Perception of own centrality in social networks

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This study explores how individuals perceive their social networks, with a focus on their own positioning. Using experimental methods and network analysis, we show that people have a limited understanding of their social standing in terms of popularity (in-degree) and centrality. Few participants accurately estimate their popularity, and even fewer correctly identify their decile of centrality. A similar pattern emerges for their perceptions of the most popular and central individuals, but we find no correlation between the ability to assess one's own position and the ability to detect key network members. Popular participants correctly perceive themselves as more popular, although they tend to misjudge their popularity more than less popular peers. They are nonetheless more accurate in estimating their centrality. Perceived centrality is only weakly correlated with actual centrality, but central individuals misperceive both their popularity and centrality to a greater extent. We further show that these misperceptions have real-world implications. Conditional on network positioning, students who see themselves as less popular and less central–and those with more accurate self-perceptions–tend to achieve higher grades, whereas individuals recognized by others as popular and central perform significantly better academically. These findings challenge theoretical models that assume accurate self-awareness of network positions and highlight the need to reconsider the implications for key-player interventions in public health, education, and organizational contexts.

Complex networks | Behavioral experiments | Centrality | Network perception | Social dynamics

Significance Statement

People's success in social and professional settings depends on understanding their own and others' roles in social networks, while accurate network perception helps target key individuals more effectively in public health, education, and organizations, strengthening trust and collaboration. We find that individuals systematically misperceive their popularity and centrality as well as that of others, an observation that is not explained by the intricacies of network structure. Importantly, these misperceptions predict academic outcomes, demonstrating their real-life impact beyond social life. Our findings suggest that boosting individuals' understanding of social structure can support both academic achievement and stronger, more connected communities, offering new pathways for interventions aimed at improving group dynamics and social inclusion.

Social networks, understood as networks of social interactions and personal relationships, have been the subject of research for almost a century.(1) Ever since, research across various disciplines has gathered substantial evidence demonstrating that the patterns of personal interactions are crucial to the evolution and functioning of human societies.(2–4) Quantitatively, social networks have been characterized by various metrics such as density, clustering coefficient, and degree distribution, revealing patterns of integration, cohesion, connectivity, and influence.(4–6) Among these metrics, centrality measures are particularly significant as they reflect different perspectives on the importance and influence of particular nodes within a network structure.(7, 8) Understanding centrality not only enhances our comprehension of network dynamics but also aids in practical applications, such as optimizing communication strategies, preventing spread of diseases or misbehaviors, and improving organizational efficiency. (9, 10) In epidemiology, understanding which individuals are 'superspreaders' can inform strategies for disease control and prevention.(11) In organizational settings, identifying central individuals can help optimize communication flows and improve decision-making processes.(12) Similarly, companies target central individuals within social networks to maximize the impact of word-of-mouth campaigns and other interventions.(13, 14) Different measures have been proposed to capture different aspects of centrality, including degree centrality,(15) closeness centrality,(9) betweenness centrality,(16) and eigenvector centrality,(17) each highlighting particular features of influence and connectivity.

Despite the widespread utility of centrality measures, a fundamental question arises when network members assess their own positioning: to what extent are individuals aware of their popularity and centrality within the networks they belong to? (18, 19) This question not only challenges our

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J.K. and P.B.-G. posed the research question and conceived the experiment(s), J.K. and J.O. analyzed the results, and all authors discussed and interpreted the results and wrote the manuscript.

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understanding of self-perception in social structures, but also raises important considerations for policy and intervention strategies.(20) Our focus on self-awareness stands in contrast to structuralist approaches that implicitly or explicitly operate under the assumption that an actor's position in the network has consequences, regardless of their awareness of that position. Thus, physical connections alone are sufficient for a virus to propagate–for instance, when an infectious person coughs in the presence of another–so the infected person's awareness of her position is irrelevant to transmission. However, people may adapt how and with whom they interact based on their awareness of their own and others' positions in the network. Likewise, adherence to mitigation strategies—such as stay-at-home recommendations targeted at highly central individuals—may depend on whether those individuals perceive themselves as occupying such roles.(21) This distinction is especially important in models of awareness diffusion during epidemics, where individuals' behavioral responses to perceived risk can influence the course of spread.(22)

At the other extreme of structuralist thinking lie classic models of network formation and behavior that assume that agents possess perfect knowledge of the underlying network.(23–26) These models—often used to inform policy—assume a level of informational sophistication that contrasts sharply with empirical findings from social psychology. There, research consistently shows that people rely on heuristics and display systematic biases in judging their own social standing.(27, 28) This tension—between structuralist assumptions, subjective self-assessment, and objective algorithmic assessments—lies at the heart of our investigation and has clear implications for the design of network-based interventions.(19, 29) Indeed, accurate self-assessment of one's network position can play a role in acquiring or maintaining power in organizations,(30) fulfilling social belonging needs,(31) and potentially influencing emotional well-being or anxiety.(3)

Previous research has primarily examined whether people can identify the most central or socially valued members of their networks, or how accurately they perceive third-party ties or the broader structure.(28, 32–38) However, there is limited understanding of how accurately individuals perceive their own social positioning. Cognitive biases and limitations might lead individuals to frequently and systematically misperceive their centrality but, if this misperception is consistent across individuals, there should still be a strong correlation between perceived and actual centralities. Common sense and the literature (32, 37) suggest that people should better assess their local embeddedness as opposed to global centrality because local positioning is simpler to gauge in complex social networks in terms of information availability, processing, and cognitive resources. Although no study has analyzed the association between the ability to perceive one's own vs. others' positioning, our initial hypothesis is that both abilities are related.

As for who might perceive her or his position more accurately, the network literature has mostly focused on different dimensions of social status, such as power, dominance, or centrality.(19, 29, 39) Clustered networks seem to enhance the accuracy of one's recall of the overall structure (28) and people seem to perceive their networks more correctly in smaller groups.(40) Regarding non-network determinants, women outperform men while perceiving the networks around them.(40, 41) Since this literature does not evaluate the ability to evaluate one's own standing within the networks, the evidence provides no clear hypothesis regarding whether popular and central people should have more or less accurate perception of their positioning, but it suggests that people in denser and smaller networks and women should better predict their social standing.

Methodologically, we first combine experimental methods and network theory. The subjects of our experiments belonged to a number of undergraduate classes across different study areas. First, we elicited their strong ties toward other members of their class. This information allows us to build a directed network of social relationships in each group. We focus on strong ties because they are the most relevant for understanding phenomena such as trust, cooperation, peer influence, and emotional support, and also because there is robust evidence that individuals are more accurate in identifying strong ties than weak ones (42, 43); see also *Discussion*. Second, we requested each subject to assess both their own popularity and centrality in the elicited networks, as well as to identify the most popular and central members of their class. The reason to ask about popularity is that it is an intuitive measure, defined as the in-degree of the participant or the number of people who report them as a strong tie. Thus, we can compare individual ability to perceive own popularity along with the case of centrality, two measures that should not be confused.(44) We them ask them to identify the key members of their class in the elicited network to be able to compare their ability to perceive own vs. others' positioning. Importantly, we financially incentivized reporting strong ties, providing correct estimates of their popularity and centrality, as well as identifying the most popular and central members of their class (see Materials and Methods). Due to the complexity of the different centrality concepts, instead of requesting directly a centrality score, we inquire about the *decile* of centrality to which each subject perceives herself to belong. See Materials and Methods for further details. Lastly, we complement the experimental and network data with administrative data on students' grades to explore real-life implications of network perception.

Perception of own and others' popularity and centrality

We collected data on social networks from 11 independent classes in Loyola University Andalucia (Fig. 1a); Materials and Methods). All participants were students in their first year at the university and have been in the same class for nine months. The elicited data reproduce the findings of the previous literature: the elicited networks resemble typical empirically observed social networks and women are perceived as less popular and less central (see below and Sections S3–S4 in the *Supplementary Information*; SI).

Descriptive statistics and correlations. In our sample, 484 (474) subjects reported their estimate of their own popularity (centrality). Figures 1b), c) depict the distributions of the true and perceived in-degree and the deciles of centrality to which participants believe they belong, respectively.

Descriptive statistics: mean differences and distributions. On average, people expect to be nominated as strong ties by 3.13

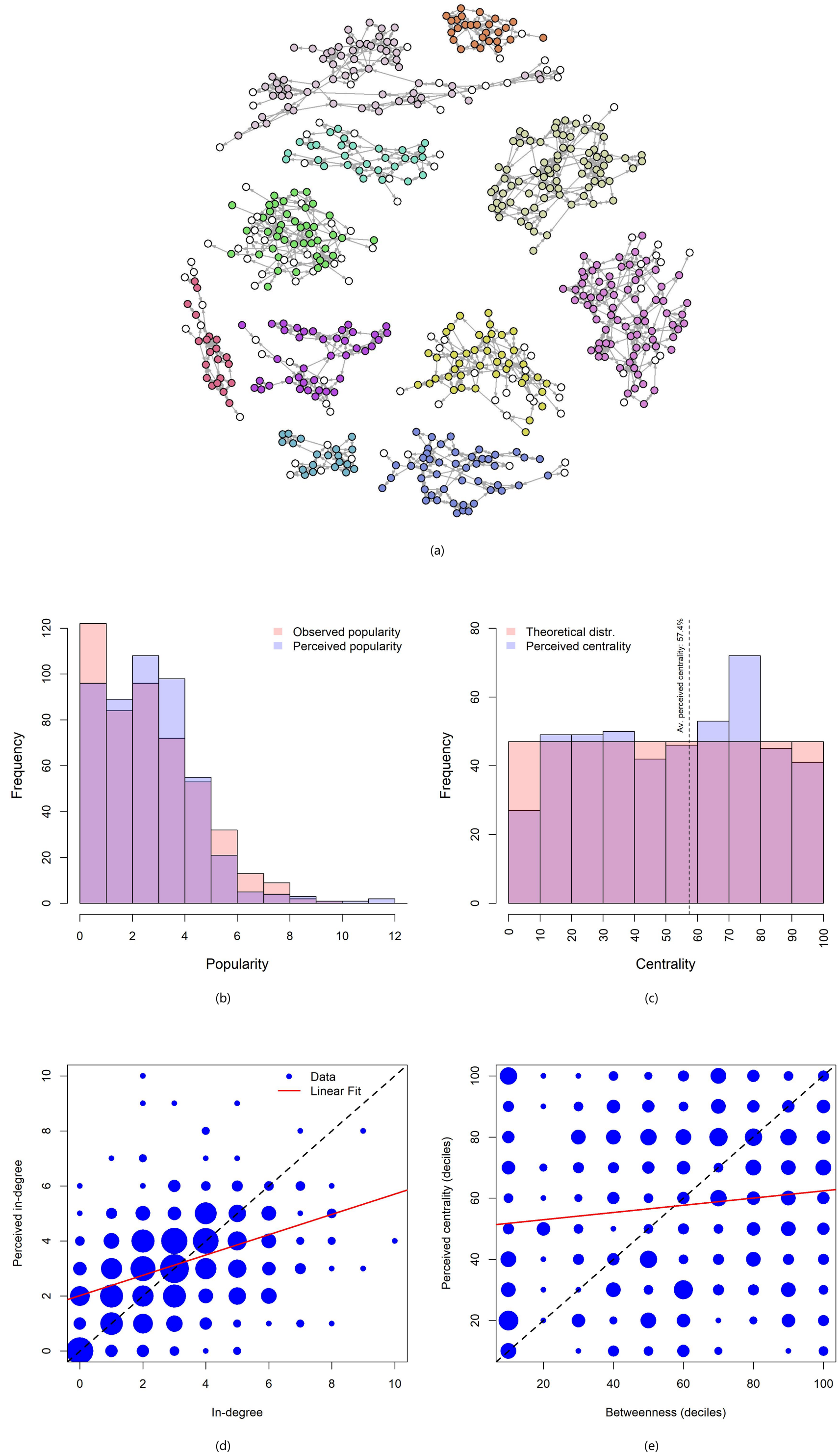

Fig. 1. (a) The 11 analyzed networks (9 isolates removed; see Fig. S1a in the Supporting Information (SI)). The nodes are colored according the class; white nodes correspond to subjects who did not participate in the experiment but were mentioned by at least one participant. (b) Density of true and perceived popularity (one outlier with perceived popularity of 25 removed from the graph for better visibility). (c) Distribution of the perceived centrality (deciles) vs. the theoretical uniform distribution. We represent the true distribution of deciles using a uniform distribution for the following reasons. By definition, each decile should contain 10% of the population; we elicited from our subjects the deciles (rather than the centrality scores); we did not specify any particular centrality measure during the elicitation stage. Figs. S1 (S2) in the SI plots equivalent graphs using the kernel density estimates for the perceived variables (the true distributions of deciles of each centrality measure under study), corroborating the conclusions from the main text. (d) The scatter plot of the perceived and true in-degree in blue and their linear fit in red (outliers again removed from the graph). (e) The scatter plot of the perceived and true deciles of betweenness centrality (see Fig. S5 for a scatter plot of the perceived deciles and the true betweenness centrality; Fig. S6 for other centrality measures). In (d) and (e), the size of the dots is proportional to the number of observations. Note the different scales on the x-axes across different panels.

other members of their network (st. dev. 2.15), while they are actually named by 3.02 (st.dev. 2.02). The average perception of the decile of centrality is 5.74 (st. dev. 2.72). Although people slightly overestimate their popularity and their decile of centralities of betweenness and closeness while understating their decile of eigenvector centrality, the differences are not significant (Wilcoxon signed-rank test, $p > 0.35$). Men perceived themselves more popular than women (Mann-Whitney test; $z = 1.835$, $p = 0.0665$), although they are not ($z = -0.808$, $p = 0.4189$), but there is gender difference neither for perceived nor true centrality (Perceived: $z = 0.949$, $p = 0.3425$; True: $p > 0.13$). As a result, men significantly overestimate their popularity ($z = 2.149$, $p = 0.0317$) whereas women do not ($z = -0.438$, $p = 0.6616$). No gender under- or overstates its decile of centrality with respect to any measure under study ($p > 0.23$).

At the aggregate level, Figures 1b), c) show that the true distributions of popularity and centrality exhibit "fatter tails" than their perceived counterparts. There is considerably higher frequency of unconnected/peripheral as well as highly connected/very central individuals in the true distribution, as compared to the distribution of perceived centralities. The discrepancies are more apparent in Figs. S1b and S1c in the SI, which show the kernel density estimates of the distributions. This indicates that the distribution of the perception of own local and global network importance is more homogeneous and less hierarchical than the true distribution. Fig. 1d) shows that the difference in case of popularity can be attributed to people at the end of the distributions systematically over- and under-stating their in-degree (see *Discussion*). However, this is not the case of centrality: Fig. 1e) rather suggests–and our regression analysis corroborates–that there is no systematic relationship between one's true and perceived centrality.

Accuracy of self-perception. As for the accuracy of subjects' perception, 24.79% of subjects estimate correctly their own in-degree, while 8.86%, 8.92%, and 8.02% position themselves into the correct decile of centrality based on the closeness, betweenness, and eigenvector centralities, resp. The success rate is higher for popularity than any centrality measure (Wilcoxon signed-rank tests; $p < 0.0001$). See Fig. S3 for the entire distribution of the mistakes. Table S2 shows that the correlation between the perceived and true popularity is $\rho = 0.3470$ ($p < 0.0001$). Although this correlation is far from one, it is considered a large effect in psychological research,(45) corresponding to Cohen $d = 0.7397$. Hence, people are to some extent aware of their true popularity. Although perceived centrality is also positively correlated with the centrality measures under consideration, the correlations are below 0.1 and never significant at less than 5% ($\rho = 0.042, 0.0772, 0.0385$; $p = 0.3409, 0.0939, 0.4029$ for closeness, betweenness, and eigenvector centrality, resp.; Cohen $d = 0.0841, 0.1549, 0.0771$). These correlations are interpreted as between very small to small effects in psychology.(45) If we instead correlate the perception with the deciles of the true centralities, the correlations increase to $\rho = 0.0910, 0.1247,$ and 0.0866, becoming more significant ($p = 0.0495, 0.0065, 0.0596$; Table S3) but still rather low.(45) This confirms the conclusions from Fig. 1e): subjects' assessment of their centrality in networks is quantitatively low, something that does not seem to be driven by the possibility that people have in their minds any particular dimension of centrality or centrality measure (Table 1, Fig. S5–S6).

Identification of key players. As for participants' ability to identify the most popular and central members of their class, 474 (475) individuals provided answers—though not necessarily the same participants who estimated their own standing. 10.76% correctly identify the most popular individual in their class and 6.53%, 6.74%, and 13.68% the most central member if we use closeness, betweenness, and eigenvector centrality, resp. The success rates are higher for popularity than centrality if we consider closeness and betweenness ($p = 0.0324$ and 0.0442) but the difference is not significant for eigenvector centrality ($p = 0.1394$). Interestingly, the success rate for popularity is uncorrelated with that of centralities ($p > 0.14$; Table S7). There is no gender difference for the most popular individual or the most central in terms of closeness or betweenness ($p > 0.39$; two-sample Wilcoxon rank-sum tests), but women predict considerably better the most central member of their class if we employ eigenvector centrality: 5.62% men predict correctly the most central individual while the figure raises to 17.78% for women ($z = -3.639; p = 0.0003$). This gender effect is not robust to formal regression analysis though (Tables S18-S19). This analysis rather reveals that more hierarchical networks, as reflected in the coefficient of variation of the in-degree distribution (46), and less women in the class increase the likelihood of predicting correctly the most popular member of the group, whereas the ability to predict the most central individual is associated with higher out-degree, lower centrality, larger network sizes, and higher link density. Interestingly, people considered as central by many others are less likely to identify the most central members, although they better predict their own popularity and centrality (see Table 1).

Lastly, we detect that the rate of successfully estimating one's own in-degree is systematically larger that the detection rate of the most popular member of the class ($z = -5.398; p < 0.0001$), while the difference is not systematically significant for centralities (Section S3). Most importantly, the ability to accurately estimate one's own positioning is largely uncorrelated with identifying the most popular and central members of the network (Table S5). This suggests that both abilities are unrelated and likely driven by different mental processes.

Regression analysis. Formal regression analysis corroborates the above findings and reveals other regularities as shown in Table 1. In the main text, we focus on linear models; equivalent non-linear and censored regressions and other model variants confirm the findings reported here (Section S5, SI). Our models analyze what determines subjects' elicited perception and its (in)accuracy, defined as the absolute value of the difference between the perceived and observed popularity and centrality, respectively (Fig. S4 plots their distributions). Therefore, less precise individuals exhibit higher values of inaccuracy. In this section, we focus on how network positioning and global network architecture shapes perception (see *Discussion* and Section S5 for non-network determinants).

Popularity. As for the perception of popularity, in-degree and out-degree are its robust and independent predictors ($p = 0.001$ and $p = 0.048$, resp.). Based on linear models, *ceteris paribus*, being reported by one additional individual as a strong tie or reporting one additional strong tie make people believe that they have more than 0.27 or 0.26, resp., additional strong ties in their network. In-degree alone explains over 12% of the variability of perceived popularity while the two variables jointly explain 15.9%; regression (1) in Table 1, which includes a series of other controls, increases this fraction only up to 18.0%. Neither the centrality measures ($p > 0.26$) nor the features of the global network architecture ($p > 0.06$) systematically predict the assessment of popularity, and their inclusion into the models barely affects the explanatory power of the model.

These conclusions are unaffected by controlling for how often people are named by others as the most popular or central member of their network, although these variables are significant predictors of perceived popularity ($p < 0.03$). Hence, on top of true popularity and centrality, people considered popular and central by others perceive themselves as more popular. On the other hand, the regressions corroborate that the ability to identify the popular and central members of one's group is unrelated to the ability to perceive one's own social standing. Overall, our regression only explains less than 18% of the dependent variable despite the inclusion of a large array of controls, suggesting the true networks predict subjects' perception of their social roles only weakly and other features will shape the perceptions.

In regard to the determinants of the (in)accuracy of perceived popularity (column (2)), both local and global positioning shapes the accuracy of perception of own popularity. True popularity is again a key predictor ($p = 0.026$). Similarly, being more central–as reflected by both betweenness and eigenvector centralities in the regressions–decreases precision ($p = 0.001$ and 0.056, resp.). That is, being more important–and, therefore, occupying a more complex position–makes people less accurate assessing their own popularity. Out-degree, the subjective number of one's friends, does not affect accuracy ($p = 0.611$). Among the global measures, only average connectivity shape the perception: more connectivity improves one's assessment ($p = 0.009$). None of the perception variables play any role. However, the predictive power of the model based on R-squared is 43% lower compared to that of the perception. Hence, both network information and perception variables provide little insight into why people misperceive their popularity.

Centrality. Concerning the perception of centrality, neither in-degree, out-degree, nor any centrality measure relate to this variable ($p > 0.14$; Table 1, Section S3 in the SI). In contrast, clustering coefficient make people feel less central, although the effect is statistically weak ($p = 0.091$). Hence, one's own true positioning only weakly shapes how central people find themselves. The only global network feature that is a strong predictor of perceived centrality is the coefficient of variation: higher coefficient of variation of the degree distribution (reflecting more hierarchy or heterogeneity in connectivity in the class (46)) make people perceive themselves as more central ($p < 0.0001$). Again, people viewed as central by others also perceived themselves as more central ($p = 0.041$). Overall, the proportion of the variance in the dependent variable explained in our most complete model is 5.54%, dramatically less than in case of popularity. Hence, since we control for the true centrality, we can conclude that people only poorly assess their global centrality.

The inaccuracy of the estimate of one's own centrality is only predicted by two variables in Table 1, but the effects are not robust to other model specifications (Tables S14–S15). In fact, the proportion of the variance in the dependent variable explained by the model is really poor this time (3.46%), corroborating that people perform poorly while estimating their centrality in our data and proving motivation for further research assessing the determinants of how people view their global positioning in their networks.

Academic consequences of network perception

The weak alignment between perceived and actual positioning and the fact that our explanatory variables account for only a small share of the variation in subjects' perceptions might generate concerns regarding the robustness of the findings. One might, for instance, wonder whether the elicited variables primarily reflect measurement error or random noise. To address this concern, this section complements the previous analysis with administrative data on students' academic performance. Specifically, we examine whether perceptions of one's own and others' centrality predict academic outcomes and evaluate which type of perception serves as a stronger predictor.

Table 2 reports estimates from simple models regressing students' cumulative grade point average (GPA) over their entire study period on the perception variables introduced earlier, the same set of network variables used in Table 1, and two additional controls known to strongly influence grades: a female dummy and an indicator for students enrolled in a double major (known as *doble grado* in the Spanish education system). The estimates in Table 2 reveal a clear pattern. Although one coefficient is not statistically significant, the overall tendency is evident: all else equal, students who perceive themselves as less popular and less central tend to achieve higher GPAs ($p = 0.028$ and 0.652, resp.), as do those who assess their position more accurately ($p = 0.037$ and 0.081). In other words, both students' perceptions of their own position—and the accuracy of these perceptions—are correlated with academic performance. Once again, the associations are stronger for perceived popularity, which is more accurately aligned with its true value, than for centrality. Section S5.3 confirms that similar results hold when we use students' GPA from the academic year of the experiment and that the associations weaken when network variables are not controlled for. Given that many network controls are statistically significant in the regressions presented in Table 2 (see Table S21), we conclude that: comparing two individuals with similar positions and networks who are perceived similarly by others, the individual who perceives themselves as less important within their network, or who has a more accurate self-assessment, performs better academically.

Another noteworthy finding is that, individuals who are perceived as popular and central by others perform significantly better academically ($p < 0.001$). In contrast, the ability to identify the key players within the group does not predict GPA under any specification ($p > 0.26$; see also Section 5.3). Thus, perceptions of one's own centrality and how others view an individual appear to play a substantial role, while the ability to identify key players does not influence academic performance in our data.

Table 1. Regressions analysis (OLS) of the determinants of perception of own popularity and centrality and its (in)accuracies (defined as the absolute value of the difference between the perceived and true in-degree and betweenness centrality, resp.; see Fig. S4). The table does not include Overestimation (simple difference between the perceptions and the true positioning) as regressing the perception and the perception minus the true positioning on the true positioning generates mechanical equivalence (see Table S10 in SI for an illustration). The models further control for individual positioning and the aggregate network architecture (see Materials and Methods for the definition of all network variables) and three perception variables: the number of people naming an individual as the most central (Central count), and dummies for whether the individual correctly identifies the most popular (Correct max. in-degree) and central (Correct max. betw.) network members. The results are robust to alternative modeling assumptions and inclusion of other controls (Section S5).

VARIABLES	(1) Popularity	(2) Inaccuracy popularity	(3) Centrality	(4) Inaccuracy centrality
Individual positioning				
In-degree	0.276***	0.134**	0.124	-0.139*
	(0.0570)	(0.0512)	(0.0782)	(0.0706)
Out-degree	0.261**	-0.0494	0.106	-0.129
	(0.116)	(0.0942)	(0.0900)	(0.0865)
Eigen. centr.	0.353	0.982***	-0.277	1.126
	(0.298)	(0.211)	(0.531)	(0.715)
Betweenness	$-1.17e^{-05}$	0.00269*	0.000383	0.00311***
	(0.000685)	(0.00124)	(0.000854)	(0.000853)
Clustering coef.	0.0258	-0.755*	-0.762*	0.666
	(0.384)	(0.344)	(0.408)	(0.506)
Global network structure				
Average in-degree	0.0217	-0.388***	0.448	-0.107
	(0.198)	(0.120)	(0.331)	(0.352)
Coef. variation of in-degree	0.597	0.967	4.496***	0.0539
	(0.954)	(0.864)	(0.749)	(1.025)
Average clustering	2.782*	1.952	2.214	1.530
	(1.359)	(1.297)	(2.047)	(1.662)
Density	27.78	6.773	301.7	-163.5
	(118.2)	(98.56)	(247.0)	(165.3)
Class size	-0.00387	0.00131	0.00899	-0.0130
	(0.00699)	(0.00613)	(0.0137)	(0.0141)
Perception				
Central count	0.123**	-0.00296	0.110**	-0.00350
	(0.0476)	(0.0404)	(0.0470)	(0.0541)
Correct max. betw.	0.0786	0.0148	-0.149	0.00496
	(0.462)	(0.131)	(0.494)	(0.355)
Correct max. in-degree	-0.267	0.207	-0.147	0.0795
	(0.316)	(0.275)	(0.453)	(0.426)
Constant	0.0668	1.051	-0.742	3.973***
	(1.105)	(1.007)	(1.105)	(1.161)
Observations	454	454	452	452
R-squared	0.180	0.102	0.055	0.035
Other controls	No	No	No	No
VIF	2.46	2.46	2.46	2.46

Robust standard errors clustered at network level in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 2. Regressions analysis (OLS) of the determinants of grade point average (GPA) over their entire study period. Each column corresponds to an OLS regression of GPA on the perception of own centrality or popularity (columns (1) and (3), resp.) or their (in)accuracies (defined as the absolute values of the difference between the perceived and true standing; columns (2) and (4)). All models further control for the number of times an individual has been named as central in the class (Central count.), the dummies for identifying correctly the most popular (Correct max. in-degree) and central (Correct max. betw.) individuals in the class, reported in the table. In addition, the models include the same set of network controls as Table 1 and a female and double-major dummies (see S21 for the complete specification of the model). The models are robust to other modeling specifications or using GPA in the academic year of the experiment as the dependent variable (Section S5.3).

	Popularity		Centrality	
	(1)	(2)	(3)	(4)
	GPA	GPA	GPA	GPA
Perception of own positioning				
Perception	-0.0343**		-0.00646	
	(0.0133)		(0.0139)	
Inacc. perception		-0.0392**		-0.0372*
		(0.0162)		(0.0192)
Perception of/by others positioning				
Central count.	0.0693***	0.0650***	0.0829***	0.0826***
	(0.0144)	(0.0138)	(0.0137)	(0.0127)
Correct max. betw.	-0.103	-0.107	-0.107	-0.106
	(0.0872)	(0.0924)	(0.0940)	(0.0905)
Correct max. in-degree	0.0567	0.0736	0.0811	0.0858
	(0.134)	(0.136)	(0.126)	(0.110)
Obs.	445	445	442	442
R-squared	0.328	0.328	0.333	0.341
Other controls	Yes	Yes	Yes	Yes
VIF	2.35	2.29	2.30	2.30

Robust st. err. clustered at network level in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$

As a consequence, although we cannot fully speculate on the cognitive processes underlying these perceptions (see *Discussion*), these findings suggest that understanding how individuals view themselves and the accuracy of these perceptions is relevant in academic settings.

Discussion

In this study, we investigate how accurately individuals perceive their own popularity and centrality within friendship networks. Our main finding is that, overall, people have limited awareness of their position in the network, as well as of who holds the most central or popular positions. Only about one-quarter of participants correctly estimated their own popularity and fewer than 10% accurately assessed their centrality rank. These figures are even lower when it comes to identifying the most popular or central individual in the network: approximately 10% correctly named the most popular person and even fewer correctly identified the most central one (although this depends on the centrality measure). The correlation between actual and perceived values of popularity shows a reasonable alignment with formally defined popularity whereas perceived own centrality exhibits little correspondence with formally defined centrality, although other-reported centrality does predict perceived own centrality to some extent. At the aggregate level, the distributions of perceived popularity and centrality are more compressed than the true distributions, which exhibit the familiar fat-tailed patterns commonly found in real-life social networks (4, 47).

Subsequent regression analyses provide further insight into the determinants of individuals' perceptions of their network importance. While true popularity robustly predicts perceived popularity, centrality—despite being positively correlated—does not significantly predict perceived centrality in our models. Interestingly, individuals who are highly popular or central consistently struggle more to assess their own standing accurately than their less prominent peers. Although we thoroughly examine the role of the most important factor, namely local positioning and broader network structure, in shaping network perceptions, the most striking finding from our analysis is the very low explanatory power of our models. This raises questions about the nature of these perceptions—whether they reflect meaningful self-assessments or are largely shaped by random noise.

Nevertheless, several pieces of evidence suggest that randomness alone does not account for the observed patterns. First, individuals' perceived number of nominations is significantly predicted by their actual in-degree, indicating that people do rely, at least to some extent, on concrete structural cues. Second, perceptions of popularity and centrality are significantly correlated with broader network measures such as betweenness and eigenvector centrality, suggesting that individuals base their beliefs on relevant—if imperfectly processed—information. Third, individuals who are regarded as popular and central by their peers also tend to perceive themselves as such, pointing to the influence of group-level information transmission in shaping self-evaluations. Finally, participants are generally better at assessing their local importance than their global centrality, and more accurate in evaluating their own position than that of others. Taken together, these findings suggest that network perceptions are not purely random, but rather reflect how individuals interpret complex and heterogeneous social environments—often in ways that lead to systematic inaccuracies.

Importantly, individuals' perceptions of their own position within the network have real-life academic consequences. Students who see themselves as less popular and those who assess their own popularity and centrality more accurately tend to achieve higher grades, both during the first year (when our experiment was conducted) and throughout their academic careers. Moreover, students who are frequently identified by their peers as the most popular and central members of their class also attain significantly better academic results. These findings suggest that, even if we cannot know exactly what individuals had in mind during the network and perception elicitation tasks, both self-perceptions and peer perceptions are consequential: they meaningfully predict academic success. While our data are limited to an academic setting, they align with recent studies documenting real-life consequences of network perceptions for well-being and information acquisition (38, 48). We therefore expect that the patterns reported here may also emerge in other domains, such as social or professional contexts.

A potential limitation of our study is that the experimental procedure captures only strong-tie relationships. As such, our data do not reflect the broader social landscape, which includes both close friendships and weaker acquaintances. However, we emphasize that participants were carefully instructed to base their responses on the elicited strong-tie network (see Materials and Methods). This makes it unlikely that the observed mismatch between true and perceived positioning stems from students evaluating a broader or different network. More importantly, our analyses support the validity and relevance of this approach. Specifically, we show that both the elicited networks and individuals' misperceptions of their own positions within them significantly predict students' academic performance throughout their studies. This suggests that—even though our measures are limited to strong ties—they capture a socially meaningful dimension of network embeddedness with real-life consequences. Given the well-established link between academic performance and a wide range of long-term life outcomes, including health, income, well-being, and even the likelihood of divorce (49), our findings underscore the importance of understanding how people perceive their positions within strong-tie networks. These perceptions appear to influence not only academic success but as least indirectly a variety of outcomes beyond the classroom. This notwithstanding, given the widely documented importance of weak ties (50), future research should analyze human perception of broader social landscapes.

A natural next question is what drives individuals' perceptions of their position in the network and the accuracy of those perceptions. Although we exhaustively examine the role of the actual network structure, we find that network properties alone have limited predictive power. Nonetheless, our analysis points to several promising research directions. First, the fact that individuals assess their local embeddedness more accurately than their global centrality, combined with the consistent finding that more popular and central individuals are less accurate in estimating their own position, suggests that the complexity of the feature being evaluated matters and highlights the possible role of information asymmetries stemming from the availability of local versus global information. While we control for cognitive reflection and general intelligence and find no significant associations (Table S9), this does not rule out the relevance of other cognitive traits. At the same time, the finding that people perceive their own popularity and centrality more accurately than those of others points to the role of limited network knowledge. Moreover, the finding that individuals viewed as popular or central by others also tend to see themselves as more prominent suggests that social feedback and the dynamics of information diffusion—possibly involving both strong and weak ties—may shape self-perceptions. Finally, Figures 1d,e indicate a pattern consistent with the Dunning–Kruger effect (27), and stand in contrast to claims that disadvantaged individuals perceive reality more accurately than privileged ones (51). We find no robust relationship between perceived and actual centrality, leaving open the question of what shapes perceptions of global social embeddedness. However, in the case of popularity, we observe a clear asymmetry: individuals with low in-degree tend to overestimate their popularity, while those with high in-degree underestimate it. This contradicts prior findings on a general tendency to overstate social standing (32, 52) and instead aligns with evidence from social cognition suggesting that self-enhancement and self-deprecation coexist in the population. These results point to explanations such as regression to the mean or social-sampling bias (53), though whether these mechanisms account for our findings remains to be tested.

Our findings have implications that range from theoretical insights to real-world applications. On the theoretical side, many economic models and algorithms assume that individuals have accurate knowledge of their position within a network. Our results clearly challenge this assumption, raising doubts about the applicability of such models and the validity of their predictions. On the practical side, the misalignment between perceived and actual centrality has significant implications for network dynamics, including information diffusion, social influence, and group cohesion. For instance, individuals who overestimate their centrality may believe they exert greater influence than they actually do, leading to ineffective communication or coordination. In public health contexts, such misperceptions could prompt risky behavior from individuals unaware of the actual extent of their influence. Conversely, those who underestimate their centrality may fail to leverage their position, missing opportunities for leadership, collaboration, or support.

Looking ahead, our results raise the following key research questions. First, what drives the limited accuracy of individuals' network self-perceptions? We document a disconnect between the ability to assess one's own position and to identify central others: the two are unrelated, and cognitive reflection has no effect on the former (Table S9) while it improves the latter (Tables S18–S19). Being perceived as popular or central increases self-perceived prominence (Table 1), but reduces one's ability to detect key players. These patterns suggest a role for cognitive and informational constraints, which could inform interventions aimed at enhancing social awareness—whether to help individuals better leverage their position or to improve it. Second, what are the consequences of such misperceptions? For example, (54) show that individuals misjudge their influence in collective action problems even when provided full information about their network. In real-world settings, the biases we observe are likely to exacerbate such effects, potentially leading to inefficient decisions. Future work should explore the underlying mechanisms through longitudinal designs, examine how perceptions evolve as networks change, and test generalizability across settings and populations. Finally, our findings suggest that theories and interventions relying on individuals at the extremes of the connectivity and centrality distribution to accurately recognize their position may be less effective than expected. Targeted interventions such as feedback or training may help individuals develop more accurate views of their social embeddedness, with implications for improving outcomes in educational, organizational, and public health contexts.

Materials and Methods

Data collection. The experiment was conducted in June 2019 at both campuses—Córdoba and Seville—of Loyola University of Andalusia (Spain). Data were collected from 16 independent class social networks from spanning different academic programs, involving 627 freshmen. To address potential statistical issues arising from incomplete network data (55), we restrict our analysis to networks with participation rates above 60%. This yields a sample of 499 participants across 11 networks. Since the strong-tie elicitation procedure presented each student with a complete list of classmates (Section S6), including those who did not participate in the study, the network in Fig. 1 includes 603 nodes.

The experiments were conducted on the days of final exams to maximize participation and ensure the best possible network representation. The Ethics Committee of the Loyola University of Andalusia approved the experiment, and all participants provided informed consent. Participants who agreed to take part were provided with instructions outlining anonymity rules, procedures, and the compensation. Instructions were provided in written form, and any queries were addressed privately. As all sessions were conducted in classrooms, data was collected using pen and paper. As a result, different variables might have different number of observations due to missing or unreadable data.

During the instruction process, participants first signed a written consent form and were informed that they would receive 5€ for their participation. They were then informed that they had the opportunity to earn additional money during the experiment. Specifically, they were informed that their choices could earn them another 5€, and they would also have the chance to participate independently in a lottery for a 1000€ prize. However, at this stage, the participants were not provided with any further details about the subsequent phases of the experiment, including the odds of earning money.

The actual experiment involved eliciting basic information about each subject and their social networks. Participants were then asked to make four guesses explained below. See Section S6 in the SI for the Spanish and English version of the instructions.

Network elicitation. To ensure that subjects revealed their true strong ties in the class, network elicitation was incentivized using a 1000€ lottery. Each participant received five lottery tickets, which could only be used if donated to someone from the class list provided to each subject. Participants were free to distribute the tickets among their classmates as they wished: they could give all the tickets to one person, distribute three tickets to one person and the remaining two to two different individuals, or allocate them to five different people. They were not obliged to give away the tickets though; they were allowed to keep some or all the ticket for themselves. However, any tickets kept were forfeited and did not contribute to the lottery. Importantly, the more tickets one person received, the higher her/his probability of winning 1000€. This feature ensured that people only donated the tickets to the members of their class about whom they cared; that is, to their strong ties in the class. The selection of a five-ticket limit is motivated by our objective to focus on strong, meaningful connections that provide emotional and social support to the ego. Network theory and cognitive science suggest that humans typically maintain between three and five strong social ties (56, 57). This approach is conservative, as one might expect less alignment between true positioning and its perception in a network of weaker, more transient social ties. See Section S4 for a summary of ticket-sharing behavior and its relation to the resulting network.

Participants were then asked to make–sequentially in this order–four incentivized guesses: (1) their own popularity, (2) their own centrality, (3) the most popular individual in their class, and (4) the most central individual. Subjects were explicitly instructed that these guesses referred to the network formed through ticket-sharing. The guesses were incentivized as follows: participants received €5 for an accurate answer, €2 if their centrality estimate was within a ± 1 error margin or if they correctly identified the second most popular or second most central individual. Otherwise, they received €0. At the end of the experiment, one of the four guesses was randomly selected for payment.

Perceived Popularity. After network elicitation, each subject was asked to estimate the number of classmates who would donate her/him at least one lottery ticket. They were explicitly instructed not to guess the "number of donated tickets" but rather the number of people who would send them at least one ticket. Accuracy in their answers was incentivized as described above. The instructions for this task included the following guidance: *If you believe you will receive none, the best response is 0; if you believe you will receive 7, then the best response is 7.*

Perceived Centrality. Since the concept of centrality may be unfamiliar to most people, we first explained to all subjects how the networks were constructed based on the distribution of lottery tickets within the entire class and provided them with a hypothetical resulting network map. Using this network, we explained the general idea of centrality, distinct from popularity, and how network members can be ranked according to their global centrality from the most central to the least central student. Participants were then asked to predict their own level of centrality, using deciles (our results are robust to implementing quintiles instead; Table S16). To facilitate this, we provided them with the ruler in Fig. 2.

Participants were instructed on how to use the ruler as follows:

- If I believe that I am between 0% and 10% of the most central people in my class, then I mark that I am within the first interval (0%-10%).
- If I believe that I am between 10% and 20% of the most central people, then I mark the second interval (10%-20%).
- ...

They were then asked to indicate the decile of centrality they perceived themselves to fit. The payment scheme described above was used to incentivize accuracy. To facilitate comparisons, we use the inverted elicited decile of centrality in all our analyses, so that higher values correspond to higher perceived centrality.

Popular and central players. After guessing their own popularity and centrality and using the same monetary incentives, subjects were shown the class list and were asked to predict the most central and the most popular individual in their class (including the option to name themselves).

Network measures. In the context of network analysis, we have used several measures for understanding the positioning of the different nodes:

- **Degree**: The degree of a node in a network is the number of edges connected to it. It represents the count of direct connections (or neighbors) a node has. In our case, the edges are directed, so the degree may be split into in-degree (number of people who send an individual at least one ticket) and out-degree (the number of people to whom an individual sends at least one tickets).
- **Closeness Centrality**: Closeness centrality is a measure of how close a node is to all other nodes in the network. It is defined as the reciprocal of the sum of the shortest path distances from the node to all other nodes in the network. A node with high closeness centrality can quickly interact with all other nodes.

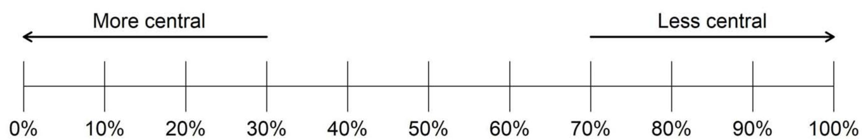

Fig. 2. Ruler used by the survey participants to estimate their centrality.

- **Betweenness Centrality**: Betweenness centrality is a measure of the extent to which a node lies on the shortest paths between other nodes. Nodes with high betweenness centrality act as bridges within the network and play a crucial role in information flow.
- **Eigenvector Centrality**: Eigenvector centrality is a measure of the influence of a node in a network. It assigns relative scores to all nodes in the network based on the concept that connections to high-scoring nodes contribute more to the score of the node in question. Nodes with high eigenvector centrality are those that are connected to many other well-connected nodes. The score is directly related to the eigenvector solution of the adjacency matrix of the graph.
- **Clustering coefficient** reflects how connected one's friends are to one another and is measured as the ratio between the actual number of connections between one's friends and the number of connections that could possibly exist between them. This ratio is not well defined for nodes with no or one friend. We set the coefficient to zero in such cases.(5)

Our results are robust to considering a fourth measure of centrality, PageRank centrality (analysis not reported). Apart from the individual measures defined above, our regression analysis in Table 1 and in the SI also employs the following global network statistics: the average and coefficient of variation of the in-degree distribution, the average clustering coefficient, the edge density defined as the ratio between the number of actual and possible connections, and the size of the network (denoted as *Class/Network size*).

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