}{\text{out links}}$
Betweenness Centrality	Intermediary Role	Choice	$\text{Betw}_a = \sum_{m\neq a\neq l}\frac{\sigma_{ml}(a)}{\sigma_{ml}}$
Closeness Centrality	Communication flow	Choice	$\text{Clo}_a = \frac{1}{\sum_{b\neq a} d(a,b)}$

Table 3–2 Summary of network measures. We represent game interactions as a network, where C_{ab} is a binary variable indicating student a chose b and S_{ab} indicates stars allocated (0 to 15). n is the number of students in their class. From these interactions, we calculate different network measures to account for interactions between students. In page rank centrality, δ represents a damping factor (0.85), in closeness $d(a,b)$ is the shortest path between a and b (geodesic distance).

Statistical Models

We employed regression models to estimate the association between SEN, particularly ASD, and network centrality and reciprocity metrics. Considering that not all observed outcomes are necessarily a consequence of diagnosed conditions, estimated coefficients in multiple regression models could be biased. To mitigate these concerns, we statistically isolated the influence of SEN on students' centrality scores and reciprocity metrics by controlling for individual characteristics and incorporating fixed effects in the regression models that account for observed and unobserved characteristics within groups.

The base model for the number of times a student a is chosen by their classmates in class j (C_{aj}) and received stars (S_{aj}) were:

$$C_a = \sum_{a \neq b} c_{ab} = \beta_0 + \beta_1 \text{SEN}_{aj} + \gamma' \mathbf{X}_{aj} + \mu_j + \epsilon_{aj} \tag{8}$$

$$S_a = \sum_{a \neq b} s_{ab} = \beta_0 + \beta_1 \text{SEN}_{aj} + \gamma' \mathbf{X}_{aj} + \mu_j + \epsilon_{aj} \tag{9}$$

where SEN_{aj} is a binary variable indicating if a student is identified as having SEN, $\mathbf{X}_{aj}$ is a vector of control variables including attendance, grades, and whether the student was active in the game (present on the day of the experiment and a sender of choices and stars). μ_j is the class-level fixed effect accounting for average constant effects in each classroom (e.g., class size, school, head teacher), and ϵ_{aj} is the random error.

Additionally, we distinguished students with SEN by categorizing them into students with SEN that have a diagnosis of ASD and students with SEN without ASD using two indicator variables: SEN(excl ASD) is a Boolean regressor that takes the value 1 if a student is identified as having SEN excluding students with ASD, and ASD indicates students with that diagnosis.

$$C_a = \sum_{a \neq b} c_{ab} = \beta_0 + \beta_1 \text{SEN(excl ASD)}_{aj} + \beta_2 \text{ASD}_{aj} + \gamma' \mathbf{X}_{aj} + \mu_j + \epsilon_{aj} \tag{10}$$

$$S_a = \sum_{a \neq b} s_{ab} = \beta_0 + \beta_1 \text{SEN(excl ASD)}_{aj} + \beta_2 \text{ASD}_{aj} + \gamma' \mathbf{X}_{aj} + \mu_j + \epsilon_{aj} \tag{11}$$

For reciprocity, we first employed a similar fixed effects (FE) ordinary least squares (OLS) approach to estimate the impact of SEN category on the reciprocity of exchanges. This involves analyzing mutual exchanges within the network to understand how SEN affects the likelihood of reciprocal relationships.

$$RC_a = \beta_0 + \beta_1 \text{SEN} + \gamma' \mathbf{X}_{aj} + \mu_j + \epsilon_{aj} \tag{12}$$

$$RC_a = \beta_0 + \beta_1 \text{SEN(excl ASD)}_{aj} + \beta_2 \text{ASD}_{aj} + \gamma' \mathbf{X}_{aj} + \mu_j + \epsilon_{aj} \tag{13}$$

We employed a similar approach for measuring the association between SEN category and reciprocity in the weighted network:

$$RS_a = \beta_0 + \beta_1 \text{SEN} + \gamma' \mathbf{X}_{aj} + \mu_j + \epsilon_{aj} \tag{14}$$

$$RS_a = \beta_0 + \beta_1 \text{SEN(excl ASD)}_{aj} + \beta_2 \text{ASD}_{aj} + \gamma' \mathbf{X}_{aj} + \mu_j + \epsilon_{aj} \tag{15}$$

Finally, to fine-tune our analyses, we observed the dyadic level exchange patterns, particularly focusing on whether the probability of a reciprocal choice is associated with any diagnostic condition.

$$P(C_{ab} = C_{ba} = 1)_j = \beta_0 + \beta_1 \text{SEN(excl ASD)}_{aj} + \beta_2 \text{ASD}_{aj} + \alpha_a + \mu_j + \epsilon_{aj} \tag{16}$$

Where $P(C_{ab} = C_{ba} = 1)_j$ represents the probability that there is a mutual choice between student a and student b in class j. This means that student a chooses student b and student b chooses student a. The model includes the diagnostic of the receiving student b as the main explanatory variable, distinguishing between SEN excluding ASD and ASD. The fixed effects at the sender level a and at the class level j are included to control for individual sender characteristics and class-level effects, respectively.

Cluster Analysis

With the aim to identify and analyze the social profiles among students with ASD, we employed k-means [41] clustering to describe and categorize the social interaction patterns of children with ASD, focusing on key network centrality measures.

We normalized PageRank centrality, betweenness centrality, and closeness centrality to ensure comparability. The k-means algorithm was then applied to partition the students into distinct clusters based on their network positions, providing insights into their diverse exchange patterns and social dynamics within neurodiverse classrooms.

3.3 Results

3.3.1 Game social network centralities

Before exploring how students with and without SEN interact within their peer groups, we first evaluated how well the social network centralities derived from our game reflect the students' declared social preferences. We analyzed the correlation between game-derived centrality measures and peer nominations across all students.

The results showed a positive association between the standardized choice in-degree and standardized stars in-strength and the willingness of the child to hang out with and be friends with certain classmates (Figure 3–3, left upper and lower boxes, and right upper and lower boxes, respectively). Conversely, a negative correlation was observed between these centrality measures and students' reluctance to socialize with and befriend specific classmates (Figure 3–3, middle upper, and lower boxes). These findings suggest an association between a student's social position within the peer group, and their interpersonal behaviors and preferences, irrespective of the diagnostic.

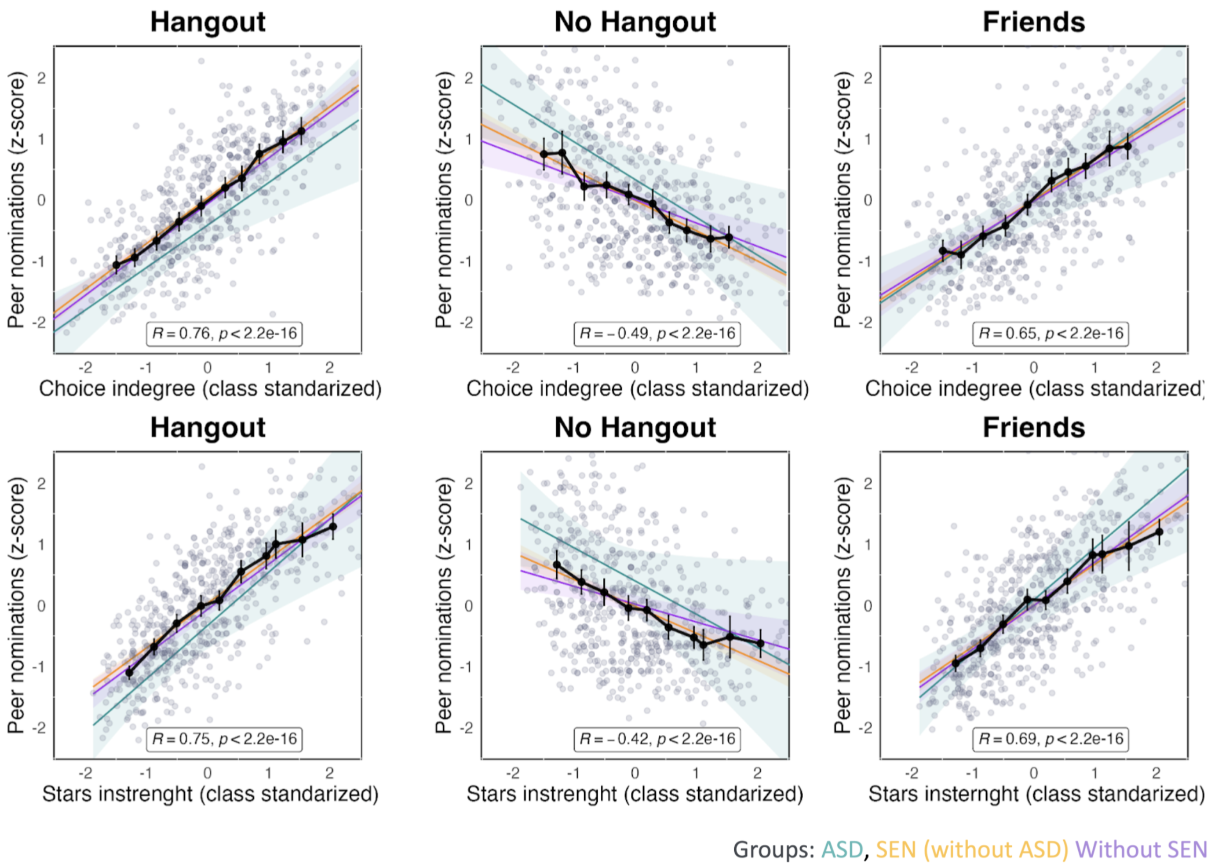


Figure 3–3 Correlations between peers' nominations and centrality measures among groups of students. The upper panel depicts the correlation between peer nominations and standardized choice in-degree (z-score), while the lower panel shows the correlation with standardized stars in-strength (z-score). A linear regression line shown in green for the group of children with ASD, in orange for the group of children with SEN excluding ASD, and tin purple for the group of children without SEN. The line in black depicts the linear regression line for the mean, with error bars showing the standard error of the mean and a 95% confidence interval for the estimation. The Pearson correlation coefficient and p-value are indicated in the black box for all students.

3.3.2 Social positioning of children with SEN and ASD

In order to comprehensively examine a child's position within their group of peers, we analyzed centrality measures based on the choices and star allocations received during the game, examining variations among children with SEN, ASD, and those without SEN.

Our results found that, compared to children without SEN, students with SEN (excluding ASD) consistently showed significantly lower centrality scores. Specifically, their average in-degree centrality was lower (Wilcoxon test, p = 0.0012) in the choice network and in-strength centrality was reduced (Wilcoxon test, p = 0.0029) in the star network. Children with ASD, in contrast, showed even larger differences in centrality; they had significantly lower in-degree centrality and in-strength centrality than both their peers with SEN excluding ASD (in-degree Wilcoxon test, p = 0.013; in-strength Wilcoxon test, p = 0.0095) and children without SEN (in-degree Wilcoxon test, p = 0.0003; in-strength Wilcoxon test, p = 0.00028). These results remain consistent even after standardizing the data by class (Figure 4). This suggests that the observed patterns and trends are robust and not influenced by variations in the data due to class-specific factors.

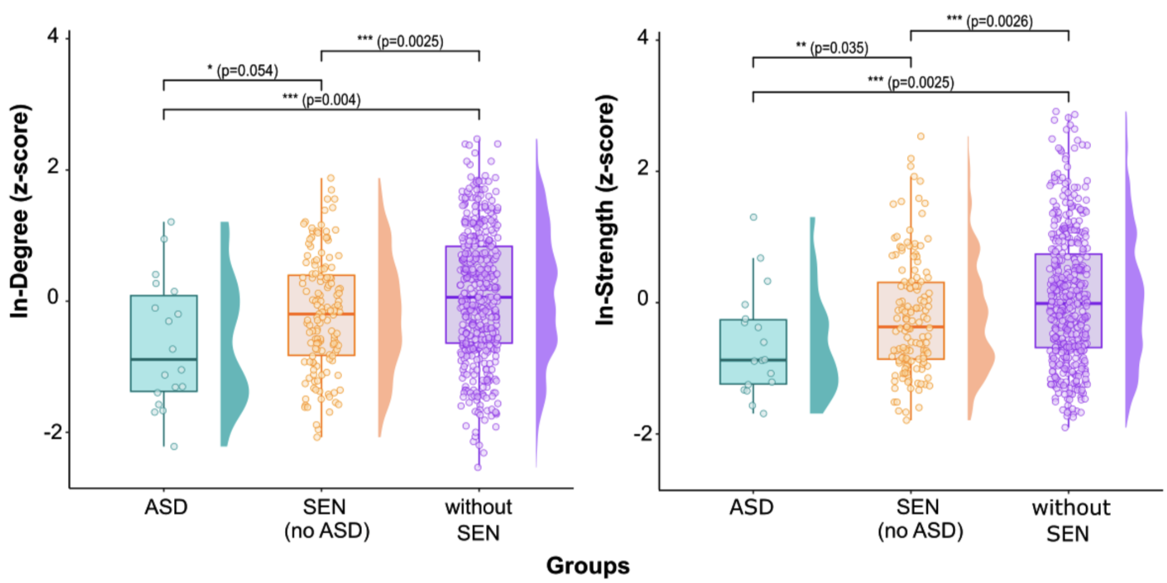


Figure 3–4 Centrality measures among groups of students. Figure shows the standardized in-degree and in-strength centrality measures. Left plot displays the selections received for the students. Right plot illustrates the stars that children received from their classmates. Each circle represents one student. Green circles represent children with ASD, orange circles represent the group of children with SEN excluding ASD, and purple circles represent the group of children without SEN. We show pairwise Wilcoxon test p-values results. Abbreviations: ASD = Autism Spectrum Disorder, SEN = Special Educational Needs. * p < 0.1, ** p < 0.05, *** p < 0.01.

To quantify the association between children's centrality within their peer groups and their diagnostics, we estimated fixed-effects linear regression models according to equations (1) to (4), summarized in Table 3–3. Our analysis showed that students with SEN, particularly those with ASD, consistently exhibited lower centrality, and received fewer choices and stars from classmates across both networks. Specifically, students with ASD received between 0.679 to 1.177 standard deviations less than the students without SEN, with significance at a 1% level for all models. This difference remains robust after adjusting for factors potentially affecting social interactions, such as active participation in the game, class attendance, grades, and the specific classroom to which a student belongs. Notably, attendance data was available for 577 of the 625 participants, and grade data for 455. Additionally, the included classroom fixed effects accounts for characteristics that are constant within each group, such as the average level of interaction in the game, the head teacher's influence, and the overall class social environment. Since in Chile, school selection is highly correlated with income and geographical location, these fixed effects also control for these factors.

Group	**Choice Network**				**Stars Network**			
	In-degree (times chosen)		Standardized in-degree (z-score)		In-strength (received stars)		Standardized in-strength (z-score)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SEN (excluding ASD)	-1.171***	-0.782	-0.293***	-0.196	-2.063**	-1.691	-0.269***	-0.234*
	(0.407)	(0.554)	(0.102)	(0.139)	(0.804)	(1.056)	(0.105)	(0.121)
ASD	-2.827***	-4.699***	-0.708***	-1.177***	-5.210***	-9.882***	-0.679***	-0.785***
	(0.998)	(1.393)	(0.250)	(0.349)	(1.697)	(2.821)	(0.221)	(0.235)
Active player	2.409***	1.507*	0.604***	0.378*	4.225***	1.806	0.551***	0.350*
	(0.490)	(0.825)	(0.123)	(0.207)	(0.846)	(1.541)	(0.110)	(0.130)
Attendance	0.017	0.014	0.004	0.003	0.032	0.012**	0.012***	0.007
	(0.014)	(0.021)	(0.003)	(0.004)	(0.027)	(0.003)	(0.003)	(0.003)
Grades	1.696***	0.425***	3.293***	0.425***				
	(0.443)	(0.111)	(0.739)	(0.111)				
Observations	625	625	625	625	455	455	577	577
R^2	0.162	0.233	0.162	0.233	0.117	0.091	0.157	0.117
Adjusted R^2	0.123	0.192	0.128	0.192	0.076	0.147	0.117	0.117

Table 3–3 Linear regression models for centrality network measures. Columns (1) through (4) depict the estimated linear regression model coefficients for the total number of times a student was chosen by their classmates, while columns (5) through (8) show the estimation for the total number of stars received by a student from their classmates. Columns (3) and (4) display the standardized coefficients corresponding to the unstandardized coefficients in columns (1) and (2), while columns (7) and (8) show the standardized coefficients corresponding to columns (5) and (6), respectively. These models include classroom fixed effects and progressively add relevant controls. Classroom-level cluster robust standard errors are shown in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

Columns (1) and (2) display the estimated models for the number of times a student was chosen by their classmates (in-degree), indicating a significant association between having a condition of SEN and students' centrality. Specifically, students with SEN, excluding those with ASD, were selected 1.2 times fewer on average (column (1), $p < 0.01$) than those without SEN. The effect was more pronounced for students with ASD, who were chosen 2.8 times fewer (column (1), $p < 0.01$) compared to peers without SEN. The negative impact of ASD on social standing becomes even larger in column (2), where ASD students were chosen 4.7 times fewer ($p < 0.01$) after adding controls for grades and attendance. The standardized coefficients for these measures are presented in columns (3) and (4), allowing comparing magnitude across models.

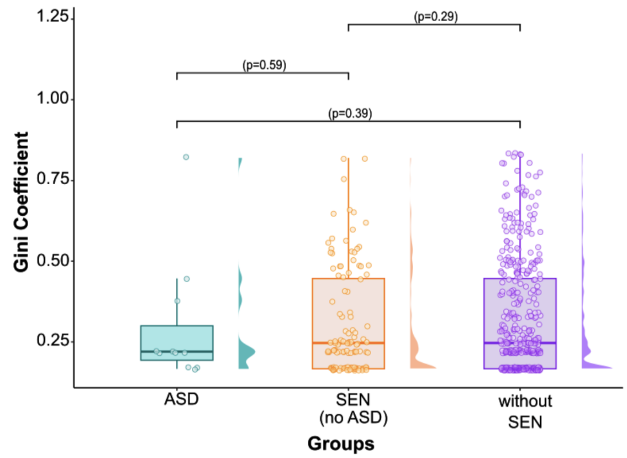
Columns (5) and (6) present the estimated coefficients for the total number of stars received by a student from their classmates (in-strength), and columns (7) and (8) are the standardized coefficients for these models. Similar to the in-degree centrality results, having a SEN condition is associated with receiving significantly fewer stars. When breaking down SEN condition into excluding ASD and ASD, we observed that students with SEN (excluding ASD) received 2.1 fewer stars (column (5), $p < 0.05$), and students with ASD received 5.2 fewer stars (column (5), $p < 0.01$) in average compared to those without SEN. This pattern remains consistent after adding controls for grades and attendance, underscoring the significant negative association between ASD condition and the number of stars received from classmates.

Regarding the control variables, active participation was positively associated with both choice and star centrality. The coefficients for active players were significant across most models, indicating that being present and actively participating in the game correlates with peer preference. Additionally, attendance and grades also play significant roles in determining students' centrality and the number of stars received, as seen in columns (2), (4), (6), and (8). In sum, statistical model results robustly showed that students with ASD were significantly less central than their classmates. Furthermore, decomposing SEN into SEN (excluding ASD) and ASD shows that the overall average negative association is driven by larger negative coefficients for ASD and smaller negative coefficients for other SEN. These associations are consistent across various models and control conditions. The inclusion of classroom fixed effects helps account for unobserved class-level characteristics, further strengthening the reliability of these findings.

3.3.3 Stars Distribution Profiles

We questioned whether the observed differences in in-strength coefficients among groups could be associated with a tailored star distribution profile for certain groups of children. To investigate this, we compared the concentration of stars allocated to children without SEN, children with SEN excluding ASD, and children with ASD. Using the Gini coefficient [42], a measure of inequality in distribution, we examined how concentrated or dispersed the star distributions were for each group. The value of the Gini coefficient ranges between 0 and 1, where a value of 0 indicates perfect equality and a value of 1 indicates maximum inequality. In the context of our game, a higher Gini coefficient indicates a greater concentration of stars, suggesting a preference for closer, more selective relationships. Conversely, a lower Gini coefficient reflects a more equitable distribution, indicating an effort to maintain fair relationships with a broader group. We found that overall, children tended to privilege more equitable distributions of stars, with an average Gini coefficient of 0.33, indicating high equity. While there was some variation within the different groups, we did not find any significant differences in the distribution patterns among the groups of children (Figure 3–5-A). This suggests that, in general, children adopted similar strategies in distributing their stars, favoring a balanced approach to maintaining social relationships. These results remain consistent after controlling the data by class (Figure 3–5-B).

A)



B)

Group	Gini coefficient
SEN (excluding ASD)	-0.024 (0.017)
ASD	-0.039 (0.036)
observations	530
R^2	0.105
Adjusted R^2	0.057

Figure 3–5 Stars distribution profiles. A) The plot shows the distribution of stars among the different groups of children. Each circle represents one student. Green circles represent children with ASD, orange circles represent the group of children with SEN excluding ASD, and purple children without SEN. We show pairwise Wilcoxon test p-values results. B) Linear regression model for Gini coefficient. This model includes classroom fixed effects. Classroom-level cluster robust standard errors are shown in parentheses.

3.3.4 Reciprocity patterns

To comprehensively assess the mutual social dynamics among different groups of children, we estimated reciprocal measures that shed light on their engagement in bidirectional relationships with their peers. This approach allows us to understand the extent of mutual preferences and interactions within the classroom. The analysis of reciprocated choices among different groups of children revealed that children with ASD engaged significantly less in reciprocal relationships compared to both their peers with SEN excluding ASD ($\chi^2(1) = 10.78$, $p = 0.001$), and their peers without SEN ($\chi^2(1) = 14.87$, $p = 0.00012$). However, children with SEN, excluding ASD, showed a non-significant tendency to have fewer reciprocal relationships compared to students without SEN ($\chi^2(1) = 2.77$, $p = 0.095$) (Figure 3–6).

As with the centrality measures, we implemented fixed-effects linear regression models to quantify the association between children's reciprocated choice scores and their diagnos-

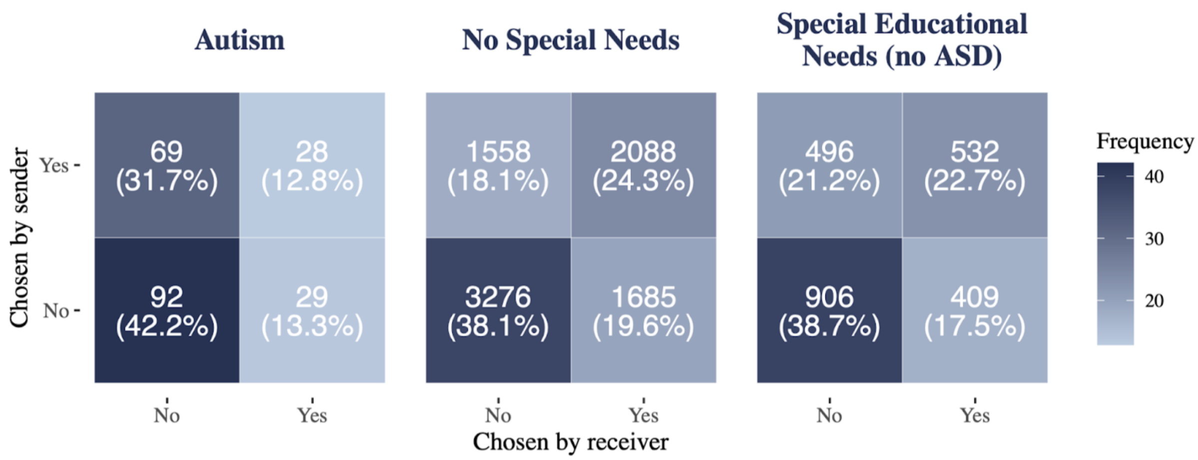


Figure 3–6 Distribution of reciprocated choices by groups of senders. In each group of students, boxes show reciprocity between senders and receivers. The upper-left box depicts the number of interactions in which the sender chooses a receiver, but the receiver does not reciprocate that selection. The bottom-right box shows an interaction in which the sender does not choose a receiver, but the receiver does choose the sender. The bottom-left box illustrates a reciprocal interaction in which neither the sender nor the receiver selects each other, while the upper-right box depicts a reciprocal interaction in which both the sender and the receiver choose each other. Chi-square test comparing categories available in Supplementary Table C–2

tic group (equation (6), Table 3–4). We controlled for participants' overall attendance and school grades and included classroom fixed effects (see the Centrality Results and Statistical Models sections for details). To ensure that a student's choice could be reciprocal, both the student making the choice and their chosen peer needed to be active participants in the game. Therefore, this analysis only includes "active players," reducing the sample size to 530.

Overall, statistical models robustly show that students with ASD engaged in fewer reciprocal exchanges compared to students without SEN. The estimated difference ranges between 1 (column (4), $p < 0.01$) to 1.3 (column (6), $p < 0.01$) standard deviation, with and without controlling for attendance and grades, respectively. Students with SEN, excluding ASD, also engaged in fewer reciprocal exchanges compared to students without SEN. This effect is smaller in magnitude and less robust than for children with ASD. Ranging between 0.2 (column (4), $p < 0.05$) and 0.07 (column (6)) standard deviations, after controlling for

Group	Reciprocated Score (reciprocated choice ratio)			Standardized Reciprocated Score (z-score)		
	(1)	(2)	(3)	(4)	(5)	(6)
SEN (excluding ASD)	-0.038**	-0.026*	-0.015	-0.191**	-0.132*	-0.074
	(0.014)	(0.015)	(0.014)	(0.042)	(0.077)	(0.071)
ASD	-0.190***	-0.209***	-0.261***	-0.950***	-1.045***	-1.307***
	(0.051)	(0.057)	(0.072)	(0.253)	(0.286)	(0.363)
Attendance	0.002***	0.001	0.001	0.012***	0.012***	0.007**
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.005)
Grades		0.055***			0.275***	
		(0.019)			(0.094)	
Observations	530	492	409	530	492	409
R^2	0.359	0.273	0.284	0.359	0.273	0.284
Adjusted R^2	0.324	0.234	0.244	0.324	0.234	0.244

Table 3–4 Linear regression models for the ratio of reciprocated choices. Columns (1) through (3) depict the estimated linear regression models for the reciprocated choice score number of times a student was involved in a mutual selection with their classmates. Columns (4) through (6) show the estimation with the relevant variables standardized in columns (1) to (3). These models include classroom fixed effects and progressively add relevant controls. Classroom-level cluster robust standard errors are shown in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

grades, is no longer significant. This statistical trend persisted when analyzing reciprocity in the stars allocation network. In this case, students with ASD engaged significantly less in reciprocated exchanges than students without SEN and with SEN excluding ASD, even after accounting for attendance, grades, and classroom fixed effects. The magnitude of the effect ranges from 0.618 to 1.153 standard deviations, with statistical significance at 10% and 5%, respectively (See Supplementary Table C.3.2). For students with SEN but not ASD, while the coefficients were negative, they were not statistically significant for any model.

To further investigate whether the observed tendency of fewer reciprocal choices in the group of students with SEN, and especially those with ASD, could be associated with a specific pattern of choices either from the sender, the receiver, or both, we conducted a dyadic-level analysis. We focused on determining whether the likelihood of a reciprocal choice was associated with the diagnostic condition (Table 3–5).

Group of Receivers	Probability of Reciprocated Choice			Probability of Mutually Non Reciprocated Choice		
	(1)	(2)	(3)	(4)	(5)	(6)
SEN (excluding ASD)	-0.064***	0.048**	0.094	0.045***	-0.002	-0.070
	(0.011)	(0.023)	(0.070)	(0.013)	(0.030)	(0.067)
ASD	-0.166***	0.017	0.348	0.112***	-0.001	-0.337***
	(0.024)	(0.067)	(0.024)	(0.039)	(0.079)	(0.094)
Group of senders Without SEN SEN (No ASD)	8,607	2,343	218	8,607	2,343	218
Observations (pairs)	8,607	2,343	218	8,607	2,343	218
$\mathbf{R^2}$	0.133	0.131	0.137	0.103	0.102	0.091
Adjusted $\mathbf{R^2}$	0.090	0.086	0.086	0.060	0.055	0.038

Table 3–5 Linear regression models for reciprocity at the dyadic level. Columns (1) through (3) describe the estimated coefficients for the probability of a pair of students choosing each other in the game, considering different combinations of senders and receivers. Columns (4) to (6) present the estimated coefficients for the probability that two students mutually don't select each other. These models include sender and classroom fixed effects. Classroom-level cluster robust standard errors are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

First, we examined the likelihood of reciprocated choices between pairs of students, taking into account the SEN condition of both senders and receivers. We found that pairs of students in which the sender did not have a SEN condition and the receiver did have a SEN condition (excluding ASD) were 6% less likely to reciprocate choices compared to pairs of students in which the receiver did not have a SEN condition (column (1), $p < 0.01$). For pairs of children involving receivers with ASD condition, the likelihood to reciprocate choices decreased further by 17% (column (1), $p < 0.01$). We then explored mutual non-selection, a distinct aspect of reciprocity in which neither student chooses the other. The results showed that when the sender was a student without SEN and the receiver was a student with SEN (excluding ASD), there was a 5% higher probability of mutual non-selection occurring (column (4), $p < 0.01$). Moreover, when the receiver was a student with ASD, the likelihood increased by 11%, compared to pairs of students without SEN (column (4), $p < 0.01$). Interestingly, these trends do not hold statistically when both the sender and receiver are children with a SEN condition or ASD (columns (3), (5), and (6)). Furthermore, the statistical trend reverses when the receiver and the sender are both children with ASD (column (8)). Nevertheless, this result should be interpreted with caution due to the very small sample size in this model. The adjusted R^2 of 0.038 indicates limited explanatory power and predictive accuracy of the estimation. In sum, these results indicate that the SEN condition, particularly the ASD condition, consistently engages in less reciprocal exchanges and is associated with a lower likelihood of reciprocal choices among pairs of students. The results are robust for ASD, and less robust for other SEN.

3.3.5 Characteristics of students with ASD. Clustering analysis.

Finally, to gain deeper insights into the social interactions and integration of children with ASD in our sample, we conducted a cluster analysis to further characterize them, using centrality measures of PageRank, Betweenness, and Closeness. PageRank centrality assesses the overall influence and importance of each child within the network. This measure helps us understand which children are most frequently chosen or referenced by their peers, indicating their central role in the social structure. Betweenness centrality evaluates how often a child serves as a bridge between different groups. High betweenness centrality suggests that the child plays a crucial role in connecting various subgroups within the network, highlighting their importance in maintaining network cohesion. Closeness centrality determines how quickly a child can connect with all other network members. This metric indicates how efficiently a child can interact or reach out to their peers, reflecting their potential to spread information or influence rapidly. To explore the heterogeneity within the group of children with ASD based on these centrality measures, we identified three distinct clusters (Figure 3–7). Cluster 1 includes three children who exhibit high PageRank and Closeness centrality, indicating they are popular and can quickly connect with others in the network. Cluster 2 comprises four children with high Betweenness centrality, suggesting they act as key connectors or bridges between different groups within the network. Finally, cluster 3 consists of 11 children with low evaluations across all centrality measures, indicating a less central and potentially more isolated position within the network.

	Cluster characteristics			
Cluster	Number children	PageRank (mean ± SD)	Closeness (mean ± SD)	Betweenness (mean ± SD)
1	3	0.797 ± 0176	0.768 ± 0.209	0.170 ± 0.223
2	4	0.241 ± 0.176	0.452 ± 0.122	0.644 ± 0.269
3	11	0.126 ± 0.114	0.268 ± 0.195	0.037 ± 0.066

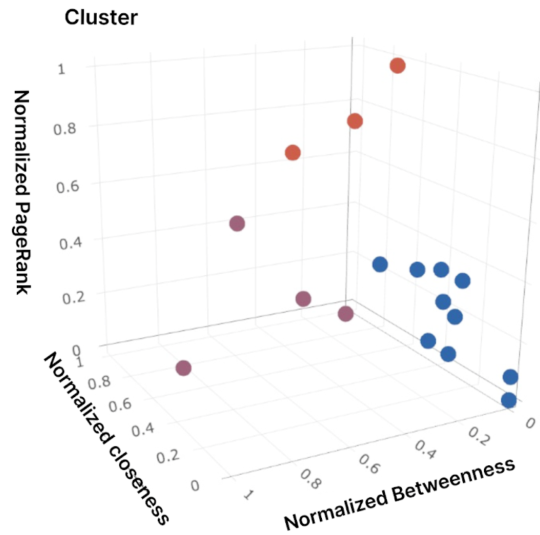


Figure 3–7 Cluster analysis of children with ASD. The figure depicts the clustering results of children with ASD based on centrality measures. Each circle represents one student. Orange circles depict children with ASD in Cluster 1, dark pink circles represent children with ASD in Cluster 2, and blue circles show children with ASD in Cluster 3.

In particular, although all the clusters included girls and boys, cluster 3 included only one girl from the 11 children that comprise it. Interestingly, this girl showed the highest Betweenness score within the cluster, which led us to question whether this feature could be similar to the girls in the other clusters. We address this question by comparing the Betweenness score between girls and boys irrespective of the cluster to which they belong. A non-parametric Wilcoxon rank-sum test showed that overall, girls with ASD had significantly higher Betweenness scores compared to boys with ASD ($p = 0.022$). Conversely, neither Closeness scores nor PageRank measures showed any statistical difference between sexes (Wilcoxon test, $p = 0.5571$ and $p = 0.2196$, respectively).

In addition, we examined these centrality measures for children with SEN (excluding those with ASD) and for children without SEN. In the case of the former, there was no statistically significant difference between sexes in PageRank (Wilcoxon test, $p = 0.7218$) and Closeness (Wilcoxon test, $p = 0.2565$) scores. However, in contrast to the group of children with ASD, the non-parametric Wilcoxon rank-sum test showed that overall, girls with SEN had significantly lower Betweenness scores compared to boys with SEN ($p = 0.02$). For children without SEN there was no statistically significant difference between sexes in PageRank (Wilcoxon test, $p = 0.9555$), Closeness (Wilcoxon test, $p = 0.9176$), or Betweenness (Wilcoxon test, $p = 0.5006$).

Taken together, these results underscore the complexity of interpreting Betweenness, which can denote both a central 'bridge' and a position on the periphery within clusters, highlighting the nuanced roles of individual nodes in network dynamics.

3.4 Discussion

In this study, we explored the role of certain neurodevelopmental conditions, such as ASD, in forming social interaction networks in elementary classrooms. We tested the hypotheses that compared to children without ASD, children with ASD are more frequently located on the periphery in the social network of their peer group, and that compared to children without ASD, children with ASD engage less in reciprocal relationships. We identified and analyzed both centrality and reciprocity measures by analyzing an experimental computational game designed to be played by children in the schools. The results obtained revealed distinct patterns related to the SEN condition of each child.

In line with our hypothesis, our results showed that children with SEN, particularly those with ASD, exhibited a lower degree of centrality compared to children without SEN. This means they were less frequently chosen and received fewer stars from their peers, indicating lower social standing and integration within their classroom networks. The association between ASD and lower social standing remained consistent across different statistical models, highlighting the robustness of these findings. Importantly, our analysis evidenced that this statistical trend could not be attributed to a pattern of unequal distribution among the children. In this respect, the Gini coefficient revealed no significant differences in how stars were allocated among children with and without SEN. Considering that, overall, children tended to distribute stars equitably, the association between SEN—particularly in the case of ASD—and lower social standing highlights the vulnerable context of these students in social relationships. These results are consistent with previous findings, which indicate that children with ASD are vulnerable to peer difficulties due to their challenges in recognizing, acknowledging, and communicating about concerning social situations [18, 12, 13, 14, 15, 19, 20].

In addition to the factors that negatively correlate with centrality measures, we also identified several variables that positively influenced students' centrality and the number of stars received, both among students with SEN and those with ASD. In this regard, active participation evidenced that students who were actively engaged in choosing classmates and sending stars were more central and preferred by their peers. Attendance and grades also significantly influenced centrality and the number of stars received, suggesting that regular attendance and academic performance are important factors in peer acceptance and social standing. These results are in accordance with previous findings that have shown the relationship between social standing and academic achievement [39, 43, 44, 45]. This underscores the significant role that social integration and acceptance play in shaping academic outcomes for all students.

Concerning the analysis of reciprocity measures, our results showed that children with SEN, especially those with ASD, engaged less in reciprocal relationships compared to their peers without SEN and those with SEN excluding ASD. However, the statistical dyadic models explained a moderate portion of the variance in reciprocal exchanges. This indicates that while diagnostic conditions are significant factors, other variables also influence reciprocity in social dynamics within educational settings. Certainly, reciprocity is a complex social phenomenon. Children with ASD often experience significant challenges in establishing reciprocal relationships, largely due to difficulties with mentalization, or the ability to understand and attribute mental states—such as thoughts, desires, and intentions—to oneself and others [21, 22, 46, 8, 47, 7]. These challenges can lead to misunderstandings in social interactions and hinder the development of mutual, two-way relationships that are critical for meaningful social integration. Reciprocity in social interactions is essential as it forms the foundation of trust and cooperation, which are key components of social networks within educational settings [2, 3]. When children can engage in reciprocal exchanges, they are more likely to be accepted and integrated into their peer groups, which not only supports their emotional and social development but also contributes to a positive and inclusive classroom environment [48, 45, 49]. Therefore, fostering reciprocal relationships is a crucial step in promoting social integration for children with ASD, as it helps bridge the gap between these students and their peers, leading to a more cohesive and supportive educational community.

Regarding cluster analysis based on centrality measures, the identification of three different clusters of children with ASD with specific features in each cluster can shed light on the heterogeneity of ASD as well as the role that each child can play in social integration. These findings highlight the importance of recognizing the unique characteristics of each child within their social networks to develop comprehensive interventions. Additionally, sex differences were observed among the groups in the cluster analysis. While in the group of children with SEN (excluding ASD), girls had significantly lower Betweenness scores compared to boys, in children with ASD an opposite pattern was observed: girls with ASD exhibited significantly higher betweenness scores compared to boys with ASD. As we previously mentioned, this result should be interpreted with caution, because Betweenness could be understood as a child that is more likely to act as a bridge within the network or a position on the periphery of the network that facilitates the communication between different parts of the network. Conversely, among children with ASD, girls exhibited significantly higher Betweenness scores than boys. Noteworthy, among children without SEN, no significant sex differences were found in any of the centrality measures, suggesting a more uniform pattern of social integration regardless of sex.

It is now known that there are several behavioral differences between girls and boys with ASD that, combined with the tendency of females to effectively mask their autistic traits, makes it more challenging to accurately identify females as with an ASD diagnosis [50, 51, 52, 53, 54, 55, 56, 57]. Social camouflage has been defined as the implementation of strategies used to appear “less autistic” in social interactions and contexts [51, 58, 59]. Interestingly, recent evidence showed that girls with ASD exhibited higher reciprocity behaviors than boys with ASD despite their similar levels of autistic traits, revealing a “behavioral camouflaging” [59]. Based on these previous findings, the sex differences that we found in our clustering results could be revealing certain social strategies that girls might be using that are making them “bridges” between different parts of the network. However, since camouflage can be experienced as stressful, confusing, and energetically draining (Howe et al., 2023) [60], teachers and parents should be attentive to any signs of stress or emotional and academic difficulties, regardless of how socially integrated a child may appear to others.

In sum, the analysis of clusters underscores the complexity of the varied social dynamics and individual roles that children with ASD can have within their peer networks. Together with the results obtained in the analysis of centrality and betweenness measures, our results showed the heterogeneity in social integration and the distinct roles of children with ASD.

This study has limitations that should be considered when interpreting the findings. A larger sample of children with a confirmed diagnosis of ASD could improve the impact of our results. Although the approximately 3% of children with ASD in our sample aligns with prevalence studies [61, 62, 63, 64], it is more important to point out that not all classrooms included children with a confirmed diagnosis of ASD. Furthermore, the study's design prevented us from examining specific characteristics of the students with ASD, such as comorbidities and intellectual performance. Understanding these variables could provide valuable insights into group and dyadic dynamics, contributing to a more comprehensive understanding of social preferences.

Additionally, the context of the pandemic revealed significant challenges faced by schools, including inequities and barriers impacting teachers and, more importantly, students [65, 66]. These issues complicated lesson planning, learning assessment, and attendance recording, leading to incomplete data on grades and attendance for all participants. To address these challenges, we implemented classroom fixed effects and standardized the results, which demonstrated robust findings across models that support our analysis. However, it is crucial to acknowledge that social and cultural inequities and barriers affected all students, their families, and the broader educational community. These disparities not only hinder the ability of students to receive necessary support but also perpetuate cycles of disadvantage, potentially impacting their long-term educational and emotional outcomes.

Our findings contribute to the understanding of social interactions in educational contexts and foster the development of integration and coexistence policies that promote inclusive and supportive classroom environments for all students, particularly those with SEN and ASD. The achievement of an inclusive education is often challenged not only by cultural variables but also by the implementation of segregated educational systems, which undermine practices that promote an education without differences [2, 3, 30]. Merely placing students with ASD, as well as those without learning barriers or neurodevelopmental conditions, in inclusive classrooms without proper support not only could fail to foster their social skills development and peer relationships but also could increase the risk of experiencing victimization and difficulties [15]. This issue underscores the importance of providing disability awareness education for students, families, and for the entire school community. By fostering an inclusive environment that promotes understanding and acceptance, we can enhance social interactions for students with ASD and create a more supportive community for everyone, including teachers, children and their families. Ultimately, this collective effort can lead to richer social experiences and a greater sense of belonging for all individuals, regardless of their differences [2, 3, 25]. Our study points out the need for larger, more comprehensive studies with detailed information on participants' characteristics and educational outcomes. Future research should consider these limitations to provide a clearer understanding of the social dynamics and educational experiences not only of children with ASD, but also of all children.

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Conclusions

Though this doctoral reseearch, we explored the dynamics of cooperation, social hierarchy, and reciprocity within the context of primary education, focusing on how these social interactions influence academic performance and social integration, particularly for students with special educational needs (SEN) such as Autism Spectrum Disorder (ASD). Across three experimental studies, cooperative social networks in public school classrooms in Chile were analyzed through the implementation of game-theoretical tools, providing empirical evidence of how social relationships shape educational environments.

The first study suggested that reciprocal cooperation has a positive effect on academic performance, even after controlling for variables such as attendance, parental education, and prior GPA. These findings indicate that reciprocal cooperative relationships are a solid predictor of students' academic improvement, opening new possibilities for educational interventions that foster these types of interactions. From a methodological perspective, the study demonstrated how game-theoretical tools can overcome biases commonly associated with survey-based methods, providing a robust framework for analyzing social capital within school contexts.

The second study focused on how friendship moderates social hierarchies in cooperative interactions. The results indicated that, in the absence of friendship, students' interactions tend to follow hierarchical norms, with lower-status individuals deferring to higher-status peers. However, the presence of mutual friendships disrupted these hierarchies, promoting more egalitarian interactions. This finding underscores the crucial role that friendships play in creating more inclusive and equitable environments, suggesting that fostering friendship in classrooms can be a powerful tool for reducing hierarchical disparities and improving social cohesion.

The third study examined students with ASD and other SEN, finding that these students were more likely to occupy peripheral positions in classroom social networks and to engage less in reciprocal relationships. Children with ASD displayed significantly lower centrality compared to their peers without SEN, indicating less social integration. However, active participation and academic performance were found to positively influence students' centrality and peer acceptance, reinforcing the importance of these factors in promoting social standing for all students. This study highlights the need to foster reciprocal relationships and social integration for students with ASD to enhance their inclusion in the educational environment. Additionally, gender differences were observed in the analysis, with girls with ASD showing higher betweenness scores than boys, potentially related to social camouflaging behaviors.

Taken together, the findings of this thesis contribute to deepen our understanding of how social dynamics influence both academic performance and social integration in primary school students. The results highlight the importance of educational interventions that promote reciprocity and friendships, especially for students with SEN, such as those with ASD. Furthermore, this thesis introduces innovative methodological approaches that combine game-theoretical experiments with social network analysis, providing new tools for understanding and managing social dynamics in classrooms.

Finally, this research opens new avenues for future studies, emphasizing the need for longitudinal research to examine how these social dynamics evolve over time and how they can be influenced by specific interventions. It also underscores the necessity of educational policies that foster truly inclusive environments—ones that not only physically integrate students with ASD and SEN but also promote their effective social integration and emotional well-being.

Appendices

Appendix A

Supplementary Material for Chapter 1

A.1 Homophily analysis

A.1.1 Homophily Index for GPA

Our proposed approach for mapping the social capital network in elementary classrooms unveils the non-existence of homophily between students regarding GPA. We calculate the homophily index [1] as follow:

$$H_r = corr\left(G_i^r, \frac{1}{N^r}\sum_{j}^{N^r} G_j^r\right), \tag{A.1}$$

where G_{ir} represents the GPA of the ego student "i" and G_{jr} represents the GPA of the alter student "j". N indicates the number of students with whom the ego shares the same reciprocity level, r. The superindex r represents the level of reciprocity in the interaction. Those levels are: i) Low reciprocity (0.0) includes the interactions where egos and alters send fewer tokens than their average amount sent to the rest of their class. ii) Positive asymmetry (0.1) includes the interactions where alters send more tokens than their average sent tokens and egos send fewer tokens than their average sent amount, regarding their class. iii) Negative asymmetry (1.0) includes the interactions where egos send more tokens than their average sent tokens and alters send fewer tokens than their average sent amount, regarding their class. iv) High reciprocity (1.1) includes the interactions where egos and alters send more tokens than their average amount sent to the rest of their class.

Fig. A–1 shows that in the "Cooperation Network" most of the classes have Homophily Indexes non-significantly different from zero, with both GPA before and after measuring. This finding is interesting because it has been shown that GPA modulates social relationship in older students–High School, undergrads, and grad students–[2, 1, 3], however, here we provide evidence on this behavioral pattern does not manifest in elementary school students. Thus, interventions to promote and boost cooperative social relationships could be possible to improve academic performance, by exposing students with low GPA to the idea flow and information of the students with high GPA [4].

These results implies that cooperative interactions in children do not seem to be driven by academic homophily.

References:

[1] I. Smirnov and S. Thurner, “Formation of homophily in academic performance: Students change their friends rather than performance,” *PLOS ONE*, vol. 12, p. e0183473, aug 2017.

[2] V. Kassarnig, E. Mones, A. Bjerre-Nielsen, P. Sapiezynski, D. Dreyer Lassen, and S. Lehmann, “Academic performance and behavioral patterns,” *EPJ Data Science*, vol. 7, p. 10, dec 2018.

[3] C. Candia, S. Encarnação, and F. L. Pinheiro, “The higher education space: connecting degree programs from individuals’ choices,” *EPJ Data Science*, vol. 8, no. 1, p. 39, 2019.

[4] A. Pentland, *Social Physics: How Social Networks Can Make Us Smarter*. Penguin Books, 2015.

Table A–1 Homophily Index of Cooperation Networks on GPA before and after measuring, by Class

Class ID	Homophily Index GPA (Before)	Homophily Index GPA (After)
10	-0.1947	0.0042
11	-0.1993	-0.3993
12	0.2509	0.5652 **
13	-0.2539	-0.3811
14	0.8272 ***	0.7763 ***
15	0.5044	0.0851
16	-0.2429	-0.2542
17	-0.2446	-0.0952
18	0.0499	-0.2112
19	0.0986	-0.1119
20	-0.0348	0.0633
21	0.0708	0.1366
23	0.0893	0.5436 ***
24	-0.1848	0.2128
25	-0.311	-0.456 **
26	-0.0834	-0.3109
27	-0.1472	-0.1304
28	0.1729	0.462 **
29	-0.5273 **	-0.2093
30	-0.3425	-0.4028
31	-0.2936	0.1011
32	-0.2142	-0.1654
33	0.3756 *	-0.1863
34	-0.8316 ***	-0.2617
35	0.5746 *	-0.2938
38	-0.1215	0.2298
39	-0.2444	-0.48 *
40	0.3102	0.6662 ***
41	0.0607	0.1991
42	-0.5799 *	-0.3401
43	0.045	-0.4457
44	-0.1497	-0.0175
45	-0.09	-0.5937
46	-0.5 **	-0.305
47	-0.6942 *	-0.6366
48	-0.8405 **	-0.6899
49	-0.3657	-0.1622
50	0.2362	0.2207
51	-0.0339	-0.1241
52	0.2206	0.4032 *
55	-0.0127	0.0591
56	-0.0086	0.4444 *
57	-0.454 **	-0.3179
58	-0.1344	0.0492
59	0.1459	-0.5666 **

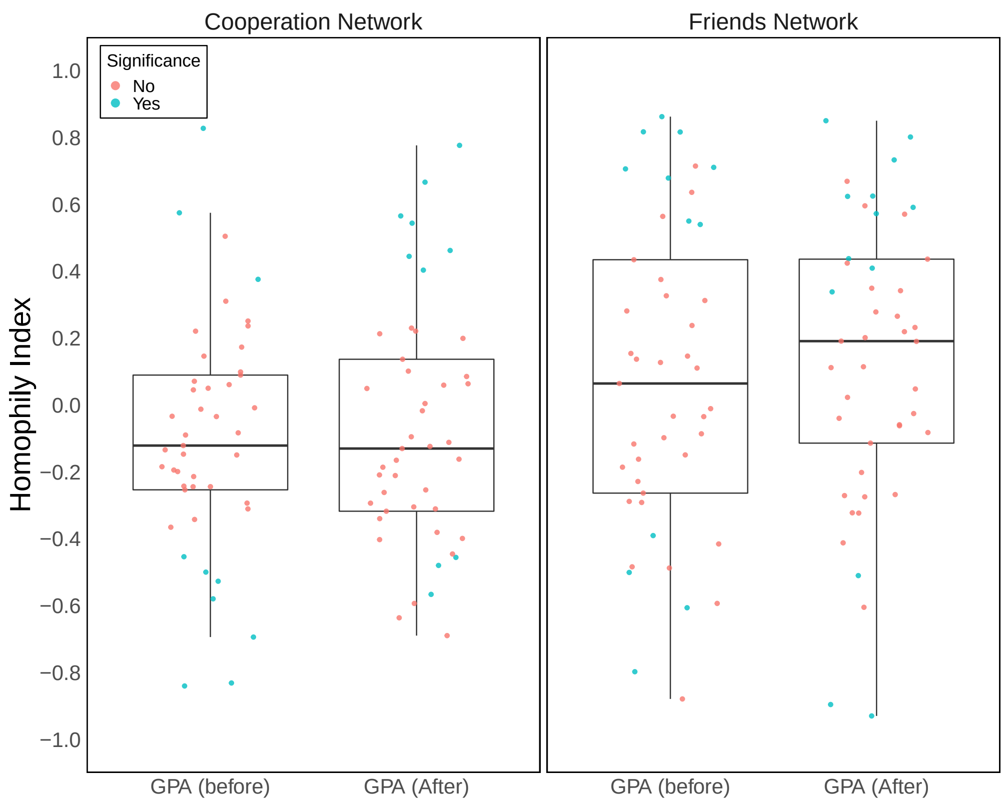

Figure A–1 Homophily index according to GPA in elementary school students. The homophily index for high reciprocity is non-significantly different from zero, which means that elementary students do not build their cooperative disposition based on the GPA of their peers. The significance is given by color, and it represents a p-value under 0.1. Most of the rest of the homophily coefficients are low if we compare them with the literature for older students [1], where the initial level of homophily is greater than 0.2 and evolves until 0.4.

A.2 Supplementary descriptives Tables

A.2.1 Classrooms descriptions

Table A–2 Class-level description.

Class ID	School ID	Age (Mean)	Age (SD)	Female (%)	Guardian education Secondary school completed (%)	GPA (Mean)	Class size	Attendance (Mean %)	Cooperation (Mean tokens)
1	1	10.03	0.57	57.6	48.5	6	33	89.3	3.97
2	2	9.09	0.51	41.7	45.8	6	24	91.9	5.59
3	2	10.17	0.51	53.3	56.7	5.9	30	90.2	4.76
4	2	10.87	0.66	43.5	56.5	5.9	23	89.2	4.39
5	3	9.15	0.99	30.8	30.8	5.7	13	89.2	6.09
6	3	9.05	0.77	56.2	50	5.6	16	93.3	5
7	3	10.39	0.9	39.1	34.8	5.8	23	91.6	4.86
8	3	10.91	0.7	33.3	50	5.7	18	93.7	4.3
9	3	11.46	1.3	52.6	52.6	5.2	19	88.9	7.14
10	4	9.17	0.64	37.5	50	6	8	94.6	7.23
11	4	10.01	0.95	42.9	28.6	6	7	97.5	4.88
12	4	11.06	0.77	42.9	38.1	6.1	21	88.9	5.1
13	5	10.05	0.72	55	30	6.6	20	90.3	5.04
14	5	10.18	0.78	58.8	35.3	6	17	91	4.21
15	5	11.22	0.63	50	30.8	5.8	26	93.7	3.54
16	6	9.41	1.05	66.7	55.6	5.9	9	92	6.25
17	6	10.3	0.95	33.3	50	5.5	12	88.3	5.92
18	6	11.66	2.56	35.7	64.3	5.8	14	89.6	4.06
19	7	9.17	0.74	73.3	26.7	6.1	15	95.2	4.38
20	7	10.3	0.84	47.6	28.6	6	21	95.3	5.9
21	7	11.24	0.73	33.3	44.4	5.8	18	94.4	4.63
22	8	9.2	0.64	46.2	43.6	5.7	39	89.8	5.08
23	8	10.11	0.64	63.6	42.4	5.9	33	92.4	4.06
24	8	11.12	0.55	48.4	45.2	5.4	31	91.2	4.34
25	9	8.98	0.63	100	44	6.2	25	88.8	6.78
26	9	9.87	0.76	100	35.7	6	14	83.7	5.32
27	9	10.73	0.65	100	50	6	14	89.4	5.31
28	10	9.07	0.92	36.4	22.7	5.7	22	86.8	3.79
29	10	9.38	1.12	61.5	30.8	5.7	13	91.3	7.22
30	10	10.12	0.59	45.5	22.7	5.8	22	85.2	3.48
31	10	10.35	0.95	50	22.7	5.6	22	84.6	4.05
32	10	11.44	1.08	53.6	25	5.7	28	88.3	3.79
33	11	8.8	0.52	0	50	5.7	14	90.7	6.81
34	11	10.3	0.43	0	75	6	12	94.3	3.92
35	11	11	0.67	0	50	6.2	10	94.2	3.09
36	12	9.47	0.83	58.3	25	5.8	12	90.8	5.59
37	12	10.2	0.88	20	30	5.6	10	87.9	4.39
38	12	11.65	1.11	35.3	47.1	5.5	17	89.3	3.2
39	13	9.92	0.5	100	69.2	6.1	26	94.2	3.62
40	13	9.97	0.49	100	38.9	5.8	18	91.8	4.67
41	13	9.8	0.61	100	70	6.2	20	94.8	5.29
42	14	8.91	0.61	100	72.2	6.3	18	96	5.33
43	14	8.97	0.69	100	50	6	18	91.6	5.6
44	14	10.04	0.56	100	63.2	6	19	91	5.11
45	14	11.7	1.64	100	73.3	6.2	15	96.2	4.09

A.2.2 Correlation Matrix

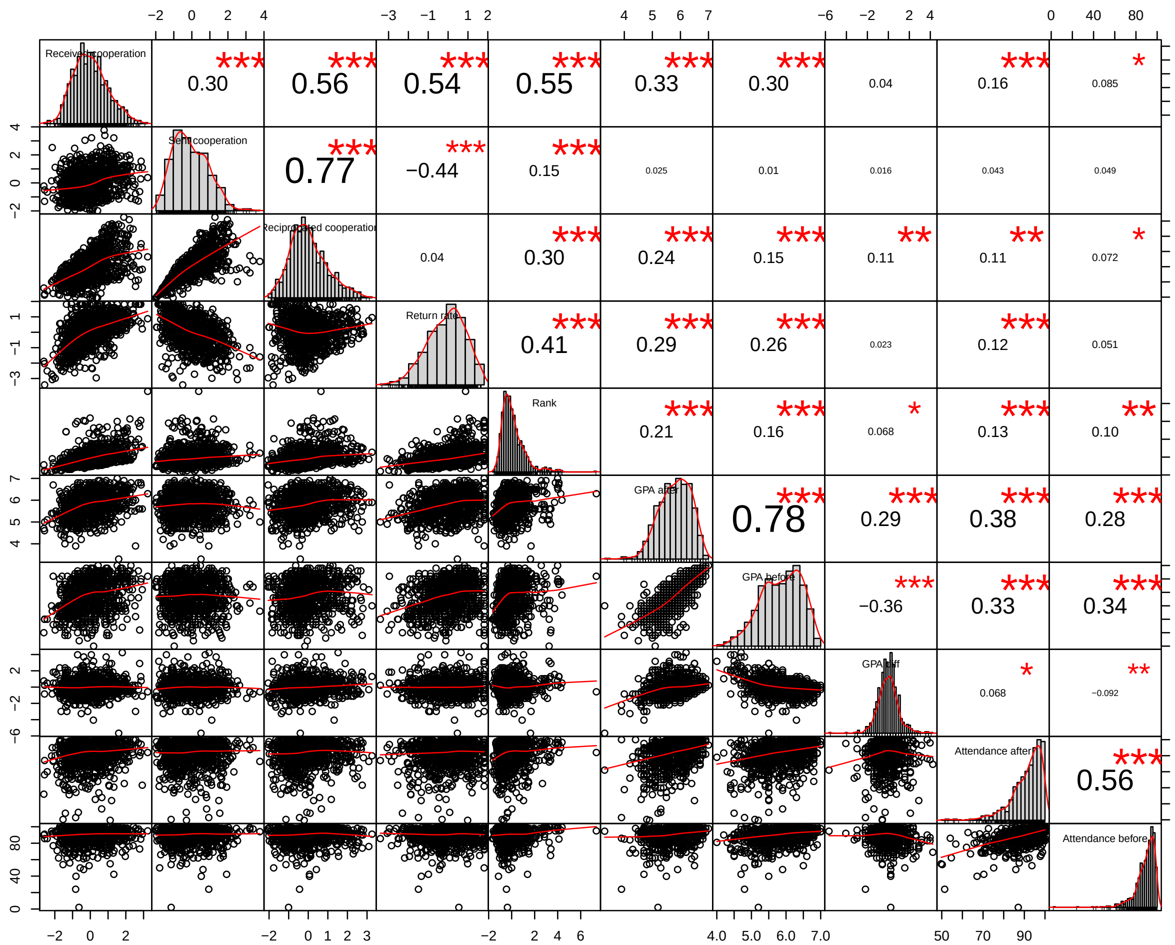

Figure A–2 Correlations between all collected, measured, and built variables.

A.2.3 Sent tokens by students

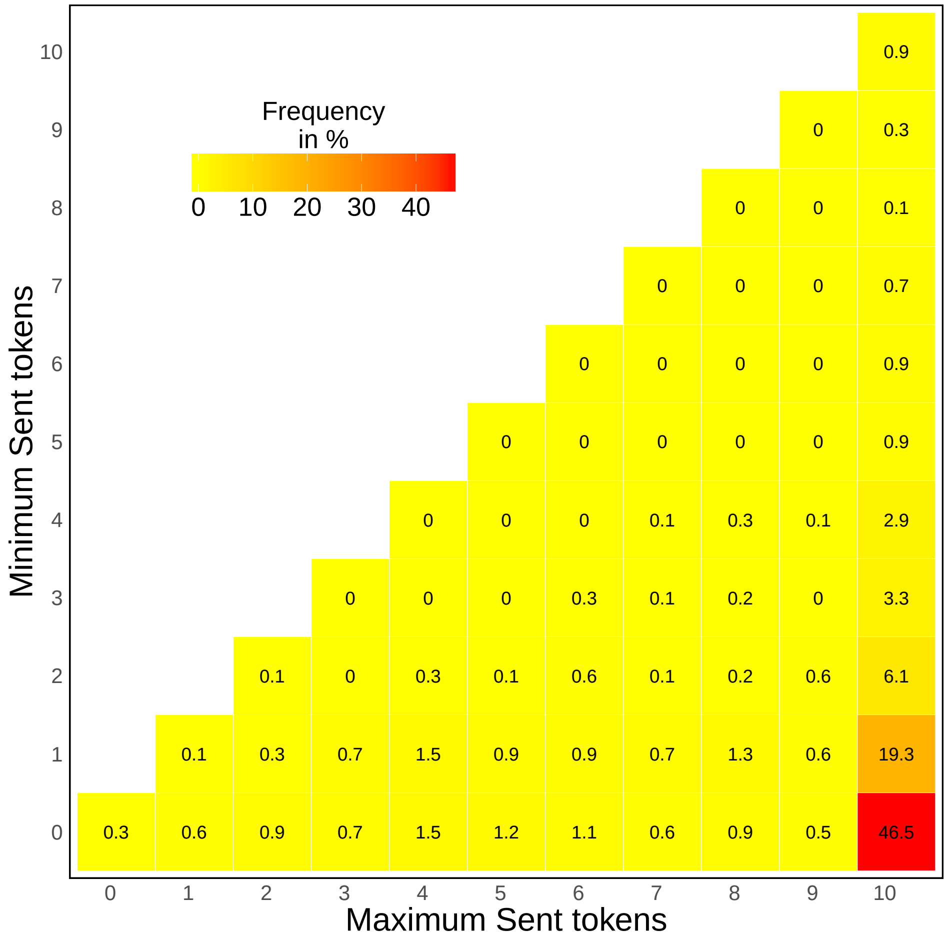

Figure A–3 Heatmap for maximum and minimum sending. At the bottom-right corner, we observe a cluster ($\approx 65\%$ of students, red/orange blocks) indicating that students send tokens in the whole range of possibilities. History between colleagues matters.

A.3 Robustness exploration

A.3.1 Explanatory Power of the Model

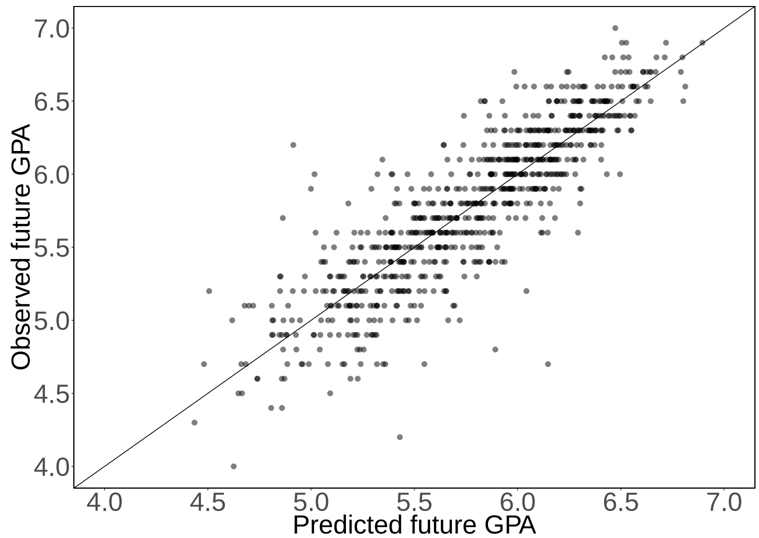

Figure A–4 Observed v/s predicted GPA (table 2 model 3)

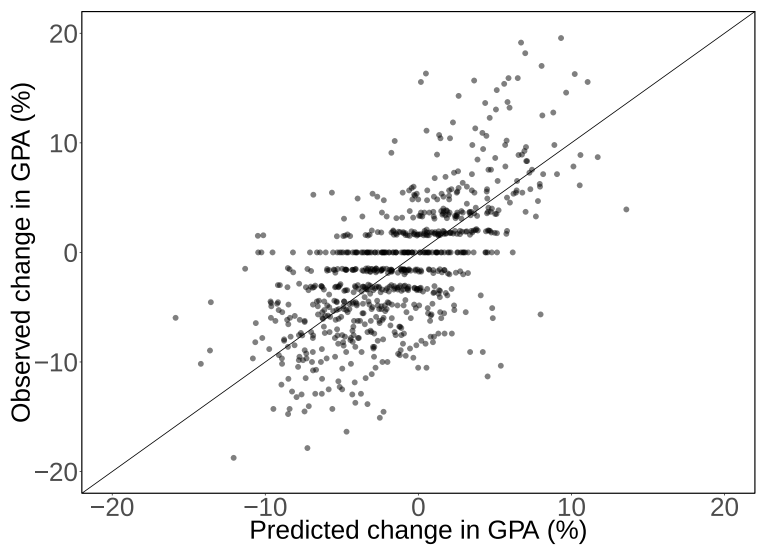

Figure A–5 Observed v/s predicted change in GPA

A.3.2 Reciprocity and confounders

	Dependent variable:						
	Reciprocity (z-score)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sent cooperation (z-score)	0.712***		0.706***			0.705***	0.705***
	(0.02)		(0.01)			(0.02)	(0.02)
Rank (z-score)		0.449***	0.425***			0.343***	0.343***
		(0.05)	(0.02)			(0.02)	(0.02)
Grades (before measuring)				0.255***	0.207***	0.158***	0.158***
				(0.05)	(0.05)	(0.03)	(0.03)
Attendance (%)					0.008**	0.003*	0.003*
					(0.00)	(0.00)	(0.00)
Tutor comp. sec. school (yes)					0.018	0.037	0.037
					(0.06)	(0.03)	(0.03)
Sex (Male)					-0.166***	-0.119***	-0.119***
					(0.06)	(0.03)	(0.03)
Constant	-0.007	-0.003	-0.007	-1.499***	-1.883***	-1.172***	-1.172***
	(0.02)	(0.02)	(0.01)	(0.29)	(0.38)	(0.19)	(0.19)
Fixed effects	Class-group	Class-group	Class-group	Class-group	Class-group	Class-group	Class-group
Observations	859	859	859	859	771	771	771
R-squared	0.815	0.507	0.868	0.465	0.489	0.883	0.883
Adjusted R-squared	0.804	0.480	0.861	0.435	0.455	0.875	0.875
R-squared within	0.665	0.108	0.761	0.032	0.053	0.784	0.784
F Statistics	1610.971	98.361	1294.442	26.729	10.085	435.206	435.206
Note:							$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table A–3 OLS Estimation of Reciprocity (class-group fixed effects)

A.3.3 Robustness of difference in difference estimation

	Dependent variable:										
	Reciprocity (Diff-in-Diff)										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Reciprocity * Time	0.039***	0.038***									
	(0.01)	(0.01)									
Time	-0.081***	-0.094***	-0.086***	-0.087***	-0.080***	-0.075***	-0.069***	-0.125***	-0.113***	-0.114***	-0.105***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
Attendance (%)		0.008***	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Bottom 10% Reciprocity * Time			-0.089**								
			(0.04)								
Bottom 20% Reciprocity * Time				-0.037							
				(0.03)							
Bottom 30% Reciprocity * Time					-0.050*						
					(0.03)						
Bottom 40% Reciprocity * Time						-0.048*					
						(0.03)					
Bottom 50% Reciprocity * Time							-0.051**				
							(0.03)				
Top 40% Reciprocity * Time								0.075***			
								(0.03)			
Top 30% Reciprocity * Time									0.060**		
									(0.03)		
Top 20% Reciprocity * Time										0.100***	
										(0.03)	
Top 10% Reciprocity * Time											0.094**
											(0.04)
Fixed effects	Individual	Individual	Individual	Individual	Individual	Individual	Individual	Individual	Individual	Individual	Individual
Observations	1710	1710	1710	1710	1710	1710	1710	1710	1710	1710	1710
R-squared	0.894	0.897	0.896	0.896	0.896	0.896	0.896	0.897	0.896	0.897	0.896
Adjusted R-squared	0.787	0.793	0.791	0.791	0.791	0.791	0.791	0.792	0.792	0.793	0.792
R-squared within	0.054	0.082	0.077	0.073	0.075	0.076	0.076	0.081	0.077	0.083	0.078
F Statistics	24.535	25.217	23.584	22.506	23.164	23.254	23.434	24.993	23.727	25.604	23.900

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table A–4 Diff-Diff Estimation of Reciprocity (individual fixed effects)

Appendix B

Supplementary Material for Chapter 2

B.1 Descriptive statistics classrooms

Class ID	School ID	Age (Mean)	Age (SD)	Female (%)	Guardian education Secondary school completed (%)	GPA (Mean)	Class size	Attendance (Mean %)	Cooperation (Mean tokens)
1	1	10.03	0.57	57.6	48.5	6	33	89.3	3.97
2	2	9.09	0.51	41.7	45.8	6	24	91.9	5.59
3	2	10.17	0.51	53.3	56.7	5.9	30	90.2	4.76
4	2	10.87	0.66	43.5	56.5	5.9	23	89.2	4.39
5	3	9.15	0.99	30.8	30.8	5.7	13	89.2	6.09
6	3	9.05	0.77	56.2	50	5.6	16	93.3	5
7	3	10.39	0.9	39.1	34.8	5.8	23	91.6	4.86
8	3	10.91	0.7	33.3	50	5.7	18	93.7	4.3
9	3	11.46	1.3	52.6	52.6	5.2	19	88.9	7.14
10	4	9.17	0.64	37.5	50	6	8	94.6	7.23
11	4	10.01	0.95	42.9	28.6	6	7	97.5	4.88
12	4	11.06	0.77	42.9	38.1	6.1	21	88.9	5.1
13	5	10.05	0.72	55	30	6.6	20	90.3	5.04
14	5	10.18	0.78	58.8	35.3	6	17	91	4.21
15	5	11.22	0.63	50	30.8	5.8	26	93.7	3.54
16	6	9.41	1.05	66.7	55.6	5.9	9	92	6.25
17	6	10.3	0.95	33.3	50	5.5	12	88.3	5.92
18	6	11.66	2.56	35.7	64.3	5.8	14	89.6	4.06
19	7	9.17	0.74	73.3	26.7	6.1	15	95.2	4.38
20	7	10.3	0.84	47.6	28.6	6	21	95.3	5.9
21	7	11.24	0.73	33.3	44.4	5.8	18	94.4	4.63
22	8	9.2	0.64	46.2	43.6	5.7	39	89.8	5.08
23	8	10.11	0.64	63.6	42.4	5.9	33	92.4	4.06
24	8	11.12	0.55	48.4	45.2	5.4	31	91.2	4.34
25	9	8.98	0.63	100	44	6.2	25	88.8	6.78
26	9	9.87	0.76	100	35.7	6	14	83.7	5.32
27	9	10.73	0.65	100	50	6	14	89.4	5.31
28	10	9.07	0.92	36.4	22.7	5.7	22	86.8	3.79
29	10	9.38	1.12	61.5	30.8	5.7	13	91.3	7.22
30	10	10.12	0.59	45.5	22.7	5.8	22	85.2	3.48
31	10	10.35	0.95	50	22.7	5.6	22	84.6	4.05
32	10	11.44	1.08	53.6	25	5.7	28	88.3	3.79
33	11	8.8	0.52	0	50	5.7	14	90.7	6.81
34	11	10.3	0.43	0	75	6	12	94.3	3.92
35	11	11	0.67	0	50	6.2	10	94.2	3.09
36	12	9.47	0.83	58.3	25	5.8	12	90.8	5.59
37	12	10.2	0.88	20	30	5.6	10	87.9	4.39
38	12	11.65	1.11	35.3	47.1	5.5	17	89.3	3.2
39	13	9.92	0.5	100	69.2	6.1	26	94.2	3.62
40	13	9.97	0.49	100	38.9	5.8	18	91.8	4.67
41	13	9.8	0.61	100	70	6.2	20	94.8	5.29
42	14	8.91	0.61	100	72.2	6.3	18	96	5.33
43	14	8.97	0.69	100	50	6	18	91.6	5.6
44	14	10.04	0.56	100	63.2	6	19	91	5.11
45	14	11.7	1.64	100	73.3	6.2	15	96.2	4.09

Table B–1 Class-level description.

B.2 Null Model Filtering Algorithm

To ensure a robust analysis of social interactions mediated by token exchanges, our study employed a filtering algorithm that reconfigures the observed data by simulating a null model and then filtering the links that are explained by chance. This model hypothesizes what the exchange patterns might look like if they were governed solely by the participants' overall tendencies to send tokens, devoid of any preferential attachment or strategic selection of receivers. Below are the detailed steps of the algorithm:

Algorithm 1 Algorithm for Simulation-Based Network Filtering

Result: A filtered adjacency matrix that keeps statistically significant token sendings
Input: A graph $G(V, E)$ with nodes V and edges E representing participants and their token exchanges.
Output: A filtered adjacency matrix where only exchanges outside the random confidence intervals are preserved.

for *each node i in V* **do**
  Extract the row corresponding to node i from the adjacency matrix, ensuring to exclude the diagonal element.
  - Shuffle the elements of the row to randomly redistribute tokens to other participants, thereby preserving the total number of tokens sent by node i but randomizing the recipients. This step maintains the specific sending strategy of node i while altering the recipient selection to simulate random sending.
  - Repeat the shuffling process to generate a large number of simulated networks, forming a robust dataset of potential exchange patterns. (In this paper, we used 2000 simulations)
end
Calculate the mean and standard deviation of token exchanges for each node across all simulations, constructing a comprehensive model of randomized exchanges.
for *each node i in V* **do**
  for *each node j* **do**
    Calculate a 95% confidence interval for the token exchanges between nodes i and j based on the simulated data. This interval represents the expected range of exchanges if they were influenced only by random chance and the general sending propensities of node i.
    if *the actual token exchange between nodes i and j falls outside this confidence interval* **then**
      Retain this exchange in the filtered matrix as it suggests a significant interaction unlikely to be due to random chance.
    else
      Set this exchange to zero in the filtered matrix, indicating that it is within the range of what could be expected from random interactions under the null model.
    end
  end
end

This detailed algorithmic approach allows us to isolate and examine those exchanges that significantly deviate from what could be expected under a random distribution model, highlighting potential underlying social dynamics or strategic considerations influencing token exchanges. After using the algorithm, the links were filtered, preserving their overall distribution, as shown in the figureB–1.

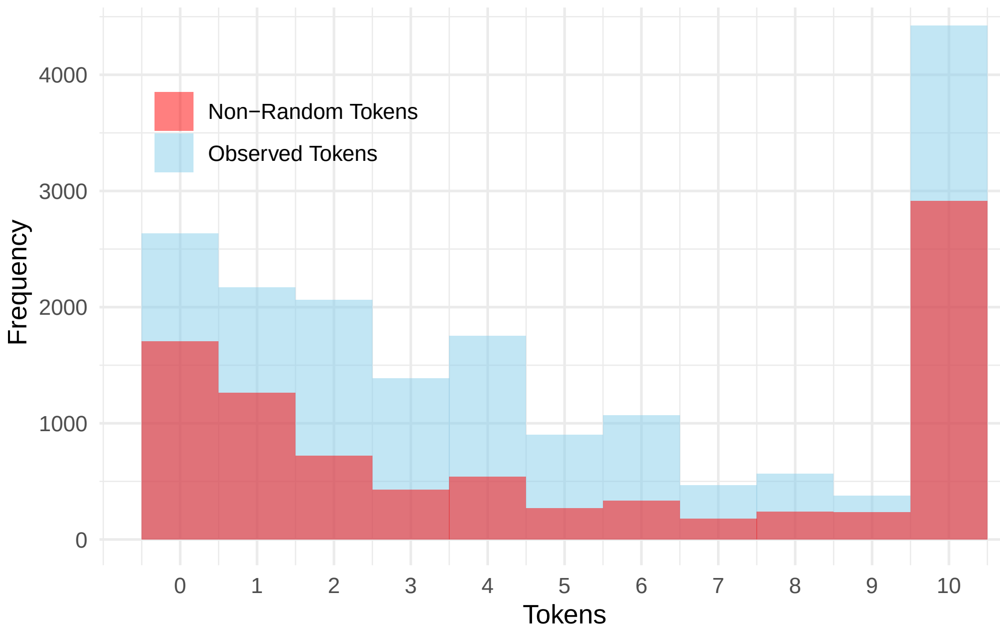

Figure B–1 Observed and filtered token sending histogram

B.3 Regression Tables: Cooperation Gap and Social Rank Gap

B.3.1 Social Rank Gap measured by popularity nominations

Table B–2 Regression Results for Observed Tokens

	Dependent variable: Observed Cooperation GAP (received - sent tokens)								
	All Sample			*Mutual Friends*			*Non Friends*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Social Rank Gap	2.584***	2.584***	2.587***	0.293	0.293	1.254	2.574***	2.574***	2.573***
(Pop. nominations)	(0.098)	(0.272)	(0.272)	(0.403)	(0.693)	(0.780)	(0.110)	(0.264)	(0.272)
Constant	-0.000			-0.000			0.000		
	(0.035)			(0.119)			(0.040)		
Class Fixed Effect	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Sender Fixed Effect	No	No	Yes	No	No	Yes	No	No	Yes
Observations	17,804	17,804	17,804	1,288	1,288	1,288	13,916	13,916	13,916
R^2	0.037	0.037	0.271	0.0004	0.0004	0.645	0.038	0.038	0.286
Adjusted R^2	0.037	0.035	0.234	-0.0004	-0.036	0.277	0.038	0.035	0.239

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table B–3 Regression Results for filtered Tokens

	Dependent variable: Filtered Cooperation GAP (received - sent tokens)								
	All Sample			*Mutual Friends*			*Non Friends*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Social Rank Gap	3.014***	3.014***	3.157***	-0.661	-0.661	-0.117	3.142***	3.142***	3.083***
(Pop. nominations)	(0.199)	(0.479)	(0.479)	(0.533)	(0.626)	(1.059)	(0.236)	(0.463)	(0.523)
Constant	-0.000			0.000			0.000		
	(0.070)			(0.157)			(0.086)		
Class Fixed Effect	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Sender Fixed Effect	No	No	Yes	No	No	Yes	No	No	Yes
Observations	17,804	17,804	17,804	1,288	1,288	1,288	13,916	13,916	13,916
R^2	0.037	0.037	0.271	0.0004	0.0004	0.645	0.038	0.038	0.286
Adjusted R^2	0.037	0.035	0.234	-0.0004	-0.036	0.277	0.038	0.035	0.239

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

B.3.2 Behavioral Social Rank Gap measured from Social Dilemma Game data

Table B–4 Regression Results Behavioral Social Rank for Observed Tokens

	Dependent variable: Observed Cooperation GAP (received - sent tokens)								
	All Sample			Mutual Friends			Non Friends		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
B. Social Rank Gap	2.869***	2.869***	2.864***	1.639***	1.639**	2.038**	2.889***	2.889***	2.777***
(Social Dilemma Game)	(0.092)	(0.320)	(0.321)	(0.367)	(0.646)	(0.873)	(0.105)	(0.320)	(0.343)
Constant	-0.000			-0.000			0.000		
	(0.035)			(0.118)			(0.039)		
Class Fixed Effect	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Sender Fixed Effect	No	No	Yes	No	No	Yes	No	No	Yes
Observations	17,804	17,804	17,804	1,288	1,288	1,288	13,916	13,916	13,916
R^2	0.051	0.051	0.277	0.015	0.015	0.649	0.052	0.052	0.291
Adjusted R^2	0.051	0.049	0.241	0.014	-0.020	0.286	0.052	0.049	0.245

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table B–5 Regression Results Behavioral Social Rank for filtered Tokens

	Dependent variable: Observed Cooperation GAP (received - sent tokens)								
	All Sample			Mutual Friends			Non Friends		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
B. Social Rank Gap	3.989***	3.989***	4.114***	0.443	0.443	-0.666	4.309***	4.309***	4.516***
(Social Dilemma Game)	(0.179)	(0.455)	(0.454)	(0.525)	(0.527)	(1.538)	(0.214)	(0.470)	(0.489)
Constant	-0.000			0.000			0.000		
	(0.068)			(0.157)			(0.083)		
Class Fixed Effect	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Sender Fixed Effect	No	No	Yes	No	No	Yes	No	No	Yes
Observations	4,486	4,486	4,486	548	548	548	3,210	3,210	3,210
R^2	0.099	0.099	0.309	0.001	0.001	0.752	0.112	0.112	0.359
Adjusted R^2	0.099	0.090	0.155	-0.001	-0.088	0.157	0.112	0.100	0.160

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Appendix C

Supplementary Material for Chapter 3

C.1 Descriptive statistics table

	ASD (N = 18, 4 girls)		SEN (excluding ASD) (N = 143, 74 girls)		Without SEN (N = 464; 214 girls, 1 NA)	
Variable	n	Mean (SD)	n	Mean (SD)	n	Mean (SD)
Age (in months)	18	97 (12)	143	103 (16)	464	100 (14)
Grades (GPA, min 1, max 8)	10	6.1 (0.56)	112	5.8 (0.69)	334	6.2 (0.6)
Attendance	16	75%	131	73%	430	79% (17)
Withdraw	18	0%	143	0%	464	1.3% (0.11)
Repeater	18	0%	143	2.1% (0.14%)	464	0.065% (0.08)
Game played at school	8	44%	67	47%	211	45%
Game played at home	8	44%	48	34%	157	34%
Game played in hybrid format	2	11%	28	20%	96	21%
Not selected	1	6%	1	1%	3	1%
Received stars	15	83%	141	99%	460	99%
Selected without stars	2	11%	1	1%	1	1%

Table C–1 Descriptive statistics of the sample, distinguishing between students with ASD, SEN (excluding ASD), and Without SEN.

C.2 Chi-Square Test for Reciprocated Choice.

C.2.1 Comparison of proportion of reciprocated choices

In this case, there is a mutual selection among students.

Comparison	Observed Chi-square	P value	Group 1 %	Group 2 %	Critical Chi-square
ASD vs. SEN	10.783	0.0010	12.84%	22.71%	3.841459
ASD vs. without SEN	14.8723	0.000123	12.84%	24.39%	3.841459
SEN vs. without SEN	2.7745	0.09586	22.71%	24.39%	3.841459

Table C–2 Comparison of proportion of reciprocated choices between different groups.

C.2.2 Comparison of reciprocated non choices

In this case, both students do not choose each other.

Comparison	Observed Chi-square	P value	Group 1 %	Group 2 %	Critical Chi-square
ASD vs. SEN	0.9037075	0.3417895	42.20%	38.67%	3.841459
ASD vs. without SEN	1.2278018	0.2678350	42.20%	38.27%	3.841459
SEN vs. without SEN	0.1066016	0.7440468	38.67%	38.27%	3.841459

Table C–3 Comparison of reciprocated non-choices between different groups.

C.3 Regression for Nomination Questionnaires

C.3.1 Friendship nominations

Dependent variable:	Friendship nomination received (z-score)				felm			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Stars Instrength	0.686***	0.675***	0.675***	0.661***	0.640***	0.674***	0.674***	0.638***
(z-score)	(0.029)	(0.033)	(0.033)	(0.035)	(0.041)	(0.031)	(0.031)	(0.042)
SEN		0.002				0.002		
(all)		(0.067)				(0.087)		
SENxInstrength		0.053				0.056		
		(0.072)				(0.076)		
ASD			0.092	0.168		-0.162	0.098	-0.171
			(0.217)	(0.242)		(0.435)	(0.134)	(0.175)
SEN			-0.002	-0.013		-0.033	-0.002	-0.029
(no ASD)			(0.070)	(0.073)		(0.083)	(0.092)	(0.109)
Attendance			0.0003			-0.003	0.0003	-0.004
			(0.002)			(0.002)	(0.002)	(0.003)
Grades				0.081		0.152	0.081	0.144
				(0.094)		(0.123)	(0.094)	(0.224)
Active player					0.113*		0.129	
					(0.062)		(0.062)	(0.103)
ASDxInstrength			0.180	0.230		0.055	0.189	0.053
			(0.218)	(0.230)		(0.361)	(0.129)	(0.151)
SEN (no ASD)			0.041	0.079		0.061	0.044	0.066
xInstrength			(0.076)	(0.080)		(0.091)	(0.077)	(0.105)
Constant	0.000	0.003	0.003	-0.084	0.003	-0.531	-0.084	-0.084
	(0.029)	(0.033)	(0.033)	(0.134)	(0.033)	(0.356)	(0.134)	(0.356)
Class FE	No	No	No	No	Yes	Yes	Yes	Yes
Observations	625	625	625	577	455	625	625	455
R2	0.471	0.471	0.472	0.479	0.471	0.472	0.472	0.471
Adj.R2	0.470	0.470	0.469	0.472	0.461	0.472	0.445	0.439
F Stat	554.907***	184.718***	110.618***	74.601***	49.568***	554.907***	554.907***	49.568***
	(df = 1; 623)	(df = 3; 621)	(df = 5; 619)	(df = 7; 569)	(df = 8; 446)	(df = 1; 623)	(df = 1; 623)	(df = 8; 446)

Table C–4 Regression Results Friendship Nominations (z-score) and Stars Instrength.
Note: *p < 0.1; **p < 0.05; ***p < 0.01

C.3.2 Hangout nominations

Dependent variable:	Hangout nomination received (z-score)				Fixed effects Model			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Stars Instrength	0.747***	0.730***	0.730***	0.733***	0.691***	0.729***	0.730***	0.687***
(z-score)	(0.027)	(0.030)	(0.030)	(0.031)	(0.037)	(0.029)	(0.029)	(0.029)
SEN (all)		-0.130**				-0.132*		
		(0.061)				(0.073)		
SENxInstrength		0.041				0.044		
		(0.066)				(0.066)		
ASD			-0.362*	-0.156		-0.024	-0.371	-0.055
			(0.197)	(0.217)		(0.388)	(0.230)	(0.184)
SEN (no ASD)			-0.098	-0.112*		-0.117	-0.100	-0.112
			(0.063)	(0.066)		(0.074)	(0.074)	(0.094)
Attendance			0.001			-0.002	-0.002	-0.002
			(0.002)			(0.002)	(0.002)	(0.002)
Grades				0.056		0.075	0.043	0.043
				(0.084)		(0.110)	(0.084)	(0.108)
Active player					0.138**		0.162**	
					(0.056)		(0.059)	(0.059)
ASDxInstrength			0.143	0.244		0.521	0.144	0.521***
			(0.198)	(0.206)		(0.322)	(0.159)	(0.163)
SEN (no ASD)			0.010	0.019		0.014	0.011	0.019
xInstrength			(0.069)	(0.071)		(0.081)	(0.069)	(0.081)
Constant	-0.000	0.036	0.036	-0.076	0.036	-0.737**	-0.076	-0.231**
	(0.026)	(0.030)	(0.030)	(0.120)	(0.030)	(0.317)	(0.120)	(0.231)
Class FE	No	No	No	No	Yes	Yes	Yes	Yes
Observations	625	625	625	577	455	625	625	455
R2	0.559	0.563	0.563	0.586	0.579	0.563	0.566	0.580
Adj.R2	0.558	0.561	0.561	0.586	0.571	0.542	0.544	0.554
F Stat	788.898***	266.324***	161.443***	114.840***	76.565***	788.898***	788.898***	76.565***
	(df = 1; 623)	(df = 3; 621)	(df = 5; 619)	(df = 7; 569)	(df = 8; 446)	(df = 1; 623)	(df = 1; 623)	(df = 8; 446)

Table C–5 Regression Results Hangout Nominations (z-score) and Stars Instrength.
Note: *p < 0.1; **p < 0.05; ***p < 0.01

C.4 Stars Reciprocity

C.4.1 Distribution of reciprocated Stars

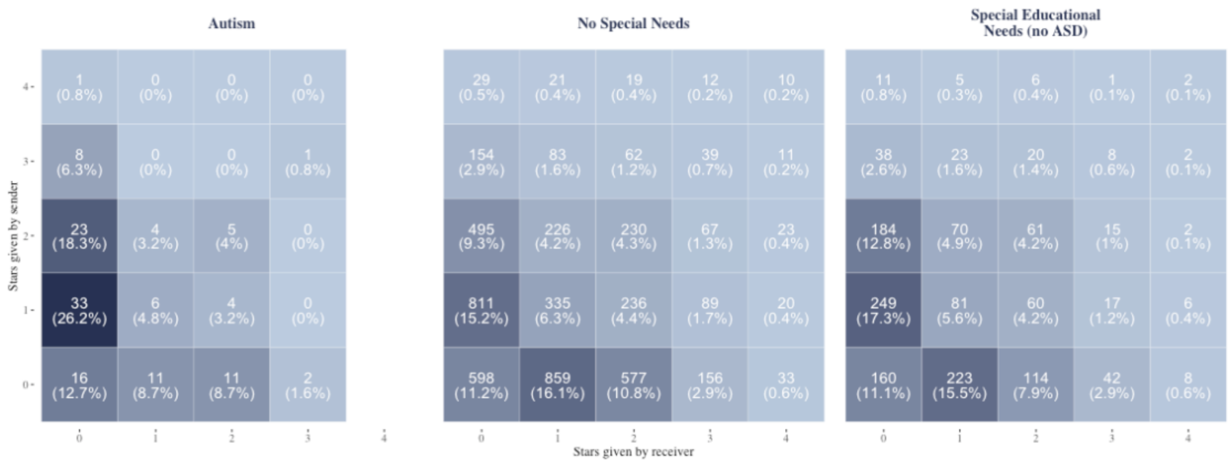

Figure C–1 Recirpocated stars by group

C.4.2 Regressions reciprocated score in Stars

Stars Network **Stars Network**	Reciprocated Score (reciprocated stars ratio)			Standardized Reciprocated core (z-score)		
Group	(1)	(2)	(3)	(4)	(5)	(6)
SEN (excluding ASD)	-0.020	-0.008	-0.004	-0.110	-0.042	-0.024
	(0.014)	(0.015)	(0.014)	(0.075)	(0.080)	(0.075)
ASD	-0.113*	-0.161***	-0.210***	-0.618*	-0.882***	-1.153***
	(0.062)	(0.051)	(0.057)	(0.335)	(0.279)	(0.314)
Attendance	0.002***	0.001**		0.009***	0.008**	
	(0.0004)	(0.001)		(0.002)	(0.003)	
Grades			0.025			0.135
			(0.018)			(0.097)
Observations	530	492	409	530	492	409
R^2	0.292	0.237	0.258	0.292	0.237	0.258
Adjusted R^2	0.254	0.197	0.215	0.254	0.197	0.215

Table C–6 Regression Results for Reciprocated Score (reciprocated stars ratio) and Standardized Reciprocated Score (z-score) in the Stars Network.
Note: *p < 0.1; **p < 0.05; ***p < 0.01

C.5 Logistic regressions

Dependent variable:	Reciprocated choice			Reciprocated non choice		
	(1)	(2)	(3)	(4)	(5)	(6)
SEN_noASD_receiver	-0.404***	0.298**	0.836*	0.215***	-0.009	-0.308
	(0.069)	(0.129)	(0.500)	(0.058)	(0.116)	(0.378)
ASD_receiver	-1.267***	-0.084	2.018*	0.516***	-0.0002	-15.917
	(0.266)	(0.405)	(1.154)	(0.168)	(0.349)	(1,088.962)
Sample	W/o SEN	SEN	ASD	W/o SEN	SEN	ASD
Class Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Sender Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,607	2,343	218	8,607	2,343	218
Log Likelihood	-4,183.185	-1,101.299	-70.524	-5,208.751	-1,426.433	-136.836
Akaike Inf. Crit.	9,178.370	2,436.599	167.049	11,229.500	3,086.866	299.673

Table C–7 Logit regression results for reciprocated choice and non-choice.
Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$