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You said, they said: A framework on informant accuracy with application to studying self-reports and peer-reports

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ABSTRACT

Informants have been used extensively to provide information on others. However, informant accuracy has rarely been systematically studied. In this paper I argue that studying informant accuracy both helps deepen our understanding about how perceptions of others are configured by personal and network factors and helps develop better methods to use informant reports to correct self-reporting bias. I propose a framework (a systematic conceptualization) that links informant accuracy to not only informant characteristics, but also alter characteristics, dyadic characteristics shared by the informant and the alter, and characteristics of the behavior being reported on. I apply the framework to analyzing self-reports and peer-reports of smoking among 4094 middle school students in China. The analyses present novel strategies to validate a behavior when the truth is unknown, confirm previous findings (e.g., central informants are more accurate) and elaborate selected mechanisms, reveal new findings, and show the distinctive logics of identifying the presence versus the absence of a behavior. The results also indicate that weighting informant reports by informants' network centrality can more effectively correct self-reporting bias. Lastly, I discuss the implications of this study for various practices, ranging from health monitoring to online rating.

Introduction

In the literature, informants typically refer to respondents who report information on alters (Marsden, 1990, 2005). As put by Bernard et al., "Understanding informant accuracy is the interface between method and theory" (Bernard et al., 1984: 512). On the theory side, studying informant accuracy helps deepen our understanding on how perceptions of others are shaped by personal and network factors. Prior studies have explored the role of selected characteristics in determining informant accuracy (adams and Moody, 2007; Bernard and Killworth, 1977; Bernard et al., 1980, 1982, 1984; Brashears et al., 2016; Brewer, 2000; Butts, 2003; Freeman and Romney, 1987; Killworth and Bernard, 1976, 1979; Marsden, 1990, 2005; Romney and Weller, 1984; Seidler, 1974). In this paper I will provide more extensive discussion on the necessity and the applicability of using informant reports (also called proxy reports in the survey literature), the types and the measurement of informant accuracy, and the determinants of informant accuracy. I will present a general framework (i.e., a systematic conceptualization) that links informant accuracy to not only the informant's characteristics as has been done in some prior studies, but also the characteristics of the reported, the dyadic characteristics shared by the informant and the reported, and features of the behavior being reported on, with illustrations based on analyses of self- and peer-reports of smoking among 4094 middle school students.

One the method side, studying informant accuracy helps develop better methods to more effectively use informant reports to correct biased self-reports. Branson and Cornell (2009) showed that as compared to self-reports more than twice as many students could be identified as bullies based on peer-reports. Yeatman and Trinitapoli (2011) showed that peer-reports provided higher and more believable estimates of sensitive health behaviors than self-reports. These studies raise concerns on simply relying on self-reports for social research and advocate using peer-reports to triangulate self-reports. This study shows that even peer-reports are not equally accurate and certain peer-reports should be given more weight than others in correcting self-reports.

This paper proceeds as follows. First I will review the literature and introduce a framework on informant accuracy with illustrations based on self-repots and peer-reports of adolescent smoking. Then I will describe the data, methods, and results. Lastly, I will conclude with discussion on the implications and the limitations of this study.

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Informant accuracy

Past studies have used informants in multiple contexts. In social surveys, informants have been used to address self-reporting bias and to obtain information on alters that are not sampled (Broom et al., 1978; Harris et al., 2009; Hill, 1987; Lee and Lee, 2012; Mare and Mason, 1980; Massagli and Hauser, 1983; Marsden, 1990; Reynolds and Wenger, 2012; Roosa et al., 1993; Sudman et al., 1994; Tein et al., 1994; Yeatman and Trinitapoli, 2011). Informants have also been used to identify hard-to-reach populations (Heckathorn, 1997; Mouw and Verdery, 2012; Salganik and Heckathorn, 2004). Some network studies have also employed multiple informants to report on the same social ties (An and Schramski 2015; Bernard et al., 1984; Butts, 2003; Freeman et al., 1987; Krackhardt, 1987; Marsden, 1990, 2005; Seidler, 1974). Overall, there are three broad issues regarding informant accuracy that are still worth more investigation.

The need and pitfalls of using informant reports

Prior research has studied whether and to what extent informant reports differ from self-reports (Laumann, 1973; Marsden, 1990; Moore, 1988; Reynolds and Wenger, 2012; White and Watkins, 2000). For example, Yeatman and Trinitapoli (2011) showed that reports on best friend yielded higher, more believable estimates of certain health behaviors than self-reports.

This paper argues that informant reports may also be used to correct self-reports. For this to work effectively, it assumes that informants are less motivated than alters to mis-report alters' behaviors. Research has shown that self-reporting bias is prevalent. For example, due to social desirability (Gould, 1969; Wyner, 1980; Tourangeau et al., 2000), subjects may over-report voting, charity-giving, or volunteering (Bielby et al., 1977a, 1977b; Broom et al., 1978; Reynolds and Wenger, 2012) while under-reporting smoking (Lloyd and Lucas, 1998; Murray et al., 1993; Wong et al., 2012) and deviant or criminal behaviors (Clark and Tifft, 1966; Wyner, 1980).

To note, there are several potential pitfalls of using informant reports as well. First, informants may lack of knowledge about alters' behaviors because the behaviors are not observable to them or because alters do not want to reveal their behaviors to informants (Bernard et al., 1984; Cowan, 2014; Shelley et al., 1995; Small, 2017). In addition, informants may not be willing to report on others, especially if the reported behavior is sensitive. Second, informant reports may not cover alters evenly. The friendship paradox (Feld, 1991) shows that people tend to connect to more central alters. In line with this, informants may be more likely to report on central subjects while providing no or only a few reports on less central subjects. Third, informant reports may be biased as well, because of stereotyping, self-projection, willingness to protect or glorify alters, collusion in the reporting, or misperception. For example, Jackson (2019) argues that as a result of the friendship paradox, perceived social norms are biased toward friends' behaviors. This misperception could cause misreporting of alters' behaviors. Arguably these informant biases, however, may still be smaller than self-reporting bias in many occasions. There are also a list of steps one can take in advance to reduce such biases. (1) Ensuring confidentiality of the informant reports can help informants report more truthfully. (2) Using multiple informants helps deter informants from mis-reporting and provide more information for validations. (3) One may require independent reporting from each informant to prevent collusion. In short, informant reports are not expected to be similarly accurate across informants or alters, or for all behaviors. This is exactly what makes it possible and interesting to study informant accuracy.

Types and measurement of informant accuracy

Past studies rarely differentiate informant accuracy in identifying the presence of a behavior versus the absence of the behavior. This may create problems. For example, a trait may be positively associated with identifying the presence of a behavior but negatively associated with identifying the absence of the behavior. If the two processes are not differentiated, the effects of the two processes may cancel out at the aggregate level and the correlation between the trait and informant accuracy may turn out to be insignificant.

Formally, suppose Y is a binary variable with one indicating the presence of a behavior and zero its absence. Let S denote a self-report and R a peer-report (as an example of an informant report), with one indicating a positive report (i.e., the presence of a behavior) and zero a negative report (i.e., the absence of the behavior). shows that given the true status of the behavior, the self-report can take one of four forms: (a) accurate report of the absence of the behavior ($S = 0|Y = 0$), (b) over-report ($S = 1|Y = 0$), (c) under-report ($S = 0|Y = 1$), and (d) accurate report of the presence of the behavior ($S = 1|Y = 1$). Similarly, the peer-report can also take one of four forms: (e) accurate report of the absence of the behavior ($R = 0|Y = 0$), (f) over-report ($R = 1|Y = 0$), (g) under-report ($R = 0|Y = 1$), and (h) accurate report of the presence of the behavior ($R = 1|Y = 1$).

A few notes are in order. First, it is important to differentiate accuracy in reporting the absence of the behavior (cells a and e) and accuracy in reporting the presence of the behavior (cells d and h) because the same attributes may be correlated with the two types of informant accuracy differently. For example, smokers may be accurate reporters of smokers but at the same time inaccurate reporters of nonsmokers. Second, for each pair of the cells, (*a, b*), (*c, d*), (*e, f*), and (*g, h*), the probabilities of observing them sum to one. For example, $P(S = 0|Y = 0) + P(S = 1|Y = 0) = 1$ and $P(R = 0|Y = 1) + P(R = 1|Y = 1) = 1$. Hence, knowing the determinants of one cell in each pair is sufficient to know the determinants of the other cell. Third, in this paper I focus on studying informant accuracy which requires paying special attention to modeling cells (e) and (h). But I will also present some tentative results on self-reporting accuracy.

To study the determinants of informant accuracy, researchers first need to measure informant accuracy. Ideally one needs to know the true status of a behaviorso that one can compare the informant reports with the truth. In the past, some researchers have looked into administrative records (e.g., hospital or police records) to obtain the truth (Ball, 1967;

Table 1
A breakdown of reporting accuracy by self-report and peer-report.

True Behavior		**0**	**1**
Self-Report	0	(a) Accurate report (S = 0 | Y = 0)	(c) Under-report (S = 0 | Y = 1)
	1	(b) Over-report (S = 1 | Y = 0)	(d) Accurate report (S = 1 | Y = 1)
Peer-Report	0	(e) Accurate report (R = 0 | Y = 0)	(g) Under-report (R = 0 | Y = 1)
	1	(f) Over-report (R = 1 | Y = 0)	(h) Accurate report (R = 1 | Y = 1)
Imputed Behavior		0	1
Examples		Self-reported nonsmokers, confirmed by multiple peers.	Self-reported smokers (confirmed by multiple peers).

Note: A binary behavior (0 = absent; 1 = present) is being reported. Y indicates the true behavior status; S the self-report; and R the peer-report.

Gould, 1969; Kenkel et al., 2003; Wyner, 1980). The problem is that such official information is only available for a limited set of outcomes and typically for a limited period of time. It is also possible that such information itself contains errors. Previous research has also used biomarkers to obtain the truth (Yeager and Krosnick, 2010; Wong et al., 2012). However, biological tests can be costly, contain errors, and are applicable to a limited scope too. In terms of smoking, for instance, the testing accuracy will vary by testing procedures (e.g., testing breath, blood, saliva, vs. urine) (Marrone et al., 2010; Murray et al., 1993), by racial and ethnic groups (Shiffman et al., 2014), by the amount, frequency, duration, timing, and age of smoking (Ho et al., 2009), and by confounding factors (e.g., second-hand smoking) (Hsieh et al., 2011). Biological testing can be especially difficult to do (both logistically and ethically) for measuring smoking status of adolescents in a long time period (e.g., in the past month). Other methods to measure the truth include conducting re-interviews (even with polygraphs) (Clark and Tifft 1966) or using diaries (Patton et al., 1998). Despite their merits, these methods may overly burden the subjects and introduce other biases into the data (Ventura et al., 2006).

Hence, given that the ground truth is usually unknown, how would one measure informant accuracy? One idea that has been usedbefore is to impute the truth based on alignment of multiple reports. For example, based on the cultural consensus theory (Romney et al., 1987; Weller, 2007), researchers have used what the majority of informant reports indicates to impute the truth (Bondonio, 1998; Krackhardt, 1987). The logic of peer validations can be adapted here too. For example, in the case of smoking, self-reported smokers receiving multiple positive peer-reports may be treated as "true" smokers while self-reported nonsmokers receiving multiple negative peer-reports as well as no positive peer-reports may be treated as "true" nonsmokers. The latter imputation requires a stronger peer validation because smoking tends to be under-reported, especially among adolescents.

There are a few issues with this imputation method to be pointed out. First, this method faces an important trade-off. On one hand, it requires a good number of peer-confirmations to impute the truth. This will help reduce or eliminate false positives/negatives. It will also help focus the analysis on (central) alters who receive multiple informant reports and where the informant reports are mostly available. On the other hand, alters receiving few or no informant reports are likely to be excluded from the analysis and thus the results may not be generalizable to them. Also, because the truth is imputed, this approach may not 100% cleanly examine informant accuracy. As a remedy, however, researchers may conduct sensitivity analysis by varying the required number of peer-confirmations to check the robustness of the results. Second, if the informant reports used to impute the behavior are also used to predict informant accuracy, then there is a circularity problem which may bias the results. This study will provide sensitivity analysis that separates informant reports used for measuring informant accuracy from those used for predicting informant accuracy. Third, informants making relatively more reports may contribute a more than fair share of information for predicting informant accuracy, which can also bias the results (i.e., by over-generalizing the predictive power of the characteristics of the active reporters). To address this issue, researchers may use only an equal number of reports from each informant. One way to do this is to use only one report from any informant even if some of them provide multiple reports. Later in this paper, I will provide such sensitivity analysis.

Determinants of informant accuracy

Past studies mostly focus on the role of informant characteristics in determining informant accuracy and have identified network centrality (Bondonio, 1998; Casciaro, 1998; Johnson and Orbach, 2002; Krackhardt, 1987; Romney and Weller, 1984), personality (), and self--projection (Bickart et al., 1990; Jussim and Osgood, 1989; Wilcox and Udry, 1986), among others, as possible factors or mechanisms that can affect informant accuracy. Overall, there is still a large gap to fully understand the determinants of informant accuracy. To help fill this gap, Fig. 1 presents a framework that connects informant accuracy to not only informant characteristics, but also alter characteristics, dyadic characteristics shared by the informant and the alter, and features of the behavior being reported on. The word "framework" is used liberally here, referring to a systematic conceptualization rather than a mathematical or methodological system. To be more concrete, below I will use

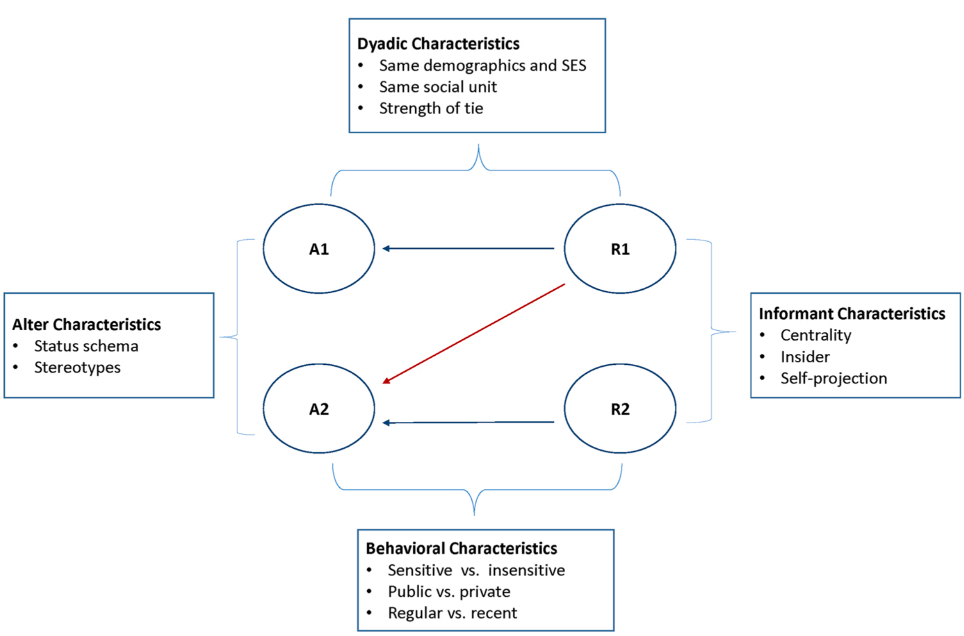

Fig. 1. A framework for understanding informant accuracy. **Note**: R1 and R2 indicate two reporters (i.e., informants). A1 and A2 are two of the reported (i.e., alters). R1 reported on both A1 and A2 while R2 only reported on A2. This paper argues that the accuracy of the reports depends on informant characteristics, alter characteristics, dyadic characteristics shared by the informant and the alter, and characteristics of the behavior being reported on. Suppose the informant reports can be classified as true or false (under reasonable assumptions). Regressing the accuracy of the reports on these various factors helps identity factors that are associated with informant accuracy. This framework can apply to either sociocentric network data (where informants and alters belong to the same group) or egocentric network data (where informants or alters may come from different groups).

self- and peer-reports of student smoking to illustrate the framework.

I. Informant characteristics

Theoretically speaking, to be a good informant one needs to (1) be exposed to the information of interest, (2) be able to recall correctly, and (3) be willing to report and report truthfully. These correspond to three mechanisms, namely, "information exposure", "cognitive advantage", and "social cooperation". In the case of reporting student smoking, two traits are probably highly correlated with informant accuracy. First is centrality (as measured by the number of received friend nominations), for three reasons. (1) Central students are informal social leaders who are more likely to be exposed to alters' activities and information about alters. This is especially likely if central students are also perceived as more trustworthy so that smokers are less willing to conceal smoking from them. (2) Prior research suggests that managing a large number of social ties requires strong cognitive capability (Dunbar, 1992; McCarty et al., 2001). Hence, centrality is likely positively correlated with cognitive capability and thus central students may be cognitively more capable to observe and recall correctly. (3) Central students may be more cooperative to provide truthful reports. This is especially plausible if cooperation is one of the reasons for a student to become central in the first place (e.g., teachers may select cooperative students as student leaders which in turn propels these students' centrality). The literature (Simpson and Borch, 2005; Simpson et al., 2011) also points out a possible negative relationship between centrality and perceptual accuracy, showing that central reporters tend to face information overload or rely more on heuristics for reporting. Hence, whether the positive effect or the negative effect of centrality will dominate is to be borne out by empirically testing the following hypothesis.

Hypothesis 1. *Central students are more accurate reporters of alter's smoking status.*

The centrality hypothesis has been studied before. For example, central subjects have been found to be more accurate reporters of social ties (Bondonio, 1998; Casciaro, 1998; Johnson and Orbach, 2002; Kashy and Kenny, 1990; Krackhardt, 1987; Romney and Faust, 1982; Romney and Weller, 1984). However, because the data used by prior research include few covariates, it has been difficult to examine the robustness of the centrality effect and the underlying mechanisms.

Second, I argue that smokers may be good informants of other smokers. According to social identity theory (Hogg et al., 1995; Stets and Burke, 2000), smokers may be viewed as constituting an informal group. As "insiders", smokers are more likely to know about other smokers and may feel less stigmatized to report others' smoking. It could also be the case that smokers, as secrete keepers, may be less willing to "snitch" on other smokers. But if confidentiality of the informant reports is ensured, this might not be a big concern. Meanwhile, as smokers are "outsiders" to nonsmokers, they may interact less with nonsmokers and so may be less accurate in identifying nonsmokers. These considerations lead to the following hypotheses.

Hypothesis 2a. *Smokers are more accurate reporters of other smokers than are nonsmokers.*

Hypothesis 2b. *Smokers are less accurate reporters of nonsmokers than are nonsmokers.*

Informants may project their own behavior onto alters (Bickart et al., 1990; Jussim and Osgood, 1989; Wilcox and Udry, 1986), which can generate results consistent with both of the above hypotheses. I will control for informants' positive reporting tendency to tease out this .

II. Alter characteristics

Informant accuracy may also vary by the characteristics of the reported. Previous research (Brewer, 1995; ; Marsden, 2005) shows that when reporting on others informants tend to follow a "status schema" in which high-status alters are more salient in informants' memories. In this study, I focus on testing three status signals: network centrality, family economic condition, and academic ranking (Chen et al., 1997).

Hypothesis 3a. *Reports on alters with a more central network position are more accurate.*

Hypothesis 3b. *Reports on alters from more affluent families are more accurate.*

Hypothesis 3c. *Reports on higher-ranked alters are more accurate.*

Informants may use "stereotypes" to help recall (Blair and Burton, 1987; Bickart et al., 1990). In this case, informants may use the risk factors for smoking (or nonsmoking) to impute their reports. For example, between a smoker with a low academic ranking and a smoker with a high academic ranking, an informant may be more likely to report the former correctly because low academic ranking is typically associated with smoker status. In general, if the relation between a status signal and reporting accuracy is negative, then it is an indication that stereotyping or risk imputation is at work. However, when the relation is positive, it will be difficult to neatly separate stereotyping from the status schema. I suggest then examining the overall patterns of the results to locate the logic. Inconsistent correlations (e.g., the existence of both positive and negative correlations) between status signals and reporting accuracy may be a sign that stereotyping instead of status schema is at work. See the results section for examples.

III. Dyadic characteristics

Past research shows that people tend to associate with similar others (McPherson et al., 2001). In this study, students may be more knowledgeable about the behaviors of alters who possess similar characteristics. I focus on testing such homophilious effects associated with gender, academic ranking, family background, and classroom.

Hypothesis 4. *Reports on alters with similar characteristics are more accurate.*

Informants may be more knowledgeable about the behaviors of alters with closer ties (Bondonio, 1998; Sudman et al., 1994). This is especially plausible if alters share "secrets" with closer friends while expecting the information to be kept confidential (Cowan, 2014) and if the behavior being reported on is not specifically "stigmatized".

Hypothesis 5. *Reports on alters with closer ties are more accurate.*

However, alters may also restrain information from close contacts when the information is offending or stigmatizing (Cowan, 2014; Shelley et al., 1995; Small, 2017). Informants may also not want to "snitch" on their close contacts for stigmatized behaviors. In this study, as smoking is not openly stigmatized and students' reports are confidential, this may be less of a concern.

IV. Behavioral characteristics

Informant accuracy may also be affected by characteristics of the behavior being reported on. First, for the method of informant reporting to work, a behavior should be public or at least knowable to informants. Second, if a behavior is insensitive, then there is less motivation for subjects to misreport and thus less benefit to be gained from using informant reports. Informant reporting may not work equally well for all sensitive behaviors either. It is possible that subjects may purposefully withhold information from close contacts because of the sensitivity of a behavior, for example, stigma attached to certain disease diagnostics. Third, the occurring pattern of a behavior also matters. This paper is interested in studying whether informants are more inclined to report on regular vs. recent behaviors when asked to report on alters' behaviors. Past studies show that recall tends to be biased toward regular patterns (Freeman et al., 1987; Freeman and Romney, 1987). But one can argue that recent behaviors are more salient to recall and so are more likely to be reported on by informants. Informants may also have different understandings about the inquiry itself and end up with reporting on differently conceptualized objects, which can produce inaccuracy in their reports (Kovar, 2000; Goldberg, 2011). In this paper I have data on both recent smoking and regular smoking. Comparing how much the same model can predict either behavior helps assess which behavior students are more likely to report on.

Data, methods, and results

The data is from the Adolescent Network and Smoking Research (ANSR) conducted by the author during 2010–2011 with students in six middle schools in a site in central China. As network data is difficult to collect, the schools are selected mostly based on accessibility. Nonetheless, additional analyses (available upon request) show that these schools may represent a significant proportion of Chinese middle schools in the rural and semi-rural areas. The study includes a baseline survey which 92% of the 4470 students on the school rosters, namely, 4094 students, completed.

The baseline survey asked students to report a list of covariates. To mitigate possible measurement error and facilitate computation (by reducing the skewedness of some covariates) and interpretation of the results, selected covariates were dichotomized, which include age (1 = older than average classmate; 0 = other), gender (1 = boy; 0 = girl), self-reported recent smoking status (1 = smoked in the past 30 days before the survey; 0 = no), academic ranking (1 = top ten in the classroom; 0 = other), personality (1 = optimistic; 0 = not optimistic), family economic condition (1 = good or very good; 0 = other).[1] Students could also report up to ten closest friends at school and their smoking status (Question: "Does your friend smoke?" Response: 1 = Yes, 2 = No, and 9 = Don't Know). Based on the reported friendships, I construct a friendship network for each school. I use indegree (i.e., the number of incoming friendship ties) to measure students' centrality (Freeman, 1979). I use outdegree (i.e., the number of outgoing friendship ties) as a proxy for a student's tendency to report others. I use the order of friend nomination to approximate the strength of friendship, assuming students tend to nominate closer friends first. Table A1 shows the summary statistics of selected student information.

Identifying self-reported smokers

Past studies show that adolescents tend to under-report their smoking (Lloyd and Lucas, 1998; Murray et al., 1993; Wong et al., 2012). In China, smoking is generally considered to be a problem (not necessarily stigmatized) behavior for adolescent students (Yang et al., 2004). Hence, presumably students have no strong motivation to over-report their smoking. But like in the U.S. some students may view smoking as a status signal (Moody et al., 2011) and thus over-report their smoking status. In the following analyses I will first assume no self over-reporting of smoking in Model A and later relax this assumption. Specifically, I select peer-reports targeted at self-reported smokers ($y_i = 1$) and conduct the below logistic regression (O'Malley et al., 2007).

$$\text{logit}\left[P\left(Z_{ji} = 1 | y_i = 1\right)\right] = a_0 + \boldsymbol{X}_i^{'}\boldsymbol{a}_1 + \boldsymbol{X}_j^{'}\boldsymbol{a}_2 + \boldsymbol{D}_{ji}^{'}\boldsymbol{a}_3 \tag{1}$$

In this regression Z_{ji} is student *j*'s report on a self-reported smoker *i*. It equals to one if the report is positive (representing an accurate report) and zero otherwise (representing a false report). The alter characteristics (X_i) includes alter's age, gender, academic ranking, personality, family economic condition, and indegree centrality (standardized). The informant characteristics (X_j) includes the same set of covariates plus the smoking status of the reporter. The dyadic characteristics (D_{ji}) includes indicators of whether the reporter and the alter are in the same classroom, have the same gender, have the same family economic condition, and have the same academic ranking as well as the strength of friendship with the alter as reported by the reporter. To account for contextual fixed effects, I include indicators for schools and grades of the alters. To address data clustering by reporters and alters, two-way clustered standard errors are used (Cameron et al., 2011; Kleinbaum et al., 2013).[2] In Model B, to address possible self over-reporting of smoking, I restrict peer-reports to those targeted at self-reported smokers who also received three or more positive peer-reports. This helps validate the self-reported smoker status and also helps reduce the impact of any single reporter on the measurement of alter's smoker status.

The results are shown in models A and B in Table 2, respectively.[3] I will use results from both models to look for consistent and robust evidence. First, one standard deviation of increase in reporter's indegree centrality is associated with an increase in the chance of "correctly" identifying self-reported smokers by about 20% in both models (e.g., $e^{0.24} = 1.27$, $P < 0.001$, in Model A). This result strongly supports Hypothesis 1. Second, the odds of self-reported smokers identifying other

[1] Original responses to "Academic ranking in the classroom" have five options (1: Top ten, 2: From 11 to 20, 3: Middle, 4: Bottom 11–20, and 5: Bottom ten). I treated the first response as one and the rest (including missing responses) as zero. Original responses to "Personality" have five options (1: Very pessimistic, 2: Pessimistic, 3: In-between, 4: Optimistic, and 5: Very Optimistic). I treated the last two responses as "Optimistic" and the rest (including missing responses) as "not optimistic". Original responses to "Family economic condition" include five options (1: Very good, 2: Good, 3: General, 4: Difficult, and 5: Very difficult). I treated the first two responses as "good" while the rest (including missing responses) as "not good". The coding likely produces conservative results on the covariate effects.

[2] I also considered using exponential random graphs models (ERGMs) to analyze the data. However, because the zero cases in the data include both non-reports and reported nonsmoking, ERGMs (typically for binary observations) are inappropriate. To address this problem, one may offset the non-reports as structural zeros, in which case it is largely equivalent to the approach used here but is less flexible and stable in terms of computation. To see an example where ERGMs are used for modeling peer detections of ego behaviors, please consult An and Doan (2015).

[3] There are 403 self-reported smokers, of whom 389 (97%) received at least one positive peer-report (shown in Model A) and 191 (47%) received at least three positive peer-reports (shown in Model B). There are 3691 self-reported nonsmokers, of whom 2596 (70%) received four or more negative peer-reports (shown in Model C) and 2158 (58%) received four or more negative peer-reports and no positive peer-reports (shown in Model D). Hence, the results seem to apply to a large proportion of the self-reported smokers or nonsmokers.

Table 2
Characteristics associated with informant accuracy in reporting alter's smoking status.

	A. Self-reported smokers			B. Peer-confirmed smokers			C. Peer-confirmed nonsmokers			D. Strongly confirmed nonsmokers			E. Pooled analysis		
Variables	Coef.	SE		Coef.	SE		Coef.	SE		Coef.	SE		Coef.	SE	
Informant Characteristics															
Indegree	0.24	0.06	***	0.20	0.07	**	0.09	0.04	*	0.16	0.06	*	0.16	0.05	***
Outdegree	-0.03	0.06		-0.02	0.07		0.08	0.04	*	0.05	0.05		0.04	0.04	
Smoking	1.32	0.14	***	1.32	0.17	***	-0.92	0.12	***	-0.57	0.20	**	0.13	0.14	
Age	0.17	0.12		0.18	0.14		-0.04	0.09		-0.02	0.12		-0.00	0.09	
Boy	0.87	0.33	**	-0.19	0.26		-0.63	0.12	***	-0.36	0.15	*	-0.41	0.13	**
Ranking	-0.16	0.27		0.09	0.30		0.06	0.12		0.07	0.15		0.11	0.13	
Personality	0.08	0.12		0.19	0.15		0.09	0.08		0.10	0.11		0.12	0.09	
Family Economic Condition	-0.15	0.25		-0.45	0.28		0.19	0.16		0.50	0.28		0.14	0.18	
Alter Characteristics															
Indegree	0.07	0.07		-0.28	0.07	***	-0.18	0.03	***	-0.12	0.03	***	-0.29	0.04	***
Outdegree	-0.10	0.06		-0.04	0.07		-0.03	0.03		-0.06	0.04		-0.00	0.04	
Age	-0.04	0.14		0.08	0.15		-0.15	0.05	**	-0.04	0.06		-0.08	0.07	
Boy	0.35	0.74		-1.62	0.94		-1.21	0.10	***	-1.23	0.13	***	-1.64	0.13	***
Ranking	-0.42	0.32		-0.12	0.29		0.30	0.08	***	0.21	0.09	*	0.41	0.10	***
Personality	-0.18	0.13		-0.12	0.13		0.06	0.05		0.08	0.06		0.04	0.06	
Family Economic Condition	0.55	0.24	*	0.03	0.26		-0.02	0.11		0.19	0.20		0.05	0.17	
Dyadic Characteristics															
Same Class	0.21	0.12		0.24	0.15		0.08	0.06		0.01	0.08		0.08	0.07	
Same Family Econ. Condition	0.02	0.21		-0.26	0.25		0.12	0.09		0.37	0.20		0.12	0.14	
Same Gender	-1.46	0.32	***	-0.31	0.24		0.66	0.10	***	0.38	0.13	**	0.37	0.12	**
Same Ranking	-0.02	0.24		0.09	0.27		0.04	0.08		0.04	0.09		0.05	0.08	
Friendship Strength	0.04	0.02	*	0.05	0.02	*	0.04	0.01	***	0.07	0.01	***	0.06	0.01	***
Constant	-1.75	0.87	*	1.34	1.11		2.16	0.23	***	2.24	0.34	***	2.70	0.29	***
Observations	3060			1836			22,708			18,249			20,085		
Informants	1473			952			3822			3575			3823		
Alters	389			191			2596			2158			2349		
Pseudo R-square	0.15			0.12			0.16			0.11			0.16		

Note: Logit models are used. The alters are self-reported recent smokers in Model A, self-reported recent smokers with three or more positive peer-reports in Model B, self-reported nonsmokers with four or more negative peer-reports in Model C, self-reported nonsmokers with four or more negative peer-reports and no positive peer-reports in Model D, and peer-confirmed smokers and strongly confirmed nonsmokers in Model E. For conciseness, coefficients for school and grade indicators are not shown. Standard errors are clustered by both informants and alters. Significance code: *, P < 0.05; **, P < 0.01; ***, P < 0.001.

self-reported smokers is about three to four times the odds of self-reported nonsmokers doing so in both models (e.g., $e^{1.32} = 3.74$, $P < 0.001$, in Model A). This result supports Hypothesis 2a.

Third, none of the other informant characteristics or the alter characteristics is consistently significant for predicting reporting accuracy. Hence, neither stereotyping nor status schema (Hypothesis 3a, 3b, 3c) is consistently supported here. Fourth, there is lack of support for Hypothesis 4. There is no evidence that reports for students in the same classroom, from similar family background, or with similar academic ranking are significantly more accurate (all $P > 0.05$). In fact, reports for students with the same gender are less accurate ($P < 0.001$ in Model A). Lastly, friendship strength is positively correlated with reporting accuracy), which supports Hypothesis 5.

Sensitivity analyses are provided in Table A2. In Model A the alters are self-reported recent smokers with ≥ 4 positive peer-reports and ≤ 4 four negative peer-reports. The stronger peer-confirmation ensures that the smokers being studied are even less likely to include false positives. Model B changes the outcome from recent smoking to regular smoking. The main findings are replicated, probably because of the high correlation between the two smoking measures. Students may be slightly more inclined to report on recent smoking than regular smoking when asked to report alter's smoking because of the slightly higher (pseudo) R-square (0.149 vs. 0.148). But the difference is so small that the evidence is indecisive. Model C examines reports on self-reported recent smokers with ≥ 3 positive peer-reports, while the first three positive peer-reports used for validating alter's smoking status are excluded from predicting reporting accuracy. This strategy helps separate measurement/validation from prediction. Model D uses only a single report from any reporter, which helps avoid over-generalizing the impact of reporters who provided multiple reports. Model E includes the positive reporting tendency for each reporter (excluding those with no reports or only a single report), which is measured as the proportion of positive reports out of all reports made by a reporter excluding the focal report in an observation. This helps account for self-projection on or misperception of alter's behavior. The estimated coefficient for informant smoking drops from 1.32 ($P < 0.001$) in Model A of Table 2 to 0.28 ($P < 0.001$), but is still sizable and significant at the 5% level. The results in all models in Table A2 confirm that central students and self-reported smokers are significantly more accurate reporters of smokers.

Because academic ranking, outdegree centrality, and personality may serve as a proxy for the capability to recall correctly, the willingness to report, and the propensity to report truthfully, respectively, the coefficients for the informant's indegree centrality and smoking status seem to mainly reflect an information exposure effect. Model F in Table A2 controls for cigarette exchange between the reporter and the reported. Cigarette exchange significantly and substantially predicts reporting accuracy (Est. = 3.16, $P < 0.001$) to the extent that the reporter's indegree centrality and smoking status become insignificant. This result further shows that information exposure is a significant part of the centrality effect.

Identifying self-reported, peer-confirmed nonsmokers

To study informant accuracy on nonsmokers, I first assume self-reported nonsmokers as "true" nonsmokers if they also received four or more negative peer-reports. The stronger peer-confirmation required here to validate the nonsmoking status is due to the consideration that self-reported nonsmokers may be more likely to be false negatives. I conduct a logistic regression on the peer-reports on these self-reported nonsmokers. Negative peer-reports are classified as ones to indicate accurate reports (i.e., $V_{ji} = 1 - Z_{ji}$) and other peer-reports as zeros.

$$\text{logit}\left[P\left(V_{ji} = 1|y_i = 0\right)\right] = B_0 + \boldsymbol{X}_i^{'}\boldsymbol{B}_1 + \boldsymbol{X}_j^{'}\boldsymbol{B}_2 + \boldsymbol{D}_{ji}^{'}\boldsymbol{B}_3 \quad (2)$$

The self-reported nonsmokers selected above may still include false negatives. To address that, in a new set of analysis I further restrict the peer-reports to those targeted at self-reported nonsmokers receiving not only at least four negative peer-reports but also no positive peer-reports. These self-reported nonsmokers are expected to include even fewer or no false negatives.

The results are shown in models C and D of Table 2, respectively. Based on the common patterns of the two sets of results, several findings are in order. First, central students are found again to be significantly more accurate reporters ($P < 0.001$). Second, self-reported smokers are significantly less accurate reporters of nonsmokers ($P < 0.001$), which supports Hypothesis 2b. Additional analysis shows that self-reported smokers are more likely to report nonsmokers as smokers rather than stating they don't know (Coef. $= 0.94$, $P < 0.001$), which presents additional evidence for self-projection. Third, girls are significantly more accurate reporters of nonsmokers ($P < 0.001$). Fourth, central nonsmokers, male nonsmokers, and lower-ranked nonsmokers are significantly less likely to be correctly identified (all $P < 0.01$). These results provide inconsistent support for the use of status schema. Meanwhile, high-indegree, male, and low ranking are typical traits of smokers, it seems like that the reporters tried "stereotyping" by associating these risk factors with smoking. Lastly, reports are significantly more accurate for students with the same gender or with closer friendship ties (all $P < 0.001$). Overall, the logics of identifying smokers and nonsmokers appear to be quite different, except that in both cases central students are consistently and significantly more accurate reporters.

Additional analyses

I also combine the samples in models B and D in Table 2 to study informant accuracy regardless of whether the reported is a smoker or a nonsmoker. The results are shown in model E in Table 2. Once again, central students are found to be significantly more accurate reporters ($P < 0.001$). As there are many more reports on nonsmokers, the results expectedly mostly resemble those shown in Model D. Interpreting the results in Model B in Table 2 in the opposite direction helps identify the characteristics associated with peer under-reporters. Similarly, interpreting the results in Model D in Table 2 oppositely helps reveal the characteristics associated with possible peer over-reporters.

I also use similar regressions to study the characteristics of possible self mis-reporters (Table A3). However, the results are tentative, as they rest on stronger assumptions. First, I define possible self under-reporters as those who self-reported as a nonsmoker but one or more peers reported them as a smoker. As shown in panel A, female students are significantly more likely to under-report smoking ($P < 0.01$), possibly because of the social norm against female smoking in China. Second, I define possible self over-reporters as those who self-reported as a smoker but no peers reported them as a smoker and four or more peers reported them as a nonsmoker. Results are shown in panel B of Table A3. One consistent result is that boys are significantly more likely to over-report smoking ($P < 0.001$) (or to smoke secretly).

I also provide cross-validation analysis in a different context where the true behavior is known. The main finding that central subjects are more accurate reporters is replicated (See online Appendix B).

Using peer-reports to correct self-reports

In light of that central students are more accurate reporters, one may weight peer-reports by peers' indegree centrality to construct a more credible measure of a subject's smoking status:

$$W_i = \frac{\sum_{j=1}^{n}(R_{ji}C_jB_{ji})}{\sum_{j=1}^{n}(R_{ji}C_j)}, \quad (3)$$

where W_i is the weighted peer-report on subject i, $R_{ji} = 1$ if subject j has reported on i and $R_{ji} = 0$ otherwise, C_j is j's indegree, and $B_{ji} = 1$ if j has reported i as a smoker and $B_{ji} = 0$ otherwise. For example, suppose student i receives three peer-reports: (1, 0, 0). The indegree of the peers are 20, 15, and 5, respectively. Then the weighted peer-report for student i is $1 \times 20/40 + 0 \times 15/40 + 0 \times 20/40 = 0.5$. In contrast, the conventional percentage method will estimate student i's smoking probability as 1/3, which is lower than the indegree-weighted estimate.

I apply this weighting method to the peer-reports in the baseline survey mentioned above. For comparison, I also use conventional methods to estimate student smoking status that are based on count or percentage of positive peer-reports received by a student and use three other centrality measures including outdegree, closeness, and betweenness to weight the peer-reports, respectively. Table 3 shows the results. The first column shows the mean error for predicting the self-reported smokers, defined as $\sum_i[Y_i(W_i - Y_i)^2]/\sum_i Y_i$ where $Y_i = 1$ for self-reported smokers and $Y_i = 0$ otherwise, and W_i is the weighted peer-report in the weighting methods, the raw percentage of positive peer-reports, or for the "count" method equals to one if a student receives four or more positive reports and to zero otherwise. The second and third columns show the number and proportion of self-reported smokers who are correctly identified as smokers by the "count" method or who receive a weighted peer-report or a raw percentage of positive peer-reports that is above 0.5. The last two columns in Table 3 show the number and proportion of self-reported nonsmokers who are identified by peers as smokers (based on the same criteria listed above). Three findings stand out. First, weighting peer-reports by peer's indegree centrality leads to the smallest mean error in predicting self-reported smokers (as shown in the first column) and the highest rate of correct predictions (as shown in the third column). Of course, this is not the ultimate proof of the superiority of the indegree-weighting method, but at least it offers a suggestive finding. To note, one can always lower the threshold (currently set at 0.5) that is used to classify smokers to increase the prediction. But this may introduce more false positives when the same threshold is used to classify self-reported nonsmokers as "smokers". Third, 99 self-reported nonsmokers are identified as smokers according to the indegree-weighted peer-reports. Hence, the actual

Table 3
Identify self-reported smokers and possibly under-reported smokers.

	A. Self-reported smokers, validated by peers			B. Self-reported nonmokers, identified by peers as smokers	
Methods	Error	N	%	N	%
Indegree	**0.46**	**151**	**37**	**99**	**3**
Percentage	0.48	125	31	69	2
Outdegree	0.49	126	31	82	2
Closeness	0.60	126	31	125	3
Count (≥ 4)	0.64	147	36	84	2
Betweenness	0.65	119	30	139	4

Note: The first column shows the mean error in predicting self-reported smokers; the second and third columns the number and proportion of self-reported smokers validated by peers; and the fourth and fifth columns the number and proportion of self-reported nonsmokers identified by peers as smokers.

number of smokers could be close to 25% higher than what is indicated by self-reports alone (i.e., 403). Of course, some of these "corrections" may be false positives. To reduce this possibility, one may increase the threshold that is used to classify nonsmokers as smokers to a higher value (e.g., 0.75).

Conclusion and discussion

The main contribution of this paper is to present a systematic conceptualization of the determinants of informant accuracy, evaluate it empirically, and apply the major finding that central subjects are more accurate reporters to combining informant reports for correcting self-reproting bias. In this paper I discussed the need and the scope of using informant reports and the types and the measurement of informant accuracy. I also proposed a general framework that links informant accuracy to not only informant characteristics, but also alter characteristics, dyadic characteristics shared by the informant and the alter, and features of the behavior of being reported on. I further illustrated the framework through a case study of self-reports and peer-reports of adolescent smoking. Among the informant characteristics, central subjects (i.e., those receiving many friend nominations) are consistently found to be significantly more accurate informants. This study also presents three mechanisms (i.e., information exposure, cognitive advantage, and social cooperation) that can contribute to the centrality effect and shows that the centrality effect mostly comes from information exposure. Of course, the current measures of recall capability and social cooperation are still preliminary. More refined estimates may be obtained when more accurate measures of these constructs are used in future work. This study also shows that rather than following the status schema as argued in previous research, informants are more likely to use risk factors to impute their reports. Among the dyadic characteristics, this study finds that informants are more accurate in reporting closer friends' smoking status.

This study also shows that there are notable differences in the logics of reporting the presence vs. the absence of a behavior. For example, smokers are significantly more accurate in identifying other smokers but significantly less accurate in identifying nonsmokers. Students in the same classroom tend to be more accurate in identifying smokers but less so in identifying nonsmokers while reports of nonsmoking (but not smoking) are more accurate between students with the same gender.

Studying informant accuracy also helps develop more effective methods to use informant reports to address self-reporting bias. The study shows that weighting peer-reports by informants' indegree centrality helps identify a significant number of self under-reported smokers. This indegree-weighted peer-reporting approach offers a sociological alternative or complement to the conventional approaches (e.g., biological testing) to addressing self-reporting bias. It may be applied in a range of practices, such as survey designs, marketing, health, criminology, education, etc. For example, on Amazon, Yelp, Rotten Tomatoes, and other review Websites one may weight reviewers' ratings by the reviewers' social network centrality in order to obtain more accurate ratings on the products of interest. Of course, this assumes there is a true product quality and more empirical work is needed to evaluate this assumption. To clarify, for weighting informant reports per se, one does not need any network information beyond an indegree centrality measure, which is increasingly available through linked social media accounts (as many websites provide log-in through social media accounts). Even if centrality measures are unavailable, one may use any available covariates to predict network centrality, e.g., through the latent space model (Hoff et al. 2002).

This study may be extended in several directions. The analytical framework may include additional higher levels of social factors such as features of the social networks the subjects are embedded in. For example, one may argue that classroom cohesion (as measured by the density of a classroom friendship network) may matter for reporting accuracy. It can either increase reporting accuracy as network cohesion encourages reporting or decrease it as cohesive networks may be more protective of personal privacy. Future work may examine such macro-micro links empirically. The scope of the informant method is also confined. In undirected networks (including ego networks) where only degree information is available, it will be difficult to pin down the mechanisms for the centrality effect, because the degree effect can reflect the effect of either centrality or reporting propensity. The method may not work well either for subjects with no friends or if friends/contacts tend to severely mis-report alters' behaviors (for example, due to defamation, overly flattering, or collusion). Future work may cross-validate the findings in this study by having a measure of the true behavior or by conducting similar research in different contexts with different behaviors (e.g., those that are less sensitive, less deviant, or less publicly observable) or different populations. Future work may also study how the results in this paper may be affected by the number of alters an informant can report and if reports on alters' multiple behaviors are simultaneously available (Goldberg, 2011). Bayesian methods that can combine reporting accuracy, self-reports, and peer-reports in a holistic model (Butts, 2003) will also be valuable.

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Appendix A

See Appendix Tables A.1–A.3.

Table A.1
Summary Statistics of Selected Student Characteristics.

Student Characteristics	Mean	SD	Min	Max
Age	13.46	1.14	10	17
Sex (1 = boy; 0 = girl)	0.45	0.50	0	1
Ranking (1 = top ten in the class; 0 = other)	0.20	0.40	0	1
Smoking (Self-reported, 1 = yes; 0 = no)	0.10	0.30	0	1
Personality (1 = optimistic; 0 = not optimistic)	0.52	0.50	0	1
Family economic condition (1 = good or very good; 0 = not good)	0.09	0.28	0	1
Incoming friendship ties from schoolmates	7.24	4.06	0	27
Outgoing friendship ties to schoolmates	7.24	2.77	0	10
Number of received peer reports on smoking (Positive)	0.63	1.55	0	15
Number of received peer reports on smoking (Negative)	5.59	3.80	0	26
Number of received peer reports on smoking (Don't know)	0.97	1.34	0	10

Note: N = 4,094.

Table A.2
More Results on Informant Accuracy in Reporting Alter's Smoking Status.

	A. Strongly Confirmed Smokers			B. Regular Smokers			C. Measurement & Prediction Seperation			D. Single Reporting			E. Control for Self-Projection			F. Control for Cigarette Exchanges		
Variables	Coef.	SE		Coef.	SE		Coef.	SE		Coef.	SE		Coef.	SE		Coef.	SE	
Informant Characteristics																		
Indegree	0.20	0.09	*	0.20	0.08	**	0.21	0.08	*	0.27	0.11	*	0.15	0.04	***	0.10	0.05	
Outdegree	0.04	0.09		-0.17	0.08	*	0.01	0.08		0.02	0.11		0.01	0.06		0.02	0.06	
Smoking	1.22	0.23	***	1.34	0.21	***	1.31	0.19	***	1.24	0.24	***	0.28	0.12	*	-0.02	0.14	
Age	0.18	0.18		0.05	0.14		0.26	0.16		0.08	0.27		0.12	0.10		0.13	0.11	
Boy	-0.05	0.26		0.85	0.46		-0.43	0.33		8.44	0.75	***	0.09	0.45		0.03	0.68	
Ranking	-0.34	0.39		-0.43	0.30		0.23	0.35		-0.10	0.65		0.15	0.24		0.08	0.25	
Personality	0.05	0.19		0.21	0.15		0.22	0.17		-0.22	0.21		0.07	0.10		0.01	0.12	
Family Econ. Cond.	-0.42	0.32		-0.61	0.43		-0.52	0.31		0.69	0.56		-0.21	0.18		-0.11	0.20	
Positive Rep. Tendency													0.51	0.02	***	0.48	0.03	***
Alter Characteristics																		
Indegree	-0.27	0.09	**	0.10	0.09		0.03	0.09		0.05	0.15		0.12	0.08		0.11	0.09	
Outdegree	0.07	0.10		-0.15	0.10		-0.04	0.10		-0.06	0.13		-0.13	0.08		-0.15	0.08	
Age	-0.01	0.16		-0.34	0.21		0.05	0.21		-0.16	0.27		-0.08	0.17		-0.10	0.17	
Boy	-1.08	0.90		0.16	0.98		-1.85	0.99		-6.99	0.87	***	0.27	0.80		0.16	0.77	
Ranking	-0.42	0.55		-1.05	0.37	**	0.06	0.38		-0.12	0.69		-0.61	0.34		-0.57	0.31	
Personality	0.13	0.15		-0.39	0.20		-0.10	0.20		-0.02	0.25		-0.29	0.16		-0.24	0.16	
Family Econ. Cond.	-0.03	0.27		0.86	0.39	*	0.02	0.40		1.21	0.58	*	0.51	0.24	*	0.61	0.25	*
Dyadic Characteristics																		
Same Class	0.47	0.19	*	0.23	0.16		0.25	0.17		0.44	0.25		0.14	0.12		0.11	0.13	
Same Family Econ. Cond.	-0.21	0.30		-0.65	0.41		-0.37	0.31		0.47	0.56		0.02	0.19		0.04	0.21	
Same Gender	-0.36	0.25		-1.26	0.46	**	-0.11	0.32		-9.61	0.76	***	-1.09	0.44	*	-1.09	0.68	
Same Ranking	-0.35	0.37		-0.10	0.30		0.49	0.31		0.16	0.62		0.11	0.24		0.04	0.24	
Friendship Strength	0.09	0.03	**	0.02	0.02		0.06	0.03	*	0.16	0.24		0.03	0.02		0.04	0.02	
Cigarette Exchange																3.16	0.26	***
Constant	1.19	1.19		-0.45	1.15		-0.52	1.30		5.80	1.33	***	-1.88	0.92	*	-2.01	0.92	*
Observations	1,125			1,532			1,263			424			3,048			3,023		
Informants	629			989			799			424			1,461			1,449		
Alters	125			193			190			246			389			389		
Pseudo R-square	0.10			0.15			0.13			0.17			0.36			0.45		

Note: Logit models are used. The alters are self-reported recent smokers with $\geq$ 4 positive peer-reports and $\leq$ 4 four negative peer-reports in Model A, self-reported regular smokers in Model B, and self-reported recent smokers with $\geq$ 3 positive peer-reports in Model C. In Model C the first three positive peer-reports used for peer-validation are excluded from predicting reporting accuracy. Models D-F are for identifying self-reported recent smokers. Model D uses only one report for any reporter. Model E accounts for self-projection and Model F controls for cigarette exchange. For conciseness, coefficients for school and grade indicators are not shown. Standard errors are clustered by both informants and alters. Significance code: * $P<0.05$; ** $P<0.01$; *** $P<0.001$.

Table A.3
Characteristics Associated with Possible Self Mis-Reporters.

	A. Self Under-Reporting, P(S=0|Y=1)						B. Self Over-Reporting, P(S=1|Y=0)					
	(1) Positive Reports ≥ 1			(2) Positive Reports ≥ 2			(3) Negative Reports ≥ 4			(4) Negative Reports ≥ 5		
Variables	Coef.	SE		Coef.	SE		Coef.	SE		Coef.	SE	
Age	-0.26	0.16		0.04	0.17		0.32	0.40		0.46	0.46	
Boy	-2.36	0.43	***	-1.71	0.62	**	2.84	0.46	***	2.70	0.46	***
Ranking	0.70	0.29	*	0.16	0.32		-1.45	0.60	*	-1.16	0.59	
Personality	0.00	0.15		-0.18	0.21		-0.20	0.38		0.29	0.44	
Family Econ. Condition	-0.21	0.23		-0.24	0.28		-0.09	0.62		-0.15	0.78	
Indegree	-0.11	0.10		-0.03	0.10		-0.06	0.24		0.11	0.23	
Outdegree	0.20	0.08	*	0.20	0.12		0.18	0.24		0.02	0.26	
Constant	4.42	0.59	***	3.67	0.72	***	-5.34	0.72	***	-6.23	0.90	***
Observations	1,025			542			2,008			1,742		
Pseudo R-square	0.12			0.09			0.09			0.09		

Note: Models 1 and 2 include self-reported nonsmokers with at least one and at least two positive peer-reports, respectively. Models 3 and 4 include self-reported smokers with no positive peer-reports and at least four or five negative peer-reports, respectively. For conciseness, coefficients for school and grade indicators are not shown. Standard errors are clustered by class. Significance code: * P<0.05; ** P<0.01; *** P<0.001.

Appendix B. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.socnet.2021.12.006.

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