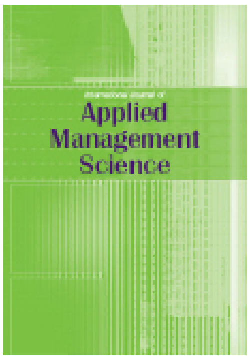

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Social network of confident attitudes with response time testing

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Abstract: Data constitutes the foundation of scientific research. The selected methodology of data collection defines its quality and research quality. In quantitative surveys and Social Network Analysis (SNA), data quality discussions strongly focus on declarative bias. Data quality would significantly improve if strong attitudes could be distinguished from the low ones since the former are more likely to be reliable and reflect individuals' social perceptions. The current paper measures attitudes with Response Time Testing (RTT). This methodology allows the identification of highly confident data by assessing the calibrated speed of a response. Simultaneously, RTT delivers in parallel classical declaration-based answers because, to the respondent, they are just like any other questionnaire. The difference between both approaches (classical and RTT) is analysed in two networks of similarity of attitudes towards COVID-19. The results show significant differences when only responses that show a high attitude accessibility are kept. Quadratic Assignment Procedure (QAP) and *T*-tests show that highly confident responses provide a significantly less cohesive network than when all the declaration-based answers are considered for analysis.

Keywords: response time testing; social network; declarative bias; attitude; confidence; data quality.

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1 Introduction

The quality of research mainly relies on the reliability and nature of its data (Savage and Vickers, 2009; Sayogo and Pardo, 2013). Data can have different origins and natures, such as observations, interviews, questionnaires, etc. Every data collection method has its advantages and limitations. The final choice of the data collection methodology will be, to a large extent, defined by the research question. In this article we address well-described and studied limitations related to self-reporting data collection methodologies. Namely, the emphasis is on the biases that can jeopardise data's reliability and quality when collected by declarative and self-administered surveys. Amongst others, we find biases from responses given mechanically or randomly, responses that rely on a rationale rather than a strong attitude, responses that correspond to what the respondent believes is socially expected or accepted, or misreported. Indeed, classical quantitative surveys hardly allow formatting the proportion of the data impacted by these biases. These classical quantitative surveys may lead to poor data quality, which impacts the whole empirical chain (Adams, 2020): the quality of the variable operationalisation, the measures, the models, the results and the conclusions. These constitutive biases can lead to a gap between what is expressed by the respondent and captured and what they actually feel. There could be consequences, mainly when the study aims to lead public or health policies, i.e., and to anticipate to what extent the population will accept them. Hence, identifying and isolating the data exempted from these biases becomes critical to ensure societal progress.

This paper aims to introduce a complementary approach to classical self-reported data collection to provide an additional quality based on the speed (response time) with which an answer is given. Speed has been identified as a good marker of the nature of the responses in self-administered surveys. The latency is a proxy that assesses to what extent an answer is given mechanically, is given rationally, is misreported, is given to follow a certain social acceptance, or refers to strong attitudes. The latter has been proven to be related to faster responses: the faster the response – to a certain extent – the stronger the attitude (Krosnick, 2018b). On the other hand, long-lasting responses can be a sign of the biases enumerated above. In the current approach, the strength of attitudes is a marker of quality. The reason to consider the strength of attitudes as a criterion for the data quality is motivated by the fact that they may be considered as drivers of behaviour (Fazio and Williams, 1986; Fazio et al., 1986; Déchaux, 2010). Thus, we can control data quality by accounting for biased data by considering the input variable of speed.

This paper's methodology is called Response Time Testing (RTT). This methodology is validated and institutionalised in related scientific disciplines such as marketing (Mast and Zaltman, 2005); personnel testing (Fine and Pirak, 2016); advertising (Lowrey et al., 2001, etc.); and language use (D'Andrade, 1995). RTT is a non-intrusive methodology that enables capturing the speed necessary to provide a response and, thus, to focus on strong attitudes. The methodology was applied to an international research project on attitudes and behaviours connected with the COVID-19 pandemic. An online self-administered questionnaire that includes RTT was sent to a representative sample of individuals living in Spain and Sweden to collect the data. We then considered, as Borgatti and Everett (1997) claimed possible, the survey, in a relational perspective, as two-mode data, namely as a NxM matrix with N representing a set of individuals and M representing a set of items the individuals had to state about. The project aimed to understand the level of homogeneity/heterogeneity of the individuals in the way they experience, understand and apprehend the virus. To do so, from the two-mode network, this study constituted a network of similarity, where we captured how the similarity is distributed amongst the sample. The relational approach appeared to us as a particularly relevant perspective since it allows the constitution of a dynamic representation of the similarities provided by Social Network Analysis (SNA) methodologies and concepts. Network data consider the variables to be interdependent and related to each other based on how similar they are. It produces a structure of interdependence and allows the constitution of clusters without losing the intra- and inter-group connections. These connections are valuable information that reveals underlying social dynamics.

We treat the data in a relational approach that bridges classical survey-based and SNA-designed research. There is reason to believe that the quantitative and SNA fields can benefit from RTT. Indeed, the reason RTT was first used in this research, namely, to control the self-administered/declarative-based survey biases, is also a consideration that runs through the field of SNA. Numerous studies over recent decades focus on the biases that can emerge when declarative and self-reported surveys collect data (Bernard et al., 1980; Conrath and Higgins, 1983; Hammer, 1984; Krackhardt, 1987; Marin, 2004; Almquist, 2012; Feld and McGail, 2020; Marineau and Labianca, 2021; Corman et al., 2021). Similar to classical surveys, there can be a gap between what is declared and what is deeply believed by the respondents (Butts, 2003). However, this systematic bias has led some network researchers to scepticism towards network surveys, where declarative and self-reported surveys remain the most prominent (Marsden, 2011). SNA would highly benefit from RTT as the relational analyses depend on the network's structure. A slight change in the network structure has implications for further inferences. Therefore, we believe that RTT can help identify how the network structure is related to the level of attitude and thus control its impact. This could, e.g., then be implemented for robustness checks or sensitivity analyses. Understanding the meaning of the relations becomes a central point for further research (Adams, 2020; Corman et al., 2021).

However, in the network field, these assessments have mainly been made for the ego network type of data (Wasserman and Faust, 2018); they can be made for any network data as long as the data is collected through declarative and self-administered surveys (Vannette and Krosnick, 2018). Using RTT in a two-mode designed research proves that the SNA approach and the tools can be used with RTT. Different methodologies have been developed to identify and evaluate the gap between the declarations and the 'real' social structure (Butts, 2003; Marsden, 2011; Krosnick, 2018a). However, no method has been developed to assist in the understanding of how the data is intrinsically structured (Butts, 2003; Stark, 2018). Answers that are randomly given and misreported with low motivation (Tourangeau, 2018b) can be easily separated from answers given with strong attitudes, especially in a forced-choice framework (Butts, 2003; Corman et al., 2021).

1.1 Contribution of the study

Data analysis drives results, and the quality of input variables determines the results. The present study looks at how RTT can be used in Social Network Analysis (SNA) to identify answers with strong attitudes and how only retaining such data affects network structural properties. It analyses data from both the self-declarative data collection and RTT data collection (to identify only strong attitudes) methods to identify networks, and findings show a difference in output when these two data collection methods are applied to the same sample. Thus, the quality of data analysed (from RTT) helps derive more definitive results as it is based on responses which have a higher level of certainty.

This contribution is structured as follows: firstly, this study briefly reviews the biases outlined in the literature of quantitative surveys and SNA for self-administered/declaration-based data. It then shortly summarises the different methodologies used to evaluate the validity and accuracy of the data. Furthermore, this study presents RTT principles and how and why they have been used in other fields. This will lead to empirical research conducted using RTT. This report collected self-declared data on people's emotions, attitudes, and behaviours in the context of the COVID-19 pandemic. Data from two countries (Spain and Sweden) will be presented; the paper will approach the data relationally. Namely, it is treated as two-mode data that captures individuals' attitudes about COVID-19. This two-mode data created a network of similarity of attitudes amongst participants, by projecting it into one mode. Finally, this report will assess the differences in network properties when the network is constituted based on strong attitudes, thanks to RTT, vs. the properties of a network when this discrimination is not made. In the conclusion section, this paper will highlight the main conclusions and consequences for further research and discuss our limitations.

2 Declarative survey: limitations and solutions

2.1 The declarative and the self-administration biases

Network data can be collected from many sources (Scott, 2017; Borgatti et al., 2018; Wasserman and Faust, 2018), such as observations, documents, experiments and declarative self-administered surveys, questionnaires and interviews. Declarative methods remain the most prominent approach to collecting network data (Marsden, 2011). There is an ongoing concern about the quality and validity of network data when collected via declarative and self-administered surveys initiated by their seminal work; Bernard et al. (1980) argued that only 50% of the declared ties encounter the observed ones. Though this assessment has not been unchallenged (Marsden, 2011, for a review), this stake is still accurate today in the SNA field (e.g., Neal et al., 2016; Lee and Butts, 2020; Marineau and Labianca, 2021; Corman et al., 2021). The debate mainly focuses on an ego network or full network of 'direct' relationships such as a friendship network, communication/interaction network, or event attendance network, also called an affiliation network. These self-administration reserves encountered in the network field are common with the debate among researchers of social sciences who use quantitative surveys (King, 2022).

Classical quantitative surveys can be conceptualised as two-mode networks. Two-mode networks can be anything as long as the network is composed of elements that belong to exactly two sets of different dimensions. This research treats individual-item surveys we encounter in classical quantitative surveys as two-mode networks. Indeed, even though this form of survey is usually not considered a network, it can be considered as such (Borgatti and Everett, 1997). These individual-item surveys can be particularly relevant when studying individuals' similarities of opinions (Norré et al., 2017), which can lead to behaviour prediction (Zhou et al., 2009).

For ego networks or individual-item surveys, responding to a survey implies four cognitive considerations (Marsden, 2011; Krosnick, 2018b): how the respondent understands the question, how he or she retrieves information that makes sense from his or her memory, how the answer is given from this retrieval and finally, how the responses can be provided according to the survey's format. The answers given are closely related to the respondent's memory, perception and will, and all three are related to the number of observations and experiences of a particular social phenomenon. There can be a gap between what is declared and what is observed (Wasserman and Faust, 2018). Moreover, there can be a gap between the 'true' structure and the 'collected' structure of a social network (Holland and Leinhardt, 1973). This can create a representation of the social environment that is variable according to the respondent. This subjective social network – or the declaration-based social network – is what Krackhardt (1987) calls for 'direct' networks, the 'Cognitive, Social Structure' (CSS). The CSS often (if not systematically) does not match the social structure in which the individual is embedded (Feld and McGail, 2020). The social ties can be imagined – falsely positively or falsely negatively (Almquist, 2012). Hence, there is what can be called a declarative bias. However, long-term and significant relations appear more accurate (Freeman et al., 1987). When considering two-mode data and its projection, the CSS will be an 'unmatching' network of similarities with the true structure of the distribution of similarities; namely, we will encounter a network of similarities that does not reflect how the individuals are structured in terms of similarity of responses.

The origin of this bias can be of three natures. First, it could be a deeply believed or a 'nonconscious' cognitive bias, inferred by answering according to the individual's perceptions and attitudes (Neal et al., 2016). The ego's perception can be influenced – not exhaustively – by the ego's socialisation and interactions (Blumer, 1998; Kashima et al., 2013; Wasserman and Faust, 2018), structural position (White, 1992; Emirbayer and Goodwin, 1994; Fuhse, 2009), cognitive constraints, e.g., memory capacity (Marsden, 2011; Lessof and Sturgis, 2018) or by personal attributes, such as the 'expansiveness Bias' or the 'attractiveness Bias' (Feld and Carter, 2002). In this context, the ego is not 'guilty' of her or his bias since her or his perception is 'really' believed to be true and does not relate to the ego's will: true beliefs, may they be representative of the 'objective' reality, or not, shape the ego's representation of the social reality and motivate his or her actions (Blumer, 1998; Poupart, 2011; Neal et al., 2016; Marineau and Labianca, 2021). The bias is the outcome of the socialisation process and is evolutive (Kashima et al., 2013). Consequently, individuals have different intrinsic capacities for observing and restituting the 'true' relations for themselves and others (Neal et al., 2016).

Second, the gap may also be due to the ego's variation in answers, itself influenced by the medium of data collection: i.e., , Conrath and Higgins (1983) assessed how data collected from a diary is more reliable than data collected from surveys; Fischer (2011) argued that the fatigue of the respondents might alter both the response rate and reliability; Johnson and Goldstein (2003) discussed that the use of defaults in the questions could also modify the responses; if the survey is conducted face to face it appears to give more accurate responses (Matzat and Snijders, 2010; Vannette and Krosnick, 2018; Yan and Tourangeau, 2018). For the first two, the variation depends on memory capacity. In contrast, for the latter three, it mainly depends on the investment and the perceived social constraints that pressure the individual to complete the survey. However, formal biases may vary from one culture to another, from one group to another, from one individual to another (Borgatti et al., 2018).

The third possible reason that impacts the gap between the declared and the 'real' social structure is a conscious declarative bias that the ego 'consciously' creates in order to 'promote' himself or herself (King, 2022). In a two-mode individual-item survey, this can be related to the expansiveness and attractiveness bias because an item can represent a popular or unpopular opinion. Thus, an item that is socially approved will tend to motivate the individual to respond to the item positively, and an item that is socially not approved will be more likely to get a negative response (Tourangeau, 2018a, 2018b). It is mainly the case when the given answer can impact the ego's image as bad or good (Marsden, 2011; Lessof and Sturgis, 2018). This is also influenced by the level of privacy with which the individual answers, e.g., if other persons are around when the respondent gives his or her answer (Tourangeau, 2018a). For instance, 70% of the surveys in India are answered with other persons present (Tourangeau, 2018b). The respondent can also consciously modify his or her answer if a given threat is perceived (Roden et al., 2020). Moreover, it is seen that individuals give random responses when forced to answer or do not feel engaged with the study (Butt, 2003; Borgatti et al., 2018; Tourangeau, 2018c; Roden et al., 2020). In this context, the bias depends on the ego's attitude and rationale.

In sum, from the four stages to answering a survey – understanding the question, retrieving from memory, summarising the information and making a choice, and finally presenting the choice in the manner that fits the format inquiries – if the respondent disengages from one of them, it has been proven that the individual may 1) select the first reasonable answer; 2) agree with assertion; 3) not differentiate in ratings; 4) answer with the default choice (when presented); 5) doing a mental coin-flip (Krosnick, 2018b). The individual will not answer accurately and perform 'motivated misreporting' (Tourangeau, 2018b, p.139).

The above-described factors make it hard to distinguish the type of answers and the kind of bias: 'We generally have no means of separating our informant assessments based on strong personal information from those in near-total ignorance' (Butts, 2003, p.136). However, no matter the nature of the bias, the data quality is impacted, and so is the quality of the measures and, eventually, the results. Improvement in methods to avoid these biases will benefit the quality of the data (Tourangeau, 2018b, 2018c).

2.2 Existing solutions

Marsden (2011); Wasserman and Faust (2018) and Adams (2020) reviewed some of the methods used to test a measure's reliability and, as a result, the data collected. These methods have been developed to assess the level of the gap between the CSS – or the declaration-based social structure – and the 'real' social structure and assess the level of trust one can have in the data collected. The reliability tests can also be used to assess the quality and the validity of the data, namely by assessing the level of coherence or regularity of an answer, with the subjacent idea that if an individual is coherent in his or her answer, then the response can be considered as genuine for the respondent.

Amongst other methods is the test-retest method (Marsden, 2011). This method involves reproducing the same study with the same population to observe if there are any variations between the two waves. Correlations are typically used to check the level of similarity. This method is quite limited because between the two waves, the individual may have experienced new realities, and thus, either his or her perception or even the 'true' social structure may have evolved (Blumer, 1998; Kashima et al., 2013; Wasserman and Faust, 2018). Moreover, if the bias is conscious, meaning that the respondent purposely modifies his or her answer, the 'true' structure will still be misrepresented.

Another way to assess the reliability is by testing different items to measure the same social dimension and see if the same structure is found (Marsden, 2011; Wasserman and Faust, 2018; Adams, 2020). It is a way to assess the level of consistency of the perception and, thus, the non-conscious part of the bias. This approach, however, questions the validity of the items, and the researchers should ensure that the chosen items measure the same dimensions. For instance, Cronbach alpha should be used to test the measures' validity (Ferligoj and Hlebec, 1995, 1999). Moreover, this method remains sensitive to conscious declarative bias.

A more advanced method, such as the Multi-Trait-Multi-Method (MTMM) (Coromina and Coendres, 2006; Marsden, 2011), has been developed. This approach combines multiple methods and items to study the same relation. This allows us to control the variance of the measure, identify which method and trait leads to which bias, and evaluate how much the data and the measures are impacted. The MTMM is expected to provide a less biased measurement quality than the other methods (Coromina and Coendres, 2006).

Lee and Butts (2020) developed a method called the Bayesian Network Accuracy Model (BNAM), which combines multiple methods to ensure the quality and the inference of the network constructed by declarative self-administered surveys. This method aims to reconstruct the 'true' structure of the social ecology when this one is not *a priori* known. The BNAM is constructed over for indicators: 1) the inferential self-consistency, i.e., the answers are compared to what is expected by the inference of network structure and error rates; 2) the split-half reliability, which refers to splitting the sample into subsamples and to comparing when we observe regularities and consistencies amongst the subsamples; 3) construct validity of the network structure, compared to referential identical networks; 4) validity construct of informant error rates, based on psychological norms.

New technologies and methods have been explored to avoid declarative and formal bias by collecting behavioural data with technological devices, such as GPS trackers, social media attendance, etc. (Lessof and Sturgis, 2018). Such methods can compare the declared data with the observed ones, thus testing the declarations' reliability. These new methods, though, pose questions of an ethical nature, quality and level of investment of the respondents, and the possible increase in nonresponse (Matzat and Snijders, 2010; Lessof and Sturgis, 2018; Adams, 2020).

As emphasised in this section, there are methodologies to assess the validity of a measure or the accuracy of the responses with the effective social structure after the data has been collected and analysed, mainly for ego or full network of 'direct' relationships. However, no apparent alternatives have been developed to be able to systematically identify and understand how the data is composed at the collection and thus to be able to discriminate the different biases and treat them accordingly (Butts, 2003; Tourangeau, 2018b, 2018c; Diviák, 2019). This is even more true for a two-mode individual-item survey, where the true structure is unpredictable. These methods remain sensitive to motivated misreporting of biased responses.

Biased responses are even more problematic in SNA research as the analyses mainly rely on the network structure, which is primarily sensitive to the respondents' answers. As all responses are interdependent, a slight change in one answer impacts the overall network. A way to control it is by including the strength of the response. However, it seems there is a lack of a way to separate the responses with strong attitudes from the motivated false ones. By incorporating methods to determine the level of trust one can have in the data would thus benefit the field and reduce the need for complex – costly – methodologies to correct the harm.

2.3 Response time testing: measuring, understanding, and improving data quality

As argued in one of the earlier sections, declarative self-report surveys have limitations. A significant reason biases exist in that conventional approach is that there is little or no data on the processes by which respondents arrive at their answers (Bassili and Fletcher, 1991), failing to accurately capture the contents of mental processes (Nisbett and Ross, 1980). Therefore, social psychologists have been seeking solutions by looking at how information is represented in the memories, how information is accessed, and how it is evaluated. Over the last few decades, survey methodology has witnessed a paradigm shift (Tanur and Fienberg, 1992), departing from conventional statistical models and embracing a movement called the Cognitive Aspect of Survey Methodology, aiming to, among others, reduce measurement error (Tourangeau, 2003).

One of the most popular methodologies with a long history in cognitive psychology is called Response Time Testing (RTT) or response latency (Bassili, 2000). In essence, it is a kind of paradata that measures the duration of time from the moment the question is posed to the moment the answer is given. Beginning in the 1860s, Donders (1868), Galton and Wilhelm (see Jensen, 2006 for a review) pioneered using RTT to measure mental chronometry and error variance. While RTT in this early research was not used extensively for surveys, its potential in measuring ‘the amount of information processing necessary to answer a question’ (Bassili and Scott, 1996) quickly proved to be a beneficial method to survey researchers. In general, the use of RTT in a survey context involves three major themes; namely, response time is a more objective indicator of (1) cognitive effort, (2) attitude strength studies in both (1) and (2) can simultaneously use RTT to improve (3) quality of survey instruments.

In the first category, response time positively correlates with the cognitive effort invested in solution behaviour (Schinipke and Scrams, 2002; Wise et al., 2006). According to the model of Tourangeau (1987), an engaged response goes through four cognitive steps: comprehending a question, retrieving information, formulating answers and selecting an answer. Thus, a longer response time indicates more significant cognitive effort. Such effort mainly comes from task complexity (Shi et al., 2018). As a rather straightforward method, RTT helps researchers to measure respondents’ ability, to understand their motivation and to investigate their efforts (e.g., Wise and Kong, 2005; Wise et al., 2006; DeMar and Wise, 2010).

Together with the benefit of measuring cognitive effort with fewer biases, researchers simultaneously employ RTT to improve validity and reliability. Callegaro et al. (2009); Wanich (2010); Zhang and Conrad (2014) and Revilla and Ochoa (2015) used RTT to optimise questionnaires, identify ‘satisficing’ tendencies and identify respondents who did not thoroughly go through or skipped cognitive steps, take a quick look at the questions and select an answer (Krosnick, 1999). Similarly, Goldhammer (2015) used RTT to detect the speed-accuracy trade-off, i.e., when respondents work quickly but with many errors. This method minimises the problems that can jeopardise the comparability of performance measures often observed in a traditional approach. Many other studies support the use of RTT in strengthening validity and reliability, identifying the impact of confounding factors such as poorly formulated questions (Bassili and Scott, 1996; Lenzner et al., 2010), conflicting beliefs (Bassili, 1995; Newby-Clark et al., 2002), uncertainty (Draisma and Dijkstra, 2004), high or low stakes (Wise et al., 2006; Wise and Kong, 2005), cultural background and interviewers (Shi et al., 2018), radio buttons versus dropdown boxes (Heerwegh and Loosveldt, 2002), race and marital status (Couper and Kreuter, 2013), attitude towards survey (Stocké, 2006), group norms (Smith and Terry, 2003), language (Phillips et al., 2015), motivation (see Gummer and Rossmann, 2015 for a review) and other factors such as age, education, and number of clauses (Yan and Tourangeau, 2008).

In the second category, response time negatively correlates with attitude strength. It is based on the assumption that for some cognitive processes, such as attitudes, over-analysing response choice may be undesirable and rather an automatic and immediate response. Most of the work in this category follows Fazio's pioneering model of attitude as an object-evaluation association (Fazio, 1990). It posits that the strength of association between an object and evaluation of that object represents attitude strength. Strong attitudes are indexed by short response time. Fazio's theory on attitude strength is one among many theories built upon the dual-process model, which assumes that information processing has the duality of two modes: automatic and deliberate (see Mayerl, 2013 for a review). Strong attitudes have high accessibility to association in the memory and will come to mind more automatically.

Building on Fazio's theory of attitude strength on attitude objects, Bassili and Fletcher (1991) pioneered in applying response time in the survey context (1993), providing researchers with a less biased measure than the declarative self-report (Bassili and Krosnick, 2000). Their research and other studies suggested that stable attitudes need a shorter response time (e.g., Mulligan et al., 2003; Heerwegh, 2003; Mayerl, 2013; Tracey and Tao, 2018). This resonates with several studies that found a relationship between response time and personalities, i.e., less consistent statements with own self-schema beliefs take a longer time to respond (Popham and Holden, 1990; Holden et al., 1990; Siem, 1996; Neubauer et al., 1997; Akrami et al., 2007; Austin, 2009; Weidner and Landers, 2019).

Similar to the first category, while using RTT to measure attitude strength with the benefit of fewer biases, researchers simultaneously employ RTT to understand data and improve the quality of surveys. According to Bassili (1993), the traditional declarative approach often relies on 'meta-measures,' i.e., deliberate self-reported answers by respondents. It requires respondents to reflect on and judge their mental processes. It may happen that they are not able to or not motivated to do so, which may lead to the possibility of cognitive biases (Bassili, 1995; Yan and Tourangeau, 2008). As discussed in the previous sections, this raises serious questions about the validity and reliability of such information (Mayerl and Faas, 2018).

In contrast, automatic answers captured by RTT indicate 'operative measures,' i.e., the ease with which information is retrieved from memory. There is no need to make them up ad hoc when a survey asks because the information is simply there (Bassili, 1995). Thus, RTT is argued to improve construct validity and measurement reliability (Lenzner et al., 2010; Mayerl, 2013; Mayerl and Giehl, 2018). For example, Tracey and Tao (2018) reported that adding RTT to self-report scales increased internal consistency and provided incremental validity to scales with few items, i.e., more prone to problems.

In another study, Scott et al. (2009) reported that RTT helped to identify the source of between-subject variation that differs from self-report surveys.

Benefits notwithstanding, RTT does not escape many limitations conventionally identified with the traditional survey approach. According to several studies (e.g., Malhotra, 2008; Meyerl, 2013; Meyerl and Gielhl, 2018), while RTT could enhance validity and reliability, it also risks acquiescence bias (i.e., an indication of carelessness), the impact of negative wording, contrast effect, and question order. However, appropriate research design can control many of these effects (Bassili, 2000). In many ways, recommendations for guarding against these effects are essentially the same as those suggested in survey literature (Mulligan et al., 2003). Solutions include mixing item order (Mayerl and Giehl, 2018), asking simple questions (Bassili and Scott, 1996), using bi-polar evaluation (Dolnicar et al., 2011; Weidner and Landers, 2019), or converting response time into a bipolar curve (Tracey and Tao, 2018), and taking into account nature of choice (Meyer and Schoen, 2014). More importantly, survey researchers should exercise caution and keep in mind the fundamental characteristics of RTT, which is not purely the measure of attitude strength or cognitive effort but 'the amount of information processing' involved in answering survey questions (Bassili, 1995).

To conclude, regardless of what RTT is used to measure and interpret, this method has the potential to contribute to assessing the quality of data collected in surveys as an added tool (Presser et al., 2004; Tracey and Tao, 2018) and standard in computer-assisted surveys (Mayerl, 2013).

3 The study

The review presented above shows how RTT enables us to control for biases and identify the strength of an attitude given in response. The present contribution introduces how RTT can be used, in the context of SNA, to identify answers with strong attitudes and how only retaining such data affects network structural properties. To compare how it may vary, we constructed two networks of similarity of COVID-19 apprehension and attitude: one with the data disaggregated by RTT, which keeps only strong attitude answers and one with the data that considers all responses as equal, no matter the speed. The latter corresponds to the network we would obtain if the data were collected with regular declaration-based data collection methodologies, which cannot distinguish strong attitudes from weak ones. These networks of similarities are projections of a two-mode respondent-item questionnaire.

4 Methods

4.1 Data collection and sample

The presented results are part of an extensive international study on attitudes, emotions, and intentions connected with the COVID-19 pandemic. This article will focus on data collected from Spain and Sweden. Country representative samples were collected via a panel agency. Table 1 provides the high-level demographics of the sample. There is a total sample of 2022 individuals (1019 from Spain and 1003 from Sweden). The 18–35 and 36–49 age classes in Spain are slightly overrepresented at the expense of the 50+

class, which is underrepresented. The gender distribution matches the population structure.

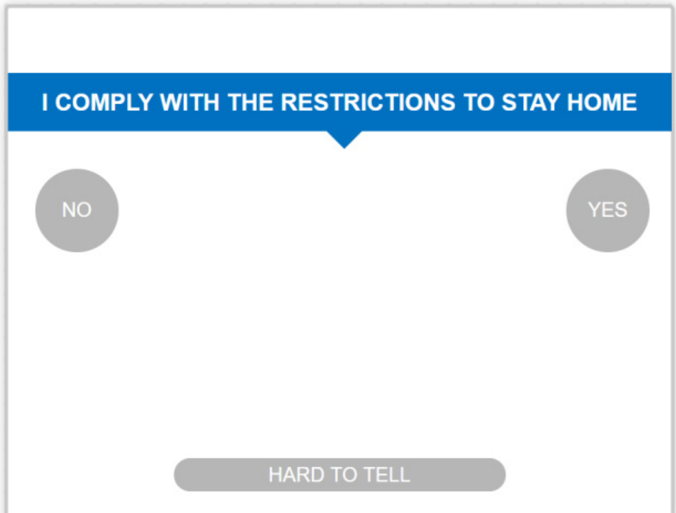
Table 1 Demographic distribution in the Spanish and Swedish sample vs. population (N=2022)

Countries	*N*	*Gender*		*Age*		
		Men	*Women*	*18-35*	*36-49*	*50+*
Spain						
Sample	1019	50%	50%	32%	32%	36%
Population		49%	51%	24%	27%	49%
Sweden						
Sample	1003	49%	51%	30%	20%	49%
Population		50%	50%	29%	23%	48%

The study was performed online in April 2020 with the iCode smart test software. Fifty statements were tested (see Appendix 1). The statements were selected to examine emotions (fears), intentions (compliance and lifestyle changes), and opinions (impact of the pandemic, evaluation of Government and Healthcare, etc.) connected with the pandemic. Quality assessment made with the SQP software (DeCastellarnau and Revilla, 2017) is also presented in Appendix 1. The respondents' task was to evaluate their agreement with the statement on the screen. The statements were shown individually in random order. The answers were given on a 3-point scale (1 yes, 0 hard to tell, –1 no) (see Figure 1). Respondents prefer a three-point scale, and Matell and Jacoby (1971) (cited in Taherdoost, 2019) found that the reliability and validity of a scale do not depend on the number of response options available. Therefore, reducing the number of response choices does not negatively impact these qualities (Ferrando and Lorenzo-Seva, 2007). RTT was applied to outline the influence of declarative biases that might occur during traditional surveys and thus distort the final outcome. It measures the instinctive reactions of respondents to assess the level of hesitation when providing an answer. Thus, we are able to measure the strength of attitudes resulting in 5 levels of response: high yes (strong positive attitude), yes (weak positive attitude), hard to tell (no attitude), no (weak negative attitude) high no (strong negative attitude). The values that are strong and accessible are expressed indicated by faster response time, whereas slower response time indicates weaker, less accessible attitudes expressed with hesitation (Fazio and Williams, 1986). This approach assesses the response time for every declarative answer provided; thus, two types of data – explicit – self-reports – and implicit – response time – are collected simultaneously.

To eliminate test biases, a warm-up phase was added. It preceded the test phase and aimed to increase familiarisation with the scale, familiarisation with the purpose of the task, and focus on the task. A control screen was also introduced to eliminate the effect of the mouse's position on the screen. It was presented before each statement, forcing a standardised position of the mouse (the distance between the yes and no answers was always the same).

Figure 1 Research screen (see online version for colours)



4.2 Data preparation

The first step of data preparation was cleaning the sample from outliers, that is, responses given too fast, suggesting speeding through the test without providing meaningful answers, too slow responses or suggesting a person got distracted from the test (Greenwald et al., 2003). Responses given with a latency lower than 500 milliseconds (ms) (suspected to have been given randomly) or higher than 10,000 ms (suspected to have been given after distraction) were discarded. The mean latency of each item is given in the appendix.

In the next step, individual differences in reaction speed were eliminated. Response time data measured in milliseconds were standardised using *z*-scores of log (latency), creating a Std-RT score with M=0 and SD=1. The final step was to develop an RTC index. The RTC index is designed to capture the implicit confidence behind a response based on the premise that quicker responses are typically more reflective of strongly held beliefs or attitudes, as supported by cognitive psychology research. By integrating response time into the analysis, the RTC index provides a richer, more accurate measure of the data's quality, highlighting responses that are not only declarative but also backed by cognitive certainty. The RTC Index combines explicit answers with response time.

Consequently, the following formula was used: For explicit Yes answers (RTC values in the range from 0 to 2): RTC = 1 – (Std-RT/2). For explicit No answers (RTC values in the range from –2 to 0): RTC = (Std-RT/2) – 1 Std-RT values above 2 and below –2 were truncated and given the value 2 or –2, respectively (this accounts for around 3% of data). We truncate values greater than 2 or less than –2 to manage the influence of outliers in our data. Indeed, values represent *z*-scores. Thus, values below –2 or above 2 significantly differ from the mean at the p-value<0.001. Keeping them does not provide any additional information. By truncating these values, we aim to stabilise the influence of response times on the RTC index and maintain a consistent scale of strength across all responses. Response times typically do not follow a normal distribution; they are often positively skewed, indicating that most responses are given relatively quickly, with a long tail of slower responses. This skewness can be attributed to the cognitive processes involved in responding, where most straightforward or strong attitudes result in quicker responses and more complex or less certain attitudes lead to longer response times. To address this, we use a logarithmic transformation followed by standardisation, which helps normalise the data, making it more suitable for creating a strength-related index that equally weighs all responses.

4.3 COVID-19 attitude networks

To highlight how retaining strong attitude-based data differs from classical data, we created two networks of similarities based on the similarity of responses given on the different items of our questionnaire (Borgatti and Everett, 1997; Norré et al., 2023): one that includes the data with no distinction and another that only contains the strong attitudes answers (based on a fast Response Time).

To operationalise each of these network variables, we proceeded in two steps. First, we consider the individual-item matrices as two-mode matrices that represent two-mode networks (Borgatti and Everett, 1997; Borgatti and Halgin, 2011), and we then projected them into one-mode networks with a focus on the individuals. The two modes on the rows are the respondents, and the different survey questions are on the columns. Therefore, the networks can be represented by two different matrices, N-by-M, where N=2022 individuals and M=100 items for the answers. The survey has 50 questions; for each, the individuals could answer ‘yes’ or ‘no’, which explains the 100 items. Each question is hence doubled. For each individual, we report their answers for each item on the column where ‘1’ signifies that the respondent did answer, and ‘0’ means that the respondent did not answer. For example, if individual n_i answered ‘Yes’ to the question m_j(yes), then the code is ‘1’ at the intersection $X^{\text{nimj(yes)}}$ and ‘0’ at the intersection $X^{\text{nimj(no)}}$.

In the strong attitude matrix, for ‘1’ to be coded, the individual’s answer has to be given within the set-up threshold. A cut-off value was identified based on a standard deviation of the process unfolded in the precedent section to determine which answer can be considered fast enough to be treated as a strong attitude. For each question, a Std-RT value obtained by the mean minus 0.5 standard deviation was taken as a threshold below which answers were treated as a strong attitude. All responses that do not reach the threshold are recorded as an ‘absence’ of response. It should also be noted that the threshold depends on the research question and design. A loosened threshold would give other distributions and results. As we discriminate based on the speed of the answers, both $X^{\text{nimj(yes)}}$ and $X^{\text{nimj(no)}}$ may be coded ‘0’ if the individual does not answer within a sufficient threshold of certainty. The zero is not considered a missing value, as a lack of attitude is a form of behaviour and apprehension of the pandemic. It should also be addressed that the ‘real’ missing values have been initially excluded from the sample.

We induce square one-mode matrices based on the rows from these two-mode matrices. Projecting a one-mode matrix from a two-mode matrix enables researchers to infer social similarities that are difficult to study directly, mainly when such relations are abstract (Borgatti and Everett, 1997), which is the case here. We capture how similar the respondents are in attitude. The basic concept is that the more individuals answered similarly to the items, the more they were expected to be similar in their apprehension of the pandemic. Thus, from a two-mode $N \times M$ matrix that resembles classical surveys, one can infer a network of similarities.

To project the two-mode networks, this paper follows the Stochastic Degree Sequence Model (SDSM) proposed by Neal (2014). The SDSM considers the propension of each individual to answer an item and the propension of an item to be answered. It also allows building a one-mode network based on a significant weight distribution of the edges. The SDSM process works as follows: first, for the observed bipartite network, two independent variables are created, one that captures the degree for each individual and another one that captures the degree for each item. We create a third one that is the product of the two variables. The dependent variable is the choice made by the individual; it is a binary variable that can take the value 0 or 1 depending on whether the respondent answered the item or not, as explained in the preceding section on the creation process of two-mode matrices. These variables serve in a binary outcome model to predict the probability of responding to an item for each pair of individual items. The probability for an individual to have answered the question is a Bernoulli trial that is given by the Scobit $Pr\left(Y=1\right)$ equation (1). In order to calculate the probability distribution, we run a Scobit regression in STATA to get the coefficients of the constant variable and the predictors. SCOBIT regressions also have a unique value, which is the alpha. We have used a skewed logistic model over other binary models because the probability of an edge being present does not follow a Bernoulli probability of 0.5. There are higher probabilities of an item to be responded to if there is social desirability, i.e., or if it refers to a largely shared item. Using a skewed model, therefore, allows for control of this skewed distribution. The Scobit model is simply an extension of the logit model, which allows more flexibility. The next step is to create 10,000 random bipartite networks that follow the probability distribution of the observed network:

$$\left(Y=1\right)=1-\frac{1}{\left(1+\exp\left(z\right)\right)^{\alpha}} \tag{1}$$

where $z=\beta_0+\left(x_1\beta_1\right)+\left(x_2\beta_2\right)+\left(x_3\beta_3\right)$ z

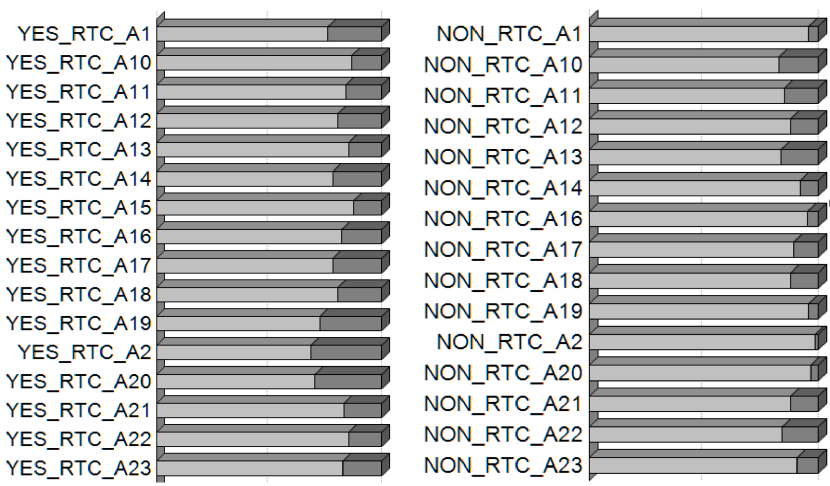
Once done, the observed network and every created network, projected for each pair of individuals, have the number of items they have in common. Those represent weighted edges. The last step is to compare the weights of the observed network with the ones created. If the edge weights are higher in less than 500 random networks, then we can infer that the similarity is significant, and thus, we can keep the tie between the dyad of individuals. Five hundred is considered the significant threshold, not 250 because we have an unsigned network and only observe values higher than those observed in random networks. Therefore, there is a one-tailed test of statistical significance.

5 Analysis and results

5.1 Building the networks

Figure 2 gives an example of how RTT enables us to discriminate the responses: it represents the proportion of each respondent to each item according to the level of strength of response (confidence). The darker surface represents high-confidence responses. The highest attitudes account for 35% of the data. It illustrates the gap that can exist between strong and weak attitudes. Even though the survey format may impact the level of answers, as online surveys are expected to have less valid responses (Matzat and Snijders, 2010), these distributions show a low level of confidence regarding the pandemic. This, however, can be explained by the fact that, at the time of this study, the COVID-19 situation was quite new to people, and only a little was announced with certainty, even at the political level and in the mainstream media. We would likely witness a higher proportion of strong attitude responses if the study were performed today.

Figure 2 Sample of the proportion of strong attitude responses for 'yes' and 'no' (N=2022)



Note: The bar corresponds to 100% of the answers for each question. Darker surfaces represent the proportion of high-confidence answers at the set-up threshold; non-answers have been removed.

Table 2 shows that the RTT discrimination process significantly reduces edges. Indeed, the mean degree for each item is significantly lower for the 'yes' (Difference in means= –689.760, p-value=0.0001) and for the 'no' (Difference in means= –411.620, p-value=0.0001) in the RTT process. Many responses do not reach the set-up threshold to be considered strong attitudes. On the rows' side, we have the mean degrees for each individual. Again, we can see that the mean degrees for both 'yes' and 'no' are significantly lower regarding strong attitudes (Difference in means for yes= –17.056, p-value=0.0001; difference in means for no= –10.179, p-value=0.0001).

Table 2 Individuals and artefacts mean degree distributions (*N*=2022)

Variables	*Mean degree for strong attitudes*	*Mean degree for all attitudes*	*Difference in means*
Items			
Yes	445.880 (126.956)	1135.640 (381.001)	689.760***
No	147.420 (107.986)	559.040 (335.740)	411.620***
Individuals			
Yes	11.026 (4.496)	28.082 (8.248)	17.056***
No	3.645 (3.232)	13.824 (6.851)	10.179***

Notes: Standard deviation in parentheses; ***$p<0.000$ for the two-tailed *T*-test.

Table 3 shows the Scobit coefficients for both networks, the one with only strong attitudes and the one with all the answers merged. These coefficients have been plugged into the Scobit $\Pr(Y=1)$ equation for each individual to create the random networks that follow the observed network's probability distribution. We can see that the model with the strong attitudes (log-likelihood=–71656.13) shows a better fit than the network that merges all the responses (log-likelihood=–105215.98). Therefore, the strong attitude network can better predict the presence of a tie, that is, an individual's likelihood to respond to an item. Once the 10,000 bipartite networks had been created, each one was projected in addition to the observed one, and the projected values of the number of observed cases were compared, and they turned out to be higher than the values of the created ones. The values higher in less than 500 random projections were used to ensure the significance of the edges was kept.

Table 3 Scobit coefficients for both networks

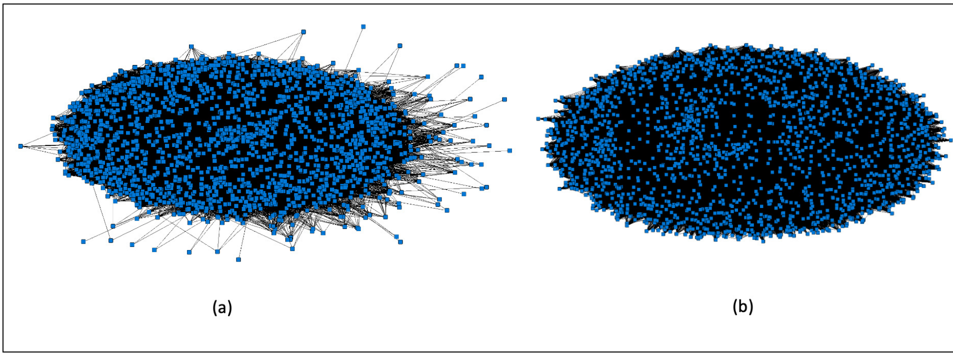
Variables	*Strong attitudes*	*Coefficients*	*All attitudes*
Individuals' degree	0.23 (0.15)***		0.042 (0.002)***
Items' degree	0.01 (0.00)***		0.001 (0.00)***
Individuals' degree *x* Items' degree	0.004 (0.00)***		0.00 (0.00)***
Constant	–4.87 (0.23)***		–3.74 (0.11)***
Alpha parameter	0.04 (0.003)		0.51 (0.02)
Log-likelihood	–71656.13		–105215.98

Note: Standard error in parentheses, ***$p<0.001$.

5.2 Networks of similarity properties

How does one interpret these networks when they are projections and not 'direct' relationships? The nodes represent individuals, and the edges represent the fact that two individuals can be considered similar in apprehending the pandemic. Namely, if there is an edge, it means that they have responded in a significantly similar manner to the questionnaire. We can eventually compare how the networks of similarity significantly differ in their structural properties. Visually, thanks to NETDRAW (Borgatti, 2002) (see Figure 3), the differences can be seen, and they tend to indicate that more individuals have an individualised way of considering the COVID-19 pandemic. This tendency is confirmed when considering the number of isolated individuals (80 for the networks with only strong attitudes vs. zero for the network that merges all attitudes).

Figure 3 Visualisation of the apprehension network depending on the level of attitude (*N*=2022). (a) network of similarity with only strong attitudes; (b) network of similarity with all attitudes; isolated not included (see online version for colours)



To make significant comparisons between these two networks, this research uses Pearson's correlation to see if the presence of one tie in one network happens in the other one (Borgatti et al., 2018; Marsden, 2011) and the Jaccard coefficient, which enables us to identify the proportion of ties that are similar between the two variables (Borgatti et al., 2002; Donnat and Holmes, 2018; Stadtfeld et al., 2020).

When dealing with relational and dyadic data, as is the case in this research, particular statistical tests are needed (Huisman and Van Duijn, 2011). In relational data, the independence of answers is not postulated. For this reason, classical statistical tests can lead to biased results due to autocorrelations and the non-independence of the answers (Borgatti et al., 2018). In such an approach, variables are matrices, not vectors (Dodsworth and Benton, 2020). To be able to relate this particular kind of relations and variables, the method called Quadratic Assignment Procedure (QAP) (Hubert and Schultz, 1976; Krackhardt, 1988) has been developed, in particular, to avoid these biases. QAP method proceeds by permutations. All statistical procedures are done with UCINET (Borgatti et al., 2002).

This study also compares the structural properties of these two variables, which are fundamental cohesion measures. Different properties of the network contribute to its cohesiveness (Wasserman and Faust, 2018). Density is one of them. To calculate it, take the number of activated ties out of the possible ties. The diameter, i.e., the shortest path between the two most distant members of the network, is also one of the components of cohesiveness. The longer the geodesic path, the less cohesive the network. Cohesiveness can also be calculated using triad transitivity, which is calculated based on the proportion of triads that have all three individuals connected out of the possible closed triads in the network. Again, since this study deals with projections, a short explanation of how to interpret the measures is needed. In the context of similarity networks, these cohesive measures indicate the extent to which the individuals have a consensus. The more cohesive the network, the more individuals tend to have similar attitudes, and inversely.

This study also analysed nodal properties that contribute to network cohesiveness. It emphasises the average normalised degree of centrality and the average geodesic path.

These properties were compared for the two variables that were operationalised. This study also measured the clustering coefficient of every actor for both networks and compared their means. The clustering coefficient allows for the calculation of the density of the open neighbourhood of each individual (Watts, 1999; Borgatti et al., 2002). The higher the coefficient, the more cohesive the network. A T-test was performed on the average normalised degree centrality, the average geodesic path length and the mean of the clustering coefficient in order to significantly test the differences between the measures. As for the QAP, particular methods are to be used for the T-test used in relational data. UCINET offers group analyses that include permutations to avoid independent bias (Van Duijn and Huisman, 2011).

Table 4 presents the results for the level of (dis)similarity for the cohesive properties of the two variables. By taking a look at the descriptive statistics, one can observe that the level of similarity between these two variables is pretty low (r=0.181, p-value<0.000 and Jaccard coefficient=0.137, p-value<0.000), which indicates that by maintaining only strong attitudes or not ends up with two variables that are quite different. Indeed, an absence of variation would have led to correlation coefficients of r=1 and a Jaccard coefficient=1. The measures have no stability, and the relations differ from one variable to another.

Table 4 Similarity measures and T-tests for the two matrices of similarity (N=2022)

Variables	*Level of variation for the two matrices*	*Similarity Matrix with high attitudes*	*Similarity Matrix with all attitudes*	*Sig. Two-tailed T-test*
Pearson correlation	0.181***			
Jaccard coefficient	0.137***			
Density		0.066	0.137	
Average *n* Degree		0.066 (0.044)	0.137 (0.121)	0.0001
Diameter		4	2	
Average Geodesic distance		1.979 (0.349)	1.863 (0.344)	0.001
Isolated		80	0	
Transitivity (triads)		0.082	0.203	
Average Cluster coefficient		0.082 (0.040)	0.203 (0.097)	0.0001

Note: ***p<0.001; Standard deviation in parentheses.

By taking a look at the structural properties of the network, one can observe that the one induced from RTT data is significantly less cohesive than the one that does not include it (RTT: density=0.066, Diameter=4, isolated=80, transitivity=0.082; no RTT: density=0.137, Diameter=2, isolated=0, transitivity=0.203). If one looks at the T-test's results for the average nDegree, we find a significant difference in means between the two variables (±0.071, p-value=0.0001), so it does for the average geodesic distance (±0.116, p-value=0.001). The clustering coefficient of every actor for each network also indicates that the one with solid attitudes is significantly lower in mean (–0.120, p-value=0.0001). Practically, it means that in the former, individuals tend to be less similar to others in their attitudes toward the pandemic and have fewer people who resemble them.

Thanks to RTT, we can assume a significant difference in results from these measures by keeping only confident answers when operationalising a variable to calculate the same dimension. Structural properties of the network are impacted. The consequence of this difference is that the measure using reaction time leads to less similar individuals – in this case, in terms of their apprehension related to the pandemic – and a less cohesive network. Strong attitudes, highlighted by RTT, enable us to discriminate the individuals better and outline their dissimilarities. On a macro level, there appears to be a general tendency expressed by the unique component – if the singletons are not considered in the RTT network. This may be interpreted as a form of common apprehension. Indeed, we do not observe the emergence of clear clusters, which could reflect clear groups of ways of reacting to the pandemic.

On the other hand, similar patterns of experiencing the virus that most individuals share are observed. RTT, and the focus on strong convictions, however, finds that the source of the consensus can be from different motivations. In other terms, there are the same consequences, but with various means to reach them. This phenomenon is even more highlighted with isolated individuals, as they uniquely apprehend the pandemic. This was only possible by considering the strong convictions differently than the weak ones. It can be interpreted as the fact that the apprehension of the crisis is more individualised, which is coherent with the concept of fluidity and fuzziness of culture (White, 1992; Emirbayer and Goodwin, 1994; Pescosolido and Rubin, 2000; Fuhse, 2009).

Our results in Tables 3 and 4 demonstrate significant differences in network cohesion and centrality measures when filtering by response confidence. For managers, this means that networks constructed from high-confidence responses are more reliable and indicate authentic influential relationships within the organisation. These insights could be pivotal in scenarios such as change management, where understanding the actual versus perceived influencers can significantly alter the strategy's effectiveness.

6 Discussion and conclusion

RTT is a scientifically validated methodology that has proven its efficiency in identifying strong attitudes in many fields. This study presented an SNA approach where RTT was used. RTT is a prolific approach to pinpointing and labelling data based on the level of certainty of the responses. It identifies randomly given answers (if the answers are given too fast) or answers due to a certain lack of interest and fatigue (if the time taken to answer is too long). The distinction between responses with strong attitudes and responses that cannot be labelled as such enables capturing networks of similarity, which end up with different structural properties. Namely, the network with only strong attitudes appeared to be less cohesive. This is interesting as it reflects a more individualised way to apprehend the pandemic and thus shows a certain heterogeneity of realities. Though reflecting a common direction, the pandemic was/is not felt in the same way by individuals, and public policies should consider that. Without RTT and with classical surveys, this heterogeneity could not have been identified. Projecting data in a network and using SNA offers a deeper understanding of how the data is structured.

In this study, emphasis was placed on fast responses since they capture attitudes. Indeed, this study argues that attitude-based responses correspond to a certain level of internalisation of a phenomenon. The data, which aims for this qualification, relates to personal perceptions of the social reality and underlying motivations that influence actions and behaviours. If there is interest in this dimension, the researchers would rather only keep quick responses. On the other hand, this study shows that longer latency can be related to a certain level of knowledge accumulated from the experience of a particular phenomenon. However, longer answers can also be due to motivated misreported responses. Thus, the composition of long-lasting answers is unclear and can be misleading. By retaining only quickly given responses, the nature of data was ensured, namely an attitudinal one.

Our findings have practical applications, extending to enhancing organisational strategies through improved stakeholder analysis and communication planning. By distinguishing between high-confidence and low-confidence ties, managers can more effectively target interventions and communications to stabilise or change organisational culture. Moreover, our approach provides a quantifiable method to assess the impact of relational dynamics, offering a direct pathway to fine-tuning leadership and development programs. This could, e.g., then be implemented for robustness checks or sensitivity analyses.

7 Limitations

Several limitations can be outlined. The first limitation identified in our study is that the std-RT is a continuous measure that we purposely transformed into a categorical dimension. The current study aimed to show how RTT pinpoints responses with strong attitudes and demonstrates how it could affect network properties. A different cut-off point would have given other distributions of the data and, thus, other network properties, which would have influenced the whole study. One can question how the study set the threshold to determine which answer can be considered confident enough. Notably, the type of task, stimuli and research design will all impact the response time obtained in a single study.

For this reason, it is not possible to set up a universal threshold for distinguishing fast response times from slow ones. In our case, we decided to use a statistical approach and choose the fast responses based on the distribution of results in our study. The chosen threshold is based on standard deviation and accounts for 35% of the fastest responses. It was helpful to develop our argument. However, researchers should be aware of this and set up thresholds according to their research object, question or design needs.

Another limitation that can be assessed is that we only considered strong attitude answers based on the speed of the responses. However, this method has been proven effective in other fields, and we assume it remains the most adapted to fieldwork since it is a non-intrusive methodology. We believe the main advantage of this method is not to disturb the respondent and to correspond to a regular survey format, making this methodology preferable and particularly relevant compared to other ones used in social psychology, which can be more intrusive and less accurate when assessing the level of certainty (Bassili, 1993).

A third limitation concerns the fact that, in the literature review, we outlined the lack of reliability of self-administration-based data with the ‘true’ social structure. A partial response was given to this problem by arguing that RTT identifies highly confident responses, and that those particular responses were expected to reduce the gap between declared responses and true beliefs, knowing that it has been proven and validated in other fields. Hence, the validity has been assumed and not tested. However, this study may fail to assess the level of validity of strong attitudes compared to weak ones. The aim of this paper was not to re-validate this postulate but rather to show how the data collected may be structured and how keeping only strong attitudes can impact the properties of the network. Further research may still be necessary to test the validity level, which would be welcomed since it has not been done in network research.

8 Further considerations

This study used this methodology in a particular SNA research design in a one-mode network projected from two-mode data. The latent reason to have conducted this study with this approach is influenced by the fact that RTT has been, thus far, exclusively used in a respondent-item questionnaire type of survey. However, this format is the most widespread in quantitative studies, if not in social sciences, and there is an element of delight in treating it in a relational approach. Notably, we are conscious that a one-mode projected network does not allow the observation of direct relations and that two-mode data only concerns particular types of data. However, the main aim of this article was twofold: On the one hand, it aimed to show that RTT can be used in a relational approach, and on the other hand, it aimed to show that a relational approach can benefit from RTT. Since a network analysis is possible with RTT methodology, a further step would be to process RTT in a 'classical' network study, where direct relations are of interest. RTT is not limited to this particular type of network (two-mode) and can be helpful in any network studies, as long as the collected data is based on declarations and attitudes (positive or negative) and is suspected to be subject to biases – conscious or unconscious. As discussed in the introduction, Ego network studies are typically the research design that would benefit from such a methodology. Full network studies would benefit from RTT as well. Mixing RTT and SNA offers an excellent opportunity to deepen the knowledge of social dynamics and behaviour. Furthermore, while RTT and classical methods may produce different outcomes, we claim that RTT enhances data quality by capturing more spontaneous and less socially desirable responses due to time constraints, which we believe reflects actual attitudes and behaviours more.

Our study advances the theoretical understanding and catalyses the practical application of SNA in management. By incorporating RTT, we provide a methodologically sound tool that can significantly influence managerial strategies and organisational policies. Future research should fully explore the application of RTT-enhanced SNA across different organisational contexts to harness its potential in practical settings.

Further steps would be to test the consequences of such an approach in inferential and predictive models. Moreover, the loss of cohesive properties is an interesting clue to follow. Only confident answers gave a less cohesive network of similarity than the network of similarity that merges all the answers. This result questions the individualisation of the social reality. A relational approach (White, 1992; Emirbayer and Goodwin, 1994; Pescosolido and Rubin, 2000; Fuhse, 2009) and an approach such as the seminal Simmelian one will help understand the fuzziness and the individualisation of confident answers. RTT will help provide metrics to measure it.

RTT is not aimed at replacing classical surveys; rather, it can deepen them by providing an additional dimension and granting new insights for further research. As outlined above, RTT provides opportunities to deepen an analysis further. This study presents this methodology to the SNA field, assuming it will benefit the field and allow researchers to reach new dimensions. Hopefully, this article will motivate others to join the relational paradigm and encourage RTT in further research.

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Appendix 1 Tested statements

Items	*Mean Latency in milliseconds*	*Standard deviation*	*Quality assessment*
I actively encourage others to follow the restrictions and guidelines	6089.98	12318.72	0.55
I comply with the recommendations for physical distancing	4397.7	10041.91	0.58
I comply with the restrictions to stay home	4161.83	4136.15	0.60
I disinfect groceries before putting them away	5141.58	18500.07	0.59
I disinfect mail and deliveries before opening them	5658.59	18194.83	0.59
I wash hands for 20 seconds when necessary	4438.44	6009.54	0.59
I would like to help people who are more vulnerable to COVID-19	5891.63	34424.91	0.57
Since COVID-19 I eat more healthy	6132.04	42845.07	0.58
Since COVID-19 I eat more unhealthy	5120.57	10754.4	0.63
Since COVID-19 I exercise less	4697.88	7360.23	0.58
Since COVID-19 I exercise at home more	4946.41	10886.32	0.60
I'm worried about my financial situation	4184.11	7590.95	0.69
I'm worried about my job situation	4046.08	5778.91	0.709
I'm worried that our country will run out of money	4685.87	3815.26	0.67
I'm worried that there will not be enough basic necessities in the stores	6338.06	19239.78	0.60
The COVID-19 outbreak will make society more unequal	5599.54	4610.57	0.59
I am worried about my own health	4209.61	10918.99	0.57
I am worried about the health of my children	4079	6392.15	0.57
I am worried about the health of my older family members	4720.63	6977.03	0.55
I am worried about the health of people in my country	5176.75	29749.71	0.55
I worry that there will be an increase in break-ins and thefts	5080.02	6672.79	0.58
I'm worried about my children's education	4146.22	5669.17	0.70
Being together all the time increases family tensions	5888.82	17358.49	0.67
COVID-19 increases domestic violence	4552.47	6973.93	0.69
COVID-19 will increase divorce rates	8601.09	176905.87	0.69
I am anxious about not being able to meet with friends	5149.16	7853.39	0.65
I am worried about not being able to meet with my family	4682.95	10204.11	0.67
I worry how living in isolation will affect me	5778.83	19407.6	0.65
Living in isolation negatively impacts my wellbeing	5540.39	9508.44	0.56

Appendix 1 Tested statements (continued)

Items	*Mean Latency in milliseconds*	*Standard deviation*	*Quality assessment*
COVID-19 will bring countries closer	5340.17	7314.01	0.65
I am grateful to our essential workers	4359,75	5918.43	0.59
I am grateful to our healthcare professionals	3649,64	2927.04	0.56
My chance of getting COVID-19 is high	4946.94	8773.18	0.57
Slowing the spread of COVID-19 is more important than the economy	6810.8	9221.34	0.67
When a COVID-19 vaccine is available, I'd like to be vaccinated	5267.98	3663.16	0.55
Coronavirus is dangerous for my health	3945.82	2819.71	0.57
Media exaggerate the situation with COVID-19	5516.15	30013.73	0.64
Media provide reliable information about the pandemic	4987.72	4658.83	0.64
Our president is doing a good job dealing with COVID-19	5091.83	4366.09	0.67
I am satisfied with how my government is handling this crisis	4260.43	3166.57	0.67
The government is doing a good job dealing with COVID-19	4274.88	3498.86	0.67
I am satisfied with how our healthcare system is handling this crisis	5390.5	8480.42	0.57
In case of a coronavirus infection, I will get appropriate medical help	6136.92	10104.21	0.57
The government discloses real numbers of coronavirus infections and deaths	5957.78	9762.08	0.67
COVID-19 reveals the best in people	6019.45	41520.93	0.60
COVID-19 reveals the worse in people	5062.03	5379.87	0.60
I believe we will beat COVID-19 soon	4588	13212.88	0.61
People will stop following the restrictions soon	5307.55	4833.59	0.61
The restrictions caused by COVID-19 will continue at least until the fall	6355.23	19005.18	0.59
The restrictions caused by COVID-19 will be over in a month	7304.27	23086.65	0.60