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Gamification, Peer Networks, and the Reconstruction of Sociograms: A Social Network Analysis in Higher Education

Federica Pelizzari

Research Centre on Media Education, Innovation and Technology (CREMIT), Università Cattolica del Sacro Cuore, 20123 Milan, Italy; federica.pelizzari@unicatt.it

Abstract

Background: Gamification is widely used in higher education, yet its consequences for the relational structure of a class are rarely measured, and sociometric data are often analyzed without attention to how the underlying matrix is built. Methods: We report an exploratory, single-case, pre–post study of a gamified master's course in Didactics and Media Education (N = 19), with a dual aim: to demonstrate a transparent procedure for reconstructing directed, weighted sociograms from raw questionnaire responses, and to explore how the peer-preference network changed over one semester of cooperative group work; inference used permutation methods suited to a small single network. Results: A pre-existing matrix contained roughly one-third of ties with no basis in the data, doubling the apparent centralization and mischaracterizing the least-chosen, most-rejected student as the most popular hub; reconstruction reversed these conclusions. On the reconstructed network, cohesion increased and previously isolated students were integrated, while centralization stayed stable—integration without hierarchy—with a reciprocal, transitive, and highly stable structure and no demographic homophily. Conclusions: Social network analysis (SNA) is a sensitive instrument for the relational evaluation of gamified courses, but the construction of the sociomatrix is itself a substantive analytic decision that must be reported transparently.

Keywords: gamification; higher education; social network analysis; sociometry; sociogram; research methodology; peer relationships; reproducibility; case study

1. Introduction

Gamification—the use of game design elements in non-game contexts—has become a prominent instructional strategy in higher education, motivated by the premise that the dynamics that make games engaging (clear goals, immediate feedback, visible progress, challenge, narrative, and social interaction) can be transposed into learning to sustain attention and effort (Deterding et al., 2011). Systematic reviews report broadly positive associations with engagement and motivation, alongside heterogeneous, context-dependent, and sometimes short-lived effects on learning, and warn that gamification is neither uniformly beneficial nor equally effective for all learners (Hamari et al., 2014; Koivisto & Hamari, 2019; Dichev & Dicheva, 2017; Hanus & Fox, 2015). More recent meta-analyses continue to report positive but design-dependent effects, including for collaborative and higher-education settings (Slamet & Meng, 2025; Gyedu et al., 2026). Bibliometric analyses document the rapid growth and consolidation of gamification research (Pelizzari, 2025), and a systematic review focused on higher education maps its uses and outcomes in that setting (Pelizzari, 2023).

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Most of this evidence is at the individual level: it concerns how gamification relates to a learner's motivation, enjoyment, self-efficacy, or grades, treating students as independent units. This focus sits uneasily with designs built around teams, cooperative missions, and recurring group work, whose intended effects are explicitly social—to increase interaction, build community, and distribute support across the class. Such outcomes are relational: they concern the pattern of ties among students rather than the attributes of students taken one at a time, and they are therefore invisible to analyses that aggregate individual scores.

Social network analysis (SNA) is the natural toolkit for this relational question, and the sociogram—its visual ancestor—was devised precisely to surface the otherwise invisible web of attractions and rejections within a group (Moreno, 1934). However, two obstacles recur. First, applications of SNA to the evaluation of gamified courses remain uncommon, and where sociometric data are gathered, they are frequently summarized descriptively rather than tested inferentially (Dado & Bodemer, 2017). Second, and less often discussed, the step from raw sociometric responses to an analyzable matrix involves consequential choices—about directionality, weighting, thresholding, and the handling of out-of-roster or self-nominations—that are rarely reported and can materially alter conclusions.

This article addresses both obstacles through an in-depth study of a single gamified master's course in Didactics and Media Education (N = 19). Its contribution is deliberately twofold. The methodological aim is to demonstrate, and argue for, a transparent reconstruction of the directed, weighted sociogram from raw questionnaire data, showing concretely how an opaque matrix can distort substantive findings. The substantive aim is exploratory: to describe how the peer-preference network of one cohort changed across a semester of cooperative, gamified group work. We emphasize at the outset that the design—a single cohort observed before and after, with no control group—supports associational, not causal, interpretation; we therefore frame our questions as exploratory (Table 1). RQ1: How is the directed, weighted sociogram best reconstructed from raw responses, and does reconstruction change the substantive picture relative to a pre-existing matrix? RQ2: How does the class network change over the semester in cohesion, reciprocity, subgroup structure, and the integration of peripheral students? RQ3: Are network positions and the perception of one's own ties associated with student attributes (gender, age, employment status, gamification user type, self-efficacy) and with the competences for which peers are chosen? We answer RQ1 and RQ2 with permutation-based inference suited to a small single network, and treat RQ3 strictly as hypothesis-generating.

Table 1. Research questions, exploratory expectations, and the indicators used to address each.

RQ	Exploratory Expectation	Primary Indicator(s)
RQ1	A matrix reconstructed from raw responses may differ materially from a pre-existing one and change substantive conclusions.	Decomposition of ties vs. questionnaire; density; degree centralization; comparison of node rankings
RQ2	A cooperative design is associated with greater cohesion and integration of peripheral students, without rising hierarchy.	Closeness; reachable pairs; zero-out degree; centralization; reciprocity/transitivity (CUG); QAP stability; modularity
RQ3	Positions, perceived reciprocity, and competence attributions may relate to attributes (treated as exploratory).	Spearman/Mann–Whitney of attributes vs. centrality; perceived vs. actual reciprocity; competence distribution

2. Theoretical Background

We use three motivational frameworks not as a battery of confirmatory hypotheses—which N = 19 cannot support—but as a lens for forming exploratory expectations about how a cooperatively designed gamified course might leave a trace in the class network. We are explicit that the present study tests only a subset of the mechanisms these theories describe (Table 2).

Table 2. Theoretical lenses, the exploratory expectations they generate for the class network, and the indicators used to examine them.

Theoretical Lens	Exploratory Expectation for the Network	Indicator
Self-Determination Theory—relatedness	ties broaden rather than narrow	density; reachable pairs; integration of isolates
Social interdependence—cooperative	more cohesion, not a few hubs	degree centralization (stable); closeness
Flow—challenge–skill balance	sustained participation	zero-out-degree students over time
Self-efficacy (Bandura)	exploratory link to position	self-efficacy × centrality (Spearman)
Hexad user types	exploratory: social profiles	by-type comparison (Mann–Whitney)
Cooperation vs. competition	reciprocal, transitive structure	CUG tests; reciprocity; transitivity
Mixed-group design	preferences cross demographic lines	E–I homophily; age assortativity

2.1. *Gamification as Instructional Design and the Question of Meaning*

Following Deterding and colleagues, gamification is the use of game design elements in non-game contexts, distinct from serious games and from game-based learning (Deterding et al., 2011; Landers, 2014). The elements most often transposed in education—points, badges, levels, leaderboards, progress mechanics, missions, and narrative (Werbach & Hunter, 2012)—provide structure, feedback, and visible markers of advancement, but can also reduce learning to the pursuit of superficial rewards (the "game effect") and rest on a novelty that fades, and critical scholars caution that gamification can reproduce competitive, individualistic logics (Hanus & Fox, 2015; Tulloch & Randell-Moon, 2018). Nicholson's (2015) meaningful gamification responds by arguing that reward layers can crowd out the behaviors they target once removed, so durable engagement requires designs anchored in learners' intrinsic and internalized motivations; building on Deterding et al.'s (2011) situated motivational affordance, he stresses that a play element motivating inside a game is not necessarily so once relocated, and must be situated within the new context. The course studied here was designed in this spirit, favoring cooperative structure over a competitive points race.

2.2. *Motivation, Flow, and Self-Efficacy*

Self-determination theory (SDT; Deci & Ryan, 2000) locates motivation in the satisfaction of needs for autonomy, competence, and relatedness; of these, relatedness—the social need—is the one whose satisfaction should leave a structural trace, leading us to expect, in a cooperative design, a broadening rather than a narrowing of the class network. Csikszentmihalyi's (1990) flow theory describes optimal experience when challenge matches skill, engineered in gamified designs through graduated challenges and continuous feedback

(Sailer et al., 2017). Bandura's (1997) self-efficacy—belief in one's capacity to organize and execute the actions needed to attain goals—may be strengthened by visible progress and attainable sub-goals; we measured generalized self-efficacy to explore, not to confirm, whether it relates to network position.

2.3. Cooperation, Competition, and Social Interdependence

Because the course is organized around group work, the cooperative–competitive dimension is central. Drawing on social interdependence theory (Johnson & Johnson, 1989), gamified designs can be individualistic (no interdependence), cooperative (positive interdependence), competitive (negative interdependence), or cooperative–competitive (positive within teams, negative between them). Cooperative features—shared goals, collective challenges—invoke positive goal interdependence and can foster community and mutual support that purely competitive designs may undermine (Morschheuser et al., 2019); competitive dynamics, by contrast, energize some students while discouraging others, an effect amplified in heterogeneous cohorts. This leads to the exploratory expectation that a cooperatively oriented design would be associated with a more cohesive and more equal network rather than one concentrated around a few high performers, and to the complementary expectation that visibility might carry social costs detectable only if rejection, as well as choice, is measured. Recent studies link cooperative, game-based designs to collaborative and transversal competences in higher education (Latorre-Cosculluela et al., 2025; Mirmotahari et al., 2025).

2.4. Player Types and the Social Reading of the Network

Learners differ in what motivates them within gamified systems. Marczewski's (2015) Gamification User Types Hexad describes six profiles tied to distinct drivers—Socializers (relatedness), Free Spirits (autonomy), Achievers (mastery), Philanthropists (purpose), Players (reward), and Disruptors (change)—with most people displaying a mix and one prevailing type (Marczewski, 2015), and recent work explores adaptive gamification tailored to such types (Zairon et al., 2025). We measured Hexad types (Tondello et al., 2016) to explore whether motivational orientation, particularly the socially oriented profiles, is associated with network position, while recognizing that such cross-sectional associations are fragile at this sample size.

2.5. Social Network Analysis, Sociometry, and the Construction of the Matrix

SNA models a class as nodes (students) connected by relations, and provides formal indicators of structure: density (connectedness), degree (popularity vs. expansiveness), betweenness and closeness centrality (brokerage and reachability), reciprocity and transitivity (returned ties and triadic closure), and modularity (subgroup structure), with centralization indices summarizing how unequally prominence is distributed (Freeman, 1978; Scott, 2017; Wasserman & Faust, 1994). The approach originates with Moreno's (1934) sociometry and the sociogram, designed to map attractions and rejections and to reveal isolation, reciprocity, and reference figures. Inference on a single observed network is the methodological crux: any descriptive value could arise by chance, so permutation approaches—the Conditional Uniform Graph (CUG) test and the Quadratic Assignment Procedure (QAP)—are needed and are appropriate even for small networks where exponential random graph models are unreliable (Krackhardt, 1988; Butts, 2008; Snijders et al., 2006).

Less discussed, but central to this paper, is that the sociomatrix is not a neutral record but the product of analytic decisions. The same questionnaire can yield very different networks depending on whether ties are treated as directed or symmetrized, binary or weighted, capped at the number of nominations the instrument allowed, and how self-nominations and nominations of people outside the roster are handled. When these decisions are undocumented, results cannot be reproduced and may be distorted. We treat the reconstruction of the matrix as a first-class object of study (RQ1) and use the present case to show how much it can matter.

Empirically, SNA has been applied in education mainly to computer-supported collaborative learning and to online interaction or communication networks, where centrality and cohesion have been linked to engagement and achievement (Grunspan et al., 2014; Carolan, 2014). A smaller body of work has applied SNA to gamified courses specifically: De-Marcos et al. (2016) showed that the interaction network of a gamified e-learning course exhibits small-world properties and that students' network positions predict achievement, and Ding et al. (2018) examined engagement in gamified online discussions through network measures. Two gaps motivate the present study. First, as Dado and Bodemer (2017) document in their methodological review, SNA applications in collaborative learning are methodologically inconsistent and rarely make the construction of the network auditable—precisely the issue we foreground. Second, existing gamification studies analyze online interaction traces, typically cross-sectionally and to predict performance; few examine pre–post change in offline peer-preference (sociometric) networks, and, to our knowledge, none pairs such an analysis with a transparent reconstruction of the directed, weighted sociogram from raw responses. The present case addresses both gaps.

3. Materials and Methods

3.1. Design and Research Questions

We adopted a single-case, exploratory, pre–post design embedded in a broader mixed-methods study of gamification in higher education. Sociometric data were collected at the beginning (T1) and end (T2) of one semester, allowing a within-cohort comparison of the class network before and after the gamified intervention. There is no control group and no random assignment to gamified versus non-gamified instruction; consequently, observed change cannot be attributed to gamification rather than to the passage of time, growing familiarity, or maturation. We state this limitation up front and frame all substantive results as associational and exploratory. The analysis is organized around the three research questions in the Introduction.

3.2. Context: The Gamified Didactics Course

The study was conducted in a Didactics and Media Education course, which was part of a master's program in Media Education at an Italian university. The course grounds students in the epistemology and methodology of media education work and the design and management of distance learning, and is organized into four graduated modules. It follows an active, student-centered approach based on the EAS method (Episodes of Situated Learning; Rivoltella, 2013), alternating in-class sessions with individual and group activities delivered online through a learning management platform, in a blended format, and has long relied on small, variable-geometry groups to circulate diverse informal knowledge.

Gamification was introduced into this existing design following the ADDIE model. The needs analysis identified two recurring problems: students—especially working students—struggling to keep pace with the online phase, and weak engagement with continuous, in-progress assessment. The response was a meaningful, cooperatively oriented layer: content divided into explicit levels with stated sequence and graduality; missions and challenges sustaining each level alongside webinars and in-class sessions; a narrative with a stable guide character (the teacher's avatar as "game master") and a module-specific persona; and a transparent points scheme tied to attendance and continuous participation. Accumulated points contributed a bonus to the final course grade. The intervention spanned one academic semester, and the sociometric questionnaire was administered one week before it began (T1) and one week after it ended (T2). Learning was structured around recurring group work: five groups of four students, formed at random and rotated at the start of each module, with a constraint to mix ages and employment status.

3.3. Participants, Ethics, and Response

Participants were the students enrolled in the course during the semester of implementation: 20 students (5 men, 15 women, as recorded in the questionnaire), none reporting special educational needs or disability. The cohort was predominantly young (about 80% aged 20–30, 20% over 30) and mixed in employment status (12 working, 60%; 8 non-working, 40%), with most coming from an undergraduate background in Educational Sciences (Table 3). The sociometric questionnaire was completed by the full cohort at both waves; of the 20 respondents, 19 constituted the sociometric network analyzed here, with 1 respondent not being part of the sociogram roster. Participation was voluntary; students were informed of the study's purpose and that participation would not affect assessment, and they provided informed consent. Consent was collected through an initial opt-in survey in which each student declared whether they wished to take part; those who declined were simply not enrolled in the study. This opt-in procedure, together with the anonymization of all responses and the guarantee that neither participation nor answers affected grades, was intended to protect voluntariness and confidentiality in the teacher–student context. The questionnaire was administered for research purposes and kept separate from grading; all responses were anonymized before analysis and were not used by teaching staff in assessment. All 19 students in the sociometric roster completed the questionnaire at both waves, so the paired analyses used complete data with no imputation. All data were anonymized prior to analysis (nodes labeled S01–S19); demographic and psychometric data were linked to network positions through a study identifier held separately from the analytic files.

Table 3. Participant characteristics (enrolled cohort, N = 20; the sociometric network comprises 19).

Characteristic	Category	n (%)
Gender	Women/Men	15 (75%)/5 (25%)
Age	20–30/over 30	16 (80%)/4 (20%)
Employment	Working/Non-working	12 (60%)/8 (40%)
Undergraduate background	Educational Sciences/Other	16 (80%)/4 (20%)
Special educational needs	None reported	20 (100%)

3.4. Instruments and Reliability

At both T1 and T2, each student completed a sociometric questionnaire designed to capture group work preferences and their change. Students named up to five peers they would most like to work with, in decreasing order of preference; rated the strength of each prospective tie on a 1–4 scale; indicated, for each choice, whether they believed it reciprocated (no/more no than yes/more yes than no/yes); named up to five peers they would prefer not to work with; and, for each chosen peer, selected up to three competences motivating the choice from four categories (relational/communicative, cognitive/informational, motivational/esteem, and organizational/strategic). The initial questionnaire additionally administered the generalized self-efficacy scale (Schwarzer & Jerusalem, 1995), the Hexad gamification user type scale (Tondello et al., 2016), and a group role inventory based on the functional task and maintenance roles of group members (Benne & Sheats, 1948), with demographic items. Internal consistency in this sample was high for the generalized self-efficacy Scale (Cronbach's $\alpha = 0.91$) and the group role inventory ($\alpha = 0.92$); the Hexad comprises six four-item subscales scored per its standard key; subscale internal consistency ranged from acceptable to good (Philanthropist ($\alpha = 0.81$), Socializer ($\alpha = 0.87$), Achiever ($\alpha = 0.82$), Disruptor ($\alpha = 0.81$), and Player ($\alpha = 0.73$)), except for Free Spirit ($\alpha = 0.61$). We note that the perceived reciprocity measure is a single ordinal item and should be interpreted with corresponding caution.

3.5. Reconstruction of the Sociomatrix (RQ1)

The directed, weighted preference network was reconstructed directly from the raw questionnaire responses: for each respondent i, a tie $i \rightarrow j$ was created with weight equal to the declared strength (1–4) of the corresponding choice; self-nominations were removed and nominees outside the 19-student roster were discarded; in addition, one respondent who was not part of the sociometric roster was excluded, yielding N = 19. Out-of-roster names given in the rejection question were recorded for descriptive purposes but were not included in the 19-node adjacency matrix. Nominee free-text was matched to roster members through a documented normalization procedure (accent and case folding, surname-based matching with a small manual variant list for spelling differences), and all matches were verified against the questionnaire. The parallel rejection network was built in the same way from the "would not work with" nominations. We contrasted the reconstructed matrices with a pre-existing matrix used in earlier descriptive work (produced with UCINET; Borgatti et al., 2002); the comparison is itself a result (Figure 1; Section 4.1).

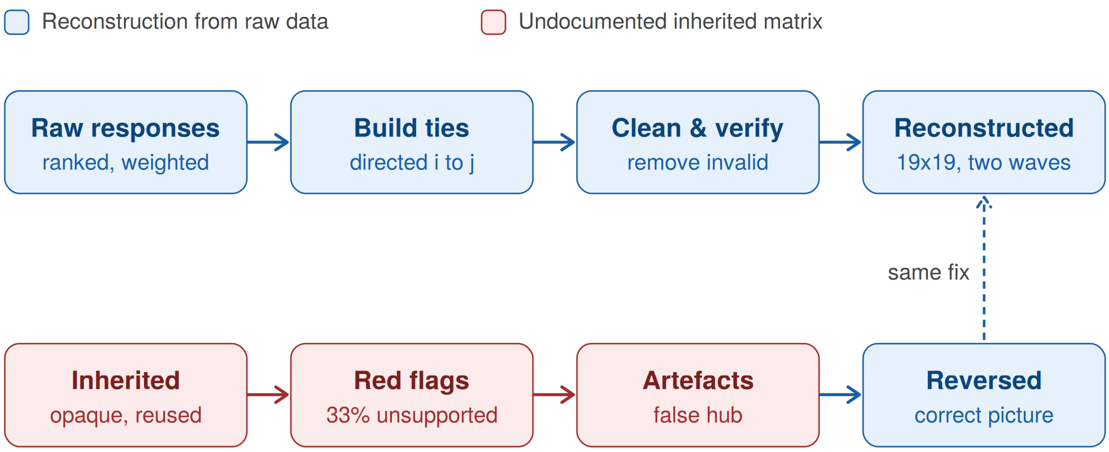

Figure 1. Reconstructing the directed, weighted sociomatrix from raw responses (RQ1). Top: ties are built from each student's ranked, strength-weighted nominations and verified against the instrument's constraints. Bottom: an undocumented inherited matrix introduces unsupported ties and artefacts—inflated density and centralization and a misidentified "hub"—that reconstruction reverses (Section 4.1).

3.6. Measures and Analytic Strategy

Node-level measures (in-degree, out-degree, betweenness, closeness, eigenvector centrality, and nodal reciprocity) and network-level indicators (density, dyad and triad census (Holland & Leinhardt, 1976), reciprocity, transitivity, degree centralization, Louvain modularity (Blondel et al., 2008), weak components, and the share of mutually reachable ordered pairs) were computed in Python (NetworkX; Hagberg et al., 2008). Inference used permutation methods: CUG tests (2000 random graphs conditioned on size and density) for reciprocity and transitivity; the QAP (2000 permutations) for the T1–T2 network correlation and homophily; the E–I index with label permutation for categorical homophily (gender and employment status) and assortativity for age. Paired pre–post change in node-level indices was tested with Wilcoxon signed-rank tests with effect sizes (r), and the stability of network indices was probed with leave-one-out jackknife. Attribute–position associations (RQ3) were examined with Spearman correlations and Mann–Whitney tests. Two cautions apply throughout. First, because the analysis comprises many tests on a single small network, we did not apply formal corrections for multiple comparisons; we therefore treat all attribute–position associations, the perceived reciprocity analysis, and any p between 0.05 and 0.10 as exploratory and hypothesis-generating, not confirmatory. Second, because closeness co-varies mechanically with density, we report closeness alongside density-independent integration indicators (weak components, zero-out-degree counts, and the share of reachable pairs) so that integration is not inferred from a single, partly tautological statistic.

We also report a sensitivity analysis to make the study's power explicit rather than implicit. With N = 19, a two-sided test at $\alpha = 0.05$ has 80% power to detect only large effects: a correlation of $|\rho| \approx 0.60$ or a paired effect size of $dz \approx 0.68$. Associations or changes smaller than these are underpowered by design; this is why we emphasize the few large, robust effects (e.g., the closeness change, $r = 0.94$) and treat moderate associations (e.g., age–brokerage $\rho = 0.55$; perceived–actual reciprocity $\rho = 0.52$) as exploratory signals requiring larger samples for confirmation.

Robustness and reproducibility. Structural indicators were computed on the binarized directed network; tie weights (1–4) were used for visualization and for a weighted-closeness robustness check (distance = 1/strength). To respect the dependence structure of network data and the questionnaire's five-nomination limit, the size- and density-conditioned CUG was complemented by a stricter null, preserving each node's out-degree; the T1–T2 change in degree centralization was tested directly with a node-level label-swap permutation; and the paired pre–post tests were corroborated by network-aware paired permutation tests, with matched-pairs rank-biserial correlations and bias-corrected bootstrap 95% confidence intervals as effect sizes. Analyses used fixed random seeds, and the anonymized reconstructed matrices and analysis code (Python 3.12; NetworkX 3.6; SciPy 1.17) are available from the author on reasonable request to permit full reproduction.

4. Results

4.1. Reconstruction Reverses Substantive Conclusions (RQ1)

We begin with the methodological result, because it conditions everything that follows. Decomposing the pre-existing matrix against the raw questionnaire showed that, of its 127 ties, only 79 corresponded to declared choices and six to received (symmetrized) choices, while 42 ties (≈33%) had no basis in any nomination, in either direction; moreover, 15 of 19 rows had more than five out-ties, exceeding the instrument's five-choice limit. These unsupported ties inflated density and, more seriously, doubled the apparent degree centralization (from $0.34 \rightarrow 0.36$ on the reconstructed network to $0.25 \rightarrow 0.51$ on the original), thereby manufacturing a narrative of "hub emergence" that the data do not support. Most strikingly, the student the original matrix portrayed as the most popular hub (in-degree 16) received, in the raw data, a single positive nomination and was the most frequently rejected peer. Reconstructing the network from raw responses reversed these conclusions (Figure 2). The original and reconstructed popularity rankings were only weakly and non-significantly correlated (Spearman $\rho = 0.36$, $p = 0.13$): 12 of the 19 students (63%) changed popularity quartile, and the student the original matrix ranked as the most-chosen hub (in-degree 17) received no positive nominations in the reconstructed data. This case demonstrates concretely that the construction of the sociomatrix is a substantive analytic decision; all results below use the reconstructed network.

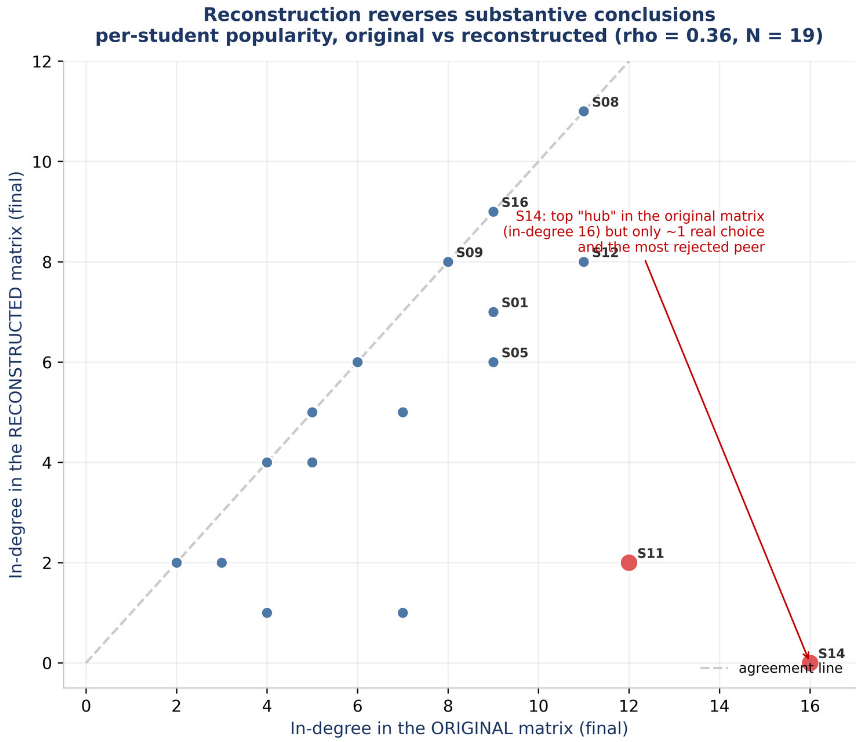

Figure 2. Reconstruction reverses substantive conclusions: per-student in-degree (popularity) in the original versus the reconstructed network (final wave, N = 19). The student marked S14 appears as the dominant hub in the original matrix but receives only a single real nomination—and is the most rejected peer—in the reconstructed network.

4.2. *The Class Network Became More Cohesive and Without Hierarchy (RQ2)*

Over the semester, the reconstructed network gained ties (81 → 91; density 0.237 → 0.266) and became more cohesive on several indicators (Tables 4–6). Node closeness increased (*Mdn* 0.42 → 0.53; Wilcoxon $p < 0.001$, $r = 0.94$), but because closeness co-varies with density, we corroborate this with density-independent measures: the number of students nominating *no* peer fell from 2 to 0, and the share of mutually reachable ordered pairs rose from 0.71 to 0.95. Together, these indicate a pattern consistent with the entry of formerly non-nominating students into the network. Notably, the two students who nominated no peer at T1 both nonetheless received nominations, so they were non-nominators rather than isolates. Because closeness co-varies with density, we treat these as complementary rather than density-independent indicators; a robustness check using weighted distances (the inverse of tie strength) showed the same increase (median 1.03 → 1.33, Wilcoxon $p < 0.001$). At the same time, degree centralization remained stable (Freeman in-degree centralization 0.34 → 0.36; a direct label-swap permutation test of the T1–T2 difference confirmed no significant change, $\Delta = +0.028$, $p = 1.00$), so the gain in cohesion was distributed rather than captured by a few prominent members: integration without hierarchy. Betweenness rose only marginally ($p = 0.078$), and in-degree and nodal reciprocity did not change significantly (Table 6). Figure 3 shows the reconstructed networks; Figure 4 traces popularity per student.

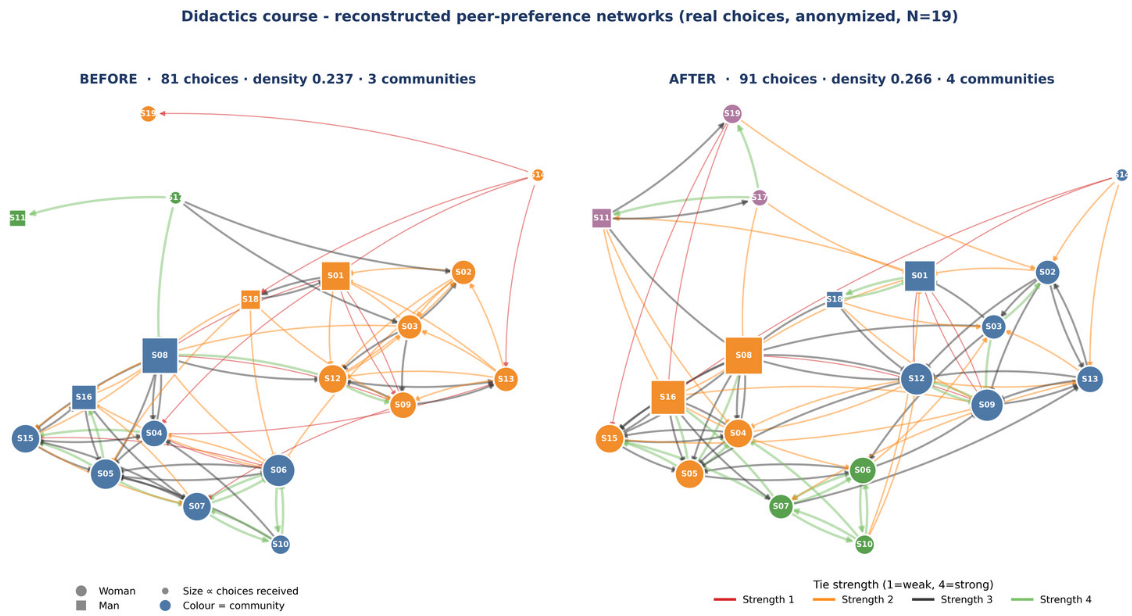

Figure 3. Reconstructed peer-preference networks before (**left**) and after (**right**) the gamified semester (N = 19, anonymized). Node size ∝ choices received; color = Louvain community; shape = gender; edge color = tie strength (1–4).

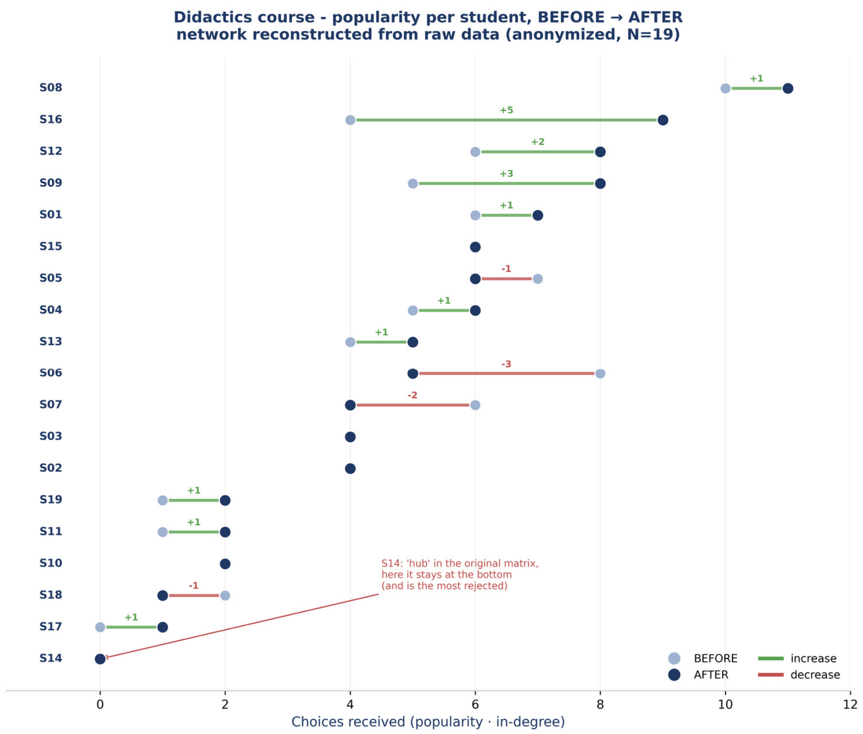

Figure 4. Change in popularity (choices received) per student, T1 → T2, on the reconstructed network.

4.3. Reciprocity, Transitivity, and Stability Exceed Chance

Both reciprocity (dyadic 0.42 → 0.40) and transitivity (0.48 → 0.40) were significantly above chance in each wave (CUG $p < 0.001$), indicating genuine reciprocal and triadic closure; transitivity declined modestly, consistent with a network that opens as new ties form. These results held under a stricter null model that preserved each student's out-degree and hence the five-nomination limit: reciprocity and transitivity remained above chance at both waves (both $p < 0.001$). The two networks were strongly correlated (QAP $r = 0.58$, $p < 0.001$), so change occurred on top of a stable relational core rather than through wholesale reshuffling. Louvain detection returned three to four weakly separated communities with stable modularity (≈0.36). Table 4 summarizes these indicators (with per-node values in Table S1 of the Supplementary Materials), and Table 5 reports the full triad census, showing the transitive and mixed configurations that underlie the above-chance transitivity.

Table 4. Network-level indicators on the reconstructed network, T1 vs. T2 (N = 19). CUG = Conditional Uniform Graph; QAP = Quadratic Assignment Procedure.

Indicator	T1	T2	Test/Note
Ties/density	81/0.237	91/0.266	—
Mutually reachable pairs	0.71	0.95	Density-independent integration
Students nominating no peer	2	0	Integration of isolates
Dyadic reciprocity	0.42	0.40	Above chance, CUG $p < 0.001$
Transitivity	0.48	0.40	Above chance, CUG $p < 0.001$
Degree centralization	0.34	0.36	Stable (jackknife SE ≈ 0.17)
Communities/modularity	3/0.36	4/0.36	Weak, stable subgroups
QAP T1–T2 correlation	—	$r = 0.58$	$p < 0.001$

Table 5. Triad census (Holland–Leinhardt 16 types) for the reconstructed network, T1 vs. T2. Key types: 030T = transitive, 300 = complete (all-mutual), 003 = empty.

Type	T1	T2	Type	T1	T2
003	281	224	030T	10	12
012	257	258	030C	1	1
102	211	189	201	14	25
021D	14	13	120D	7	12
021U	21	36	120U	4	8
021C	32	42	120C	8	5
111D	57	86	210	21	14
111U	21	34	300	10	10

4.4. No Statistically Detectable Homophily by Gender, Age, or Status

Tie formation showed no statistically detectable homophily: E–I indices for gender, employment status, and age assortativity were all non-significant under permutation, indicating that preferences crossed demographic lines rather than clustering within them. This formally substantiates, with a test, what previous descriptive readings had asserted only visually, and is consistent with a course that deliberately mixes ages and backgrounds in its groups.

4.5. The Competence Basis of Peer Choice

Students indicated, for each chosen peer, the competences motivating the choice (188 attributions at T1; 231 at T2), allowing the reasons behind ties to be examined (Figure 5). At T1, relational/communicative competence was the single most common reason (31% of attributions); by T2, the profile had leveled out, with relational competence falling to 28% while organizational/strategic competence rose from 21% to 25%. As the groups matured, students appear to have chosen partners somewhat less for affinity and more for their capacity to make the group function—a movement from affiliative toward task-oriented criteria. The most central students were valued on a broad front, accumulating attributions roughly evenly across all four categories, suggesting that centrality reflected multidimensional desirability rather than a single salient strength. We present this descriptively; the modest counts per node preclude strong inferential claims.

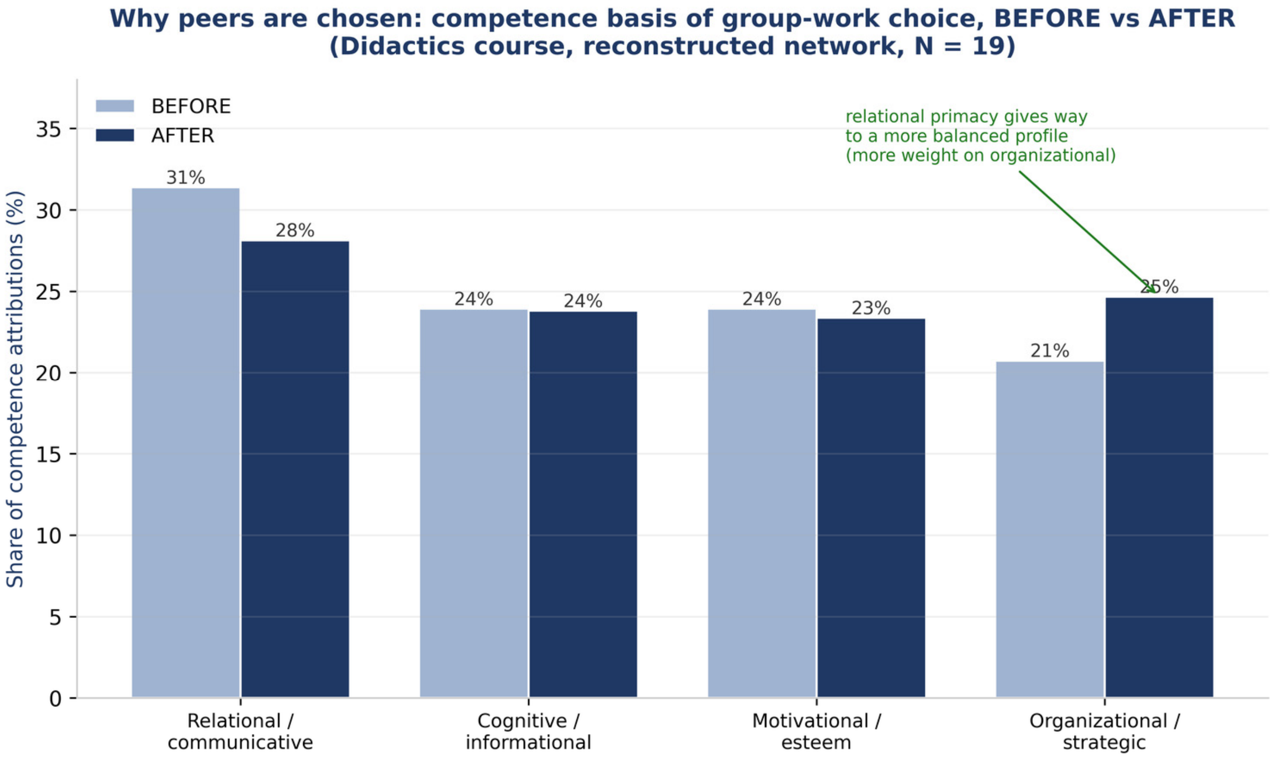

Figure 5. Competence basis of group work choice before and after the gamified semester: share of competence attributions across the four categories (N = 19).

4.6. Exploratory Attribute–Position Associations (RQ3)

The following associations are reported as exploratory and uncorrected for multiple comparisons; with N = 19, they are hypotheses for confirmatory work, not findings. Age was unrelated to popularity ($\rho = 0.30$, n.s.) but positively related to gains in brokerage (Δ centrality $\rho = 0.55$, $p = 0.015$; betweenness $\rho = 0.48$, $p = 0.035$), suggesting that older students may take on bridging roles. Hexad type, generalized self-efficacy, and group role orientation showed no robust association with centrality; a marginal negative self-efficacy–popularity gain relation ($\rho = -0.44$, $p = 0.06$) is noted only as a hypothesis. Tellingly, several associations that appeared significant on the original (inflated) matrix—a negative Philanthropist–popularity link and a gender effect on centrality—did not survive reconstruction, a further illustration of how matrix construction can generate spurious attribute effects. Table 6 reports paired pre–post tests and key associations.

Table 6. Paired node-level change (Wilcoxon, with effect size r) and exploratory attribute–position associations (Spearman ρ) in the reconstructed network (N = 19). Associations are uncorrected and hypothesis-generating.

Measure/Association	T1 → T2 (Mdn) or ρ	p	Note
Closeness (Wilcoxon)	0.42 → 0.53	<0.001	r = 0.94, 95% CI [0.77, 1.00]
Betweenness (Wilcoxon)	0.03 → 0.05	0.078	r = 0.47, 95% CI [−0.05, 0.89]
In-degree (Wilcoxon)	4 → 5	0.207	n.s.; r = 0.37, CI [−0.21, 0.90]
Nodal reciprocity (Wilcoxon)	0.36 → 0.40	0.796	n.s.; r = 0.07, CI [−0.48, 0.66]
Age → Δ centrality/betweenness	ρ = 0.55/0.48	0.015/0.035	Exploratory
Age → popularity	ρ = 0.30	0.22	n.s.
Self-efficacy → Δ popularity	ρ = −0.44	0.06	Exploratory
Perceived → actual reciprocity (T2)	ρ = 0.52	0.02	Exploratory (Section 4.7)

Note: n.s. = not statistically significant ($p \geq 0.05$); r = matched-pairs rank-biserial correlation; ρ = Spearman correlation; CI = 95% bootstrap confidence interval.

4.7. Perceived Versus Actual Reciprocity (Exploratory)

Because both perceived reciprocity (a single ordinal item) and actual reciprocity (from the matrix) were available, their correspondence could be examined. At T1, the two were unrelated (ρ = 0.17, n.s.); at T2, they were associated (ρ = 0.52, p = 0.02). Read cautiously, this is consistent with students becoming more accurate about their own reciprocal ties over a semester of collaboration. We stress, however, that the measure is a single item, the sample is small, and the test is uncorrected; the result is offered as a hypothesis—that sustained cooperation may improve the calibration of social perception—to be tested with validated multi-item measures in larger samples, rather than as an established effect.

4.8. Popularity and Rejection Are Inversely Related

The rejection network (density ≈ 0.14, stable across waves) reinforces the reconstruction's central lesson. Being chosen and being rejected were negatively associated at both waves (Spearman ρ = −0.63, p = 0.004 at T1; ρ = −0.47, p = 0.042 at T2): the least-chosen students were the most rejected. The clearest case is the student that the original matrix portrayed as the popular hub, who received no positive nominations and 16 rejections in the reconstructed data (Figure 6). An earlier analysis on the pre-existing matrix had suggested the opposite—a positive, non-significant "polarization" trend—but that pattern was itself an artefact of the inflated matrix, in which the same student appeared simultaneously as the most chosen and the most rejected; reconstruction removes this contradiction and aligns the rejection results with Section 4.1. Rejection was also directed more diffusely than positive choice: nearly half of the rejection nominations (46% at T1, 43% at T2) targeted classmates outside the 19-student core. Because one student (16 rejections and no positive choices) is an influential extreme case, we re-estimated the association without her: the negative relationship held at T1 (ρ = −0.56, p = 0.015) and remained negative but non-significant at T2 (ρ = −0.37, p = 0.128), so the T2 estimate should be read as suggestive and sensitive to that single case.

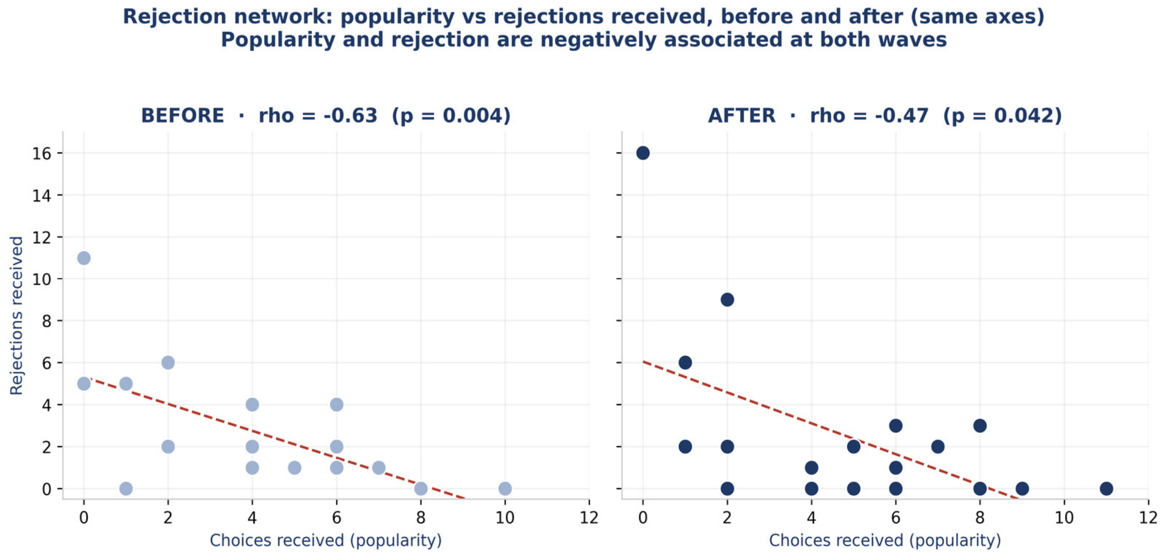

Figure 6. Choices received (popularity) versus rejections received, before and after, on identical axes. Popularity and rejection are negatively associated at both waves (Spearman $\rho = -0.63$, $p = 0.004$ at T1; $\rho = -0.47$, $p = 0.042$ at T2). A leave-one-out check excluding the single extreme case (16 rejections, no positive choices) leaves the T1 association significant ($\rho = -0.56$, $p = 0.015$) and the T2 association negative but non-significant ($\rho = -0.37$, $p = 0.128$).

5. Discussion

This study pursued a methodological and a substantive aim, and the methodological one is, in our view, the more secure contribution. Answering RQ1, we showed that a pre-existing sociomatrix can contain a large fraction of ties with no basis in the data—here, one-third—and that such ties are not cosmetic: they doubled the apparent centralization, fabricated a "hub emergence" story, and inverted the standing of the single most-rejected student into that of the most popular. Because sociometric matrices are often inherited, shared, or produced by point-and-click tools without an auditable trail from raw responses, this is a general hazard rather than a local mishap. The practical lesson is concrete: reconstruct the directed, weighted network from raw nominations; document the treatment of weighting, self-nominations, out-of-roster nominees, and name-matching; and verify the result against the instrument's constraints (for example, that no out-degree exceeds the number of nominations allowed).

Turning to RQ2 and reading the results as associational, the cohort's network became more cohesive over the semester while remaining flat in its centralization. The convergence of several indicators—integration of students who initially named no one, a rise in mutually reachable pairs from 0.71 to 0.95, increased closeness—makes a density-only explanation unlikely, although we are careful not to over-read closeness alone. This pattern of integration without hierarchy is what a cooperatively oriented, meaningful design organized around rotating groups and shared missions would be expected to produce, and it aligns with SDT's emphasis on relatedness and with social-interdependence accounts of cooperative structure (Deci & Ryan, 2000; Johnson & Johnson, 1989). The absence of demographic homophily indicates that the class did not fragment along gender, age, or status lines, consistent with a course that deliberately mixes its groups. We frame these as patterns consistent with the design rather than as effects caused by it, since the single-cohort pre–post design cannot exclude maturation or familiarity.

On RQ3, we are deliberately restrained. The shift in the competence basis of choice—from relational toward organizational criteria, with central students valued across all four competence dimensions—is a descriptive pattern we find suggestive of maturing, task-oriented collaboration, but it rests on modest counts. The exploratory associations (older students gaining brokerage; the calibration of perceived to actual reciprocity) are intriguing and theoretically resonant, but with N = 19, uncorrected tests, and, in the reciprocity case, a single-item measure, they must be treated as hypotheses. The fact that several attribute effects visible on the inflated matrix vanished after reconstruction is itself instructive: at this scale, attribute–position inference is fragile and especially vulnerable to artefacts in the network itself. The rejection results, once the matrix is corrected, show that the most visible students are the least rejected; collecting rejection alongside positive choice remains valuable and, here, further exposed the artefact in the inherited matrix.

Practical Implications

Three implications follow, stated at a level that the evidence supports. First, sociometric measurement is a sensitive and inexpensive instrument for the relational evaluation of gamified courses: a short pre–post questionnaire surfaced the integration of peripheral students and the multidimensional basis of peer regard that grade- or satisfaction-based evaluation would miss, and the integration of students who initially named no one is a concrete, monitorable outcome for instructors. Second, when community and inclusion are the goal, the relational signature to look for is increased cohesion and reachability without rising centralization, rather than the emergence of star performers; collecting rejection as well as positive choice helps reveal whether prominence carries social costs. Third, and cutting across the others, the construction of the sociomatrix must be transparent and reproducible; we recommend that studies report their reconstruction procedure and share, at minimum, the anonymized matrices and the code that produced them.

Toward a reporting standard for sociomatrix reconstruction. Because the analytic consequences of matrix construction are large, studies that build a sociogram from raw responses should report, at minimum: (i) the direction of ties (who nominates whom); (ii) whether and how ties are weighted; (iii) any nomination cap or threshold and how it is enforced; (iv) the treatment of self-nominations; (v) the treatment of nominees outside the analyzed roster; (vi) the provenance and validation of any pre-existing or inherited matrix; and (vii) the checks performed against the raw data. Reporting these choices—and sharing the resulting matrices and code—lets readers see, as here, when a substantive conclusion depends on a construction decision rather than on the data.

Reading through the framework in Table 2, the observed changes are consistent with the course's cooperative design without requiring a causal claim: randomly formed, rotating groups repeatedly exposed each student to new collaborators, a plausible route to the rise in mutually reachable pairs and to the integration of previously non-nominating students; shared, interdependent missions are consistent with reciprocity and transitivity above chance; and the absence of a competitive leaderboard fits cohesion increasing while centralization stayed flat. These are interpretive mappings, offered as hypotheses for a controlled test, not as established mechanisms.

6. Limitations and Future Research

The limitations are substantial and bound our claims. This study is a single-cohort, pre–post case study without a control group (N = 19); it cannot attribute change to gamification rather than to time, familiarity, or maturation, and supports associational, not causal, inference. The most plausible rival explanation is simple maturation: over a semester, classmates grow familiar regardless of any intervention, which could by itself raise cohesion. We cannot rule this out; however, maturation alone does not obviously predict the specific pattern observed—integration without a rise in centralization, alongside reciprocity and transitivity above chance and a shift in the competence basis of choice—so the relational signature reported here remains informative as a description, even though it is not a causal estimate. Finally, the instrument used a fixed-choice format (a maximum of five nominations); like all limited-nomination designs, this truncates weaker ties and can affect degree-based measures, so estimates are conservative for the densest part of the network. The small size precludes exponential random graph modeling and limits statistical power; we relied on permutation methods, which are appropriate but less expressive than generative models. Because the analysis comprises many tests, we did not correct for multiple comparisons and have flagged all attribute–position and perceived-reciprocity results as exploratory; some are likely to be false positives. The closeness result co-varies with density and should be read together with the density-independent indicators we report. The perceived-reciprocity measure is a single ordinal item, and gender and age are partially confounded in this cohort.

Four directions would strengthen future work. First, a comparison group—ideally a non-gamified offering of the same course—would permit causal attribution. Second, the course formed half of its groups at random and half by student choice; recovering that assignment would enable a quasi-experimental comparison of how the network evolves under imposed versus chosen collaboration. Third, replication across disciplines, cohorts, and gamified designs (cooperative versus competitive), with validated multi-item measures and confirmatory hypotheses, would test the exploratory patterns reported here, including by pairing peer-attributed competences with self-declared group roles to assess the accuracy of peer perception. Fourth, triangulating the network data with the learning-analytics, observational, and interview data available in the wider study would connect relational structure to behavior and experience. The companion course in the same program offers an immediate opportunity to move from one network to two.

7. Conclusions

Two conclusions are warranted. Methodologically, the construction of the sociomatrix is a substantive analytic decision: in our case, a pre-existing matrix contained a third of ties with no basis in the data, doubled the apparent centralization, and inverted the standing of the most-rejected student into that of the most popular, all of which reconstruction from raw responses reversed. Sociometric research should therefore reconstruct directed, weighted networks transparently from raw nominations and share the matrices and code. Substantively, and as exploratory evidence, one semester of cooperative, gamified group work in this cohort was associated with a more cohesive and more inclusive class network—greater reachability, integration of formerly isolated students, no rise in hierarchy, reciprocal and transitive structure beyond chance, and no demographic segregation—while several attribute-level and perceptual patterns emerged as hypotheses for confirmatory study. SNA thus offers a sensitive lens on the relational dimension of gamified learning that individual-level measures cannot provide, provided its inputs are built with care and its inferences kept proportionate to a small, single network.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/educsci16091465/s1. Table S1: node-level network indices per student (in-degree, out-degree, betweenness, closeness, and nodal reciprocity) at T1 and T2; Data S1: the anonymized reconstructed adjacency matrices for the positive and rejection networks at both waves, in spreadsheet form; Data S2: the analysis code (Python) reproducing all reported statistics and figures.

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Institutional Review Board Statement: This study was conducted in accordance with the Declaration of Helsinki. Formal approval by an Institutional Review Board was not required for this study: at Università Cattolica del Sacro Cuore, no institutional ethics-committee approval is mandated for anonymous, non-interventional survey research of this kind, and, in accordance with standard doctoral practice, ethical oversight was provided by the doctoral supervisor (and, where applicable, the Faculty Board). The research involved a voluntary, anonymous questionnaire, with no sensitive personal data, no clinical intervention, and no foreseeable risk to participants.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study. Participation was voluntary and had no effect on students' academic assessment; all data were anonymized prior to analysis.

Data Availability Statement: The anonymized reconstructed adjacency matrices and the analysis code supporting the reported findings are available from the author upon reasonable request. Raw questionnaire data are not shared in order to protect participant privacy in a small cohort.

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