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A network approach to understanding social distancing behaviour during the first UK lockdown of the COVID-19 pandemic

Jilly Gibson-Miller^a , Orestis Zavlis^a, Todd K. Hartman^b, Kate M. Bennett^c, Sarah Butter^a, Liat Levita^a , Anton P. Martinez^a, Liam Mason^d, Orla McBride^e, Ryan McKay^f, Jamie Murphy^e , Mark Shevlin^e , Thomas V. A Stocks^a and Richard P. Bentall^{a,c}

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ABSTRACT

Objective: Given the highly infectious nature of COVID-19, social distancing practices are key in stemming the spread of the virus. We aimed to assess the complex interplay among psychological factors, socio-demographic characteristics and social distancing behaviours within the framework of the widely used Capability, Opportunity, Motivation-Behaviour (COM-B) model.

Design: The present research employed network psychometrics on data collected during the first UK lockdown in April 2020 as part of the COVID-19 Psychological Research Consortium (C19PRC) Study. Using a network approach, we examined the predictions of psychological and demographic variables onto social distancing practices at two levels of analysis: macro and micro.

Results: Our findings revealed several factors that influenced social distancing behaviour during the first UK lockdown. The COM-B model was successful in predicting particular aspects of social-distancing via the influence of psychological capability and motivation at the macro-and micro-levels, respectively. Notably, demographic variables, such as education, income, and age, were directly and uniquely predictive of certain social distancing behaviours.

Conclusion: Our findings reveal psychological factors that are key predictors of social distancing behaviour and also illustrate how demographic variables directly influence such behaviour. Our research has implications for the design of empirically-driven interventions to promote adherence to social distancing practices in this and future pandemics.

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In 2020, the highly infectious coronavirus (COVID-19), and all its variants, spread quickly across the world, creating a global pandemic of proportions never experienced before in modern times. A burgeoning amount of research has provided

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vital information to government and policy makers around the globe about the extensive social, economic and health impacts of the pandemic, which has been crucial in shaping the way governments respond to the current pandemic, as well as future ones. It is clear that human behaviour has been critical in shaping the progression and spread of COVID-19 and will continue to be a key feature of efforts to stem the spread of the virus (Kissler et al., 2020; Moore et al., 2021; Walker et al., 2020).

A crucial set of behaviours that citizens around the world have been asked to engage in were termed ‘social distancing’ practices. These practices entailed restrictions on outdoor movement and group meetings, and the maintenance of physical distance from others, to name a few. The novel term ‘social distancing’ was initially understood and applied in different ways during national lockdowns, making its enactment complex and nuanced. During lockdowns in the United Kingdom (UK), for instance, although instructed to stay at home, individuals were also allowed to exercise outside of their home. Citizens of Spain and Italy, in contrast, were subject to bans on outdoor exercise, and yet other countries (for example, Sweden and Japan) enforced very lenient guidelines (Buchholz, 2020; European Centre for Disease Prevention & Control, 2021). Not only has social distancing required profound shifts in typical social-behavioural norms, which are difficult to achieve (Bavel et al., 2020), but enacting such behaviours during lockdowns has had a cost to health and well-being in some groups (Brooks et al., 2020; Shevlin et al., 2020).

In addition to the complex factors driving social behaviour during lockdowns, the extent of adherence to social distancing practices varied between different groups of individuals. For example, researchers have reported that young males were particularly prone to breaking the social distancing guidelines: in the UK, over half of men aged 19–24 years breached social distancing rules at the height of the first lockdown in March 2020 (Levita et al., 2020). For other groups in society, it is likely that enacting social distancing practices is difficult for practical or structural reasons. Population surveys have found that 1 in 4 individuals struggled to follow UK social distancing guidelines due to difficulties in meeting up with family or friends outside; because the weather was poor; or because they were feeling worn out by the crisis (Duffy & Allington, 2020). Likewise, individuals who did not have access to a garden, shared space with other families, or were required to work may not have had the opportunity to comply with social distancing and were thus inevitably at increased risk of exposure and infection (Reicher & Drury, 2021). Such ‘structural’ factors are likely to negatively impact adults’ ability to comply with social distancing, especially for those who are already economically disadvantaged and faring worse—reflecting the ‘slow burn of inequality’ exposed by epidemics, as described by Marmot (2020).

Given the central role of social distancing behaviour in ameliorating the spread of COVID-19, behavioural scientists faced the challenge of swiftly developing an in-depth understanding of such behaviour that could inform interventions to maintain adherence to social distancing practices that accounted for complex influences on behaviour (Michie et al., 2020; Michie & West, 2020). However, little evidence exists on how such population-wide changes in social distancing behaviour could be achieved (West et al., 2020). To inform such interventions, an understanding of the factors that underpin social distancing behaviours was required.

The Capability, Opportunity, Motivation-Behaviour (COM-B: Michie et al., 2011) model of behaviour change serves as one framework for understanding the influences on social distancing behaviours. This model proposes that a person must have sufficient psychological and physical capability (e.g. knowledge; strength); physical and social opportunity (e.g. time; social cues); and reflective and automatic motivation (e.g. intentions; planning; emotion regulation) in order to enact a given behaviour. The COM-B model is at the centre of the Behaviour Change Wheel (BCW), which is a toolkit for designing behaviour change interventions (BCIs: Michie et al., 2014). This model has been employed successfully in the design of a wide range of BCIs; for example, children's health checks (Alexander et al., 2014) and medication adherence (Jackson et al., 2014). Michie et al. (2020) argue that deficits in each of the COM-B components contribute to lower levels of adherence to social distancing practices than are needed to prevent the spread of COVID-19. Based on the BCW, Michie et al. (2020) produced initial guidelines on developing intervention options for increasing adherence to social distancing measures. West et al. (2020) presented a preliminary behavioural 'diagnosis' for 'staying at home except under specifically defined circumstances' in relation to the COM-B model, which is useful for broadly understanding the conditions that must be in place for this behaviour to be successfully enacted at a population level.

However, it is clear that the determinants of social distancing behaviours are complex. In order to accommodate for this complexity, we used Psychometric Network Analysis (PNA) to graphically illustrate how the psychological components of the COM-B model and several socio-demographic factors influenced social distancing behaviour during the first UK lockdown—a time early on in the pandemic when the individuals were asked to urgently adapt their usual social behaviour in a novel situation.

Our network approach allows for the exploration of unique relations within a set of variables. Using a network approach, statistical associations can be visualized as connections ('edges') that link variables ('nodes') in network models (Epskamp & Fried, 2018). Such statistical associations usually reflect conditional relations between variables that remain even after adjusting for the effect of other variables in the network. Here, we employed PNA in this manner to assess how psychological (COM-B variables) and sociodemographic (e.g. age, sex, income) factors uniquely influence social distancing behaviour. By including all relevant variables in our network models, we control for all relevant factors when revealing the most robust predictions of these factors. This presents an advantage over traditional regression approaches because it allows for the combination of prediction and exploration: PNA allows us to conceptualize a set of variables as 'predictors' (i.e. COM-B or demographic factors) of another set of variables (i.e. social-distancing behaviours), whilst also gaining insight into how the predictors interact with one another (see [Supplementary Materials I](#) for a methodological rationale).

To further scrutinize these predictions, two network models of increasing complexity were employed. The first network model, *macroscopic*, assessed the predictive utility of the three broad COM-B components (that is, the latent factors capability, opportunity, and motivation) on social distancing behaviour. The second network model, *microscopic*, broke down these components to their constituent elements (i.e. specific behaviours and beliefs) to assess these associations at a more refined level of analysis. These effects were assessed before and after covariate adjustment.

For this study, we used data from the second wave of the COVID-19 Psychological Research Consortium (C19PRC) Study panel survey. The data were collected from a representative sample between 22nd of April and 1st of May 2020, one month after the first national lockdown was imposed in the UK. To our knowledge, this is the first study to explore the influences on social distancing practices within the framework of the COM-B model and with the use of a novel analytical approach. In this way, we were able to reveal the aspects of the COM-B model that predicted social distancing behaviour and illustrate how key demographic variables directly influenced behaviour. Our research thereby adds to our understanding of social distancing behaviour and can inform the design of empirically-driven interventions to promote adherence to social distancing practices for the current pandemic as it unfolds, as well as for future pandemics.

Methods

Participants and procedure

A detailed methodological account of the longitudinal, multi-country C19PRC Study is available elsewhere (McBride et al., 2021). Briefly, UK fieldwork for Wave 1 (W1) of the C19PRC Study, an internet-based survey fielded by the survey company Qualtrics, commenced on 23 March 2020, 52 days after the first case of COVID-19 had been confirmed in the UK, and was completed on 28 March 2020 (i.e. during the first week of the UK lockdown). Quota sampling was used to recruit a panel of adults ($N=2025$) who were nationally representative of the UK population in terms of age, sex, and household income. Participants were aged 18 years or older at the time of the survey, must have been able to complete the survey in English, and resident in the UK. If consenting, adults completed the survey online and were reimbursed by Qualtrics for their time. Approximately 30 days later, all W1 respondents were re-contacted and were invited to participate in Wave 2 (W2), the first follow-up wave, the fieldwork for which was conducted during 22 April to 1 May 2020. The retention rate for Wave 2 was 69.4% ($N=1406$). Ethical approval for this research was provided by a UK University Psychology department (Reference number: 033759).

Measures

The current data were taken from the Wave 2 of the C19PRC Study. For more details on the variables as well as their preparation procedure, please refer to the online-accessible code and the [Supplementary Information II](#).

Social distancing behaviour

Social distancing practice, in accordance with government guidelines during the first UK lockdown, were assessed using a list of 7 statements with respect to the past week, e.g. 'Stayed at least 2 metres (6ft) away from other people' or 'Met up with friends or extended family (outside of your home)'. Response scales were: not at all; 1–2 days per week; 3–4 days per week; most days; every day. The social distancing

items were coded such that higher scoring reflected greater endorsement of social distancing practices, e.g. the item 'Engaged in close contact greetings with people outside of your family (e.g. shaking hands, hugging)' was reversed-scored. For more information on these items see [Table 2](#).

COM-B measures

Participants completed 17 items relating to the COM-B model of behaviour change in relation to mandatory UK social distancing practices in March 2020. Items were adapted from a preliminary version of the COM-B self-evaluation questionnaire (COM-B-Qv1: Michie et al., 2014) and other guidelines (West et al., 2020) and respondents indicated the extent to which they agreed with seventeen statements on a 5-point ordinal scale (labelled as: strongly disagree, disagree, neither agree nor disagree, agree, strongly agree). Three items measured psychological capability, e.g. 'I knew about why it was important and had a clear idea about how the virus was transmitted'. Two items measured physical opportunity (e.g. 'It was easy for me to do it') and five items measured social opportunity (e.g. 'I had support from others'). Five items measured reflective motivation (e.g. 'I intended to do it') and two items measured automatic motivation (e.g. 'I would feel bad if I didn't do it'). Please see [Table 1](#) for descriptive statistics of COM-B items.

Covariates

Covariates included: age (continuous); sex (male/female); urban (city/urbanicity); ethnicity (white/non-white); education (non-post-secondary/post-secondary); religion (atheist/any-religion); and 2019 household income (£0–300; £301–490; £491–740; £741–1,111; £1,112+ per week).

Table 1. Descriptive statistics for COM-B items.

Subscale	Item	Item description	Mean (SD)
Psychological capability	P1	'I knew about why it was important and had a clear idea about how the virus was transmitted.'	4.4 (0.8)
	P2	'I knew about how and when to do it.'	4.4 (0.7)
	P3	'I was able to overcome the physical and/or mental barriers that might have stopped me from doing it.'	4.2 (0.9)
Physical opportunity	O1	'I had the necessary time and facilities to do it.'	4.4 (0.8)
	O2	'It was easy for me to do it.'	4.2 (1)
Social opportunity	O3	'People were doing it around me.'	4.1 (1)
	O4	'I had reminders that prompted me.'	3.8 (1.2)
	O5	'I felt like people would disapprove if I didn't do it.'	3.9 (1.1)
	O6	'I had support from others.'	3.8 (1.1)
	O7	'I felt like doing it was normal and expected.'	4.2 (0.9)
Reflective motivation	M1	'I intended to do it.'	4.3 (0.8)
	M2	'I felt that I wanted to do it.'	4.3 (0.9)
	M3	'I believe that it was a good thing to do.'	4.4 (0.8)
	M4	'I developed a specific plan for doing it.'	3.7 (1.1)
	M5	'I developed a habit of it in my everyday routine.'	4.2 (0.9)
Automatic motivation	M6	'I would feel bad if I didn't do it.'	4 (1.1)
	M7	'I felt like I could control or cope with how it made me feel so I could do it.'	4 (1)

Table 2. Frequencies of social distancing behaviours.

Item	Item description	Not at all (%)	1–2 days per week (%)	3–4 days per week (%)	Most Days (%)	Everyday (%)
B1	'Met up with friend or extended family (outside your home).'	88.8	7.6	3.6	0	0
B2	'Gathered in a group of more than two people in a park or other public space?'	92.6	4.6	2.8	0	0
B3	'Worked from home?'	57.8	5.4	6.6	17.5	12.7
B4	'Stayed at least 2 metres (6ft) away from others when in public'	7.2	11.9	6.6	14.1	60.3
B5	'Engaged in close contact greetings with other people outside your family (e.g. shaking hands)?'	91.7	5.3	3.1	0	0
B6	'Been instructed to go home or to leave an area or been dispersed by the police?'	92.6	3.8	3.6	0	0
B7	'Been taken home, arrested, or fined by the police for breaking the social-distancing rules?'	92.7	4.3	3.1	0	0

Statistical analyses

All statistical analyses were conducted using the statistical software R (version 3.6.1). The R code to reproduce our results is available in the [Supplementary Information](#); to this end, all adjacency matrices (for the current network models) are also reported there.

Confirmatory factor analysis

For the macroscopic network model, reflective latent variables were computed for the COM-B (psychological capability, opportunity and motivation) and social distancing factors. These factors were estimated using separate Confirmatory Factor Analyses (CFAs). Skewed distributions of factor scores were normalized using the nonparanormal transformation (Liu et al., 2009). Since the COM-B and social distancing items were measured at an ordinal level, CFA models were conducted based on polychoric correlations and the WLSMV estimation procedure, using the R package *lavaan* (Rosseel, 2012). The CFAs revealed acceptable levels of fit for each latent factor (please refer to [Supplementary Information II](#) for more details on CFA and Network psychometrics).

Network psychometrics

Two network models were estimated at two levels of analysis: a macroscopic level (comprising latent variables) and a microscopic one (comprising the indicators of those latent variables). In network models, 'nodes' represent variables and 'edges' represent statistical associations between them. The colour cadet blue was used to depict positive associations, and red was used to depict negative ones. The networks were visualized using the Fruchterman-Reingold algorithm (Fruchterman & Reingold, 1991), through the R-package *qgraph* (Epskamp et al., 2012).

Network estimation

Given the mixed nature of C19PRC Study data (that is, categorical and continuous data), Mixed Graphical Models (MGMs) were estimated with the use of the R-package

mgm (Haslbeck & Waldorp, 2020). In these models, statistical associations are estimated through the use of iterative regressions and are reflective of conditional (*in*)dependencies between variables (see Epskamp & Fried, 2018; Haslbeck & Waldorp, 2020). Since we are investigating predictive effects among our variables, we employed LASSO (least absolute shrinkage and selector operator; Tibshirani, 1996), a regularization technique, in order to shrink our parameter estimates and thereby reduce the probability of obtaining false-positive findings. For the final model selection, we chose to minimize the EBIC (Extended Bayesian Information Criterion), setting its hyperparameter, gamma, to 0.5, so as to achieve a more conservative network estimation procedure (that is, a sparse network structure with fewer edges and thus a lower probability of having Type I errors; Foygel & Drton, 2010). Thus, our networks were estimated so as to err on the side of caution (that is, we had a preference for specificity over discovery) in order to reveal the most robust predictions between our predictors (demographic and COM-B variables) and social-distancing factors. For a full methodological rationale, the interested reader is referred to [Supplementary Information I](#).

Predictability

Node predictability estimates were computed in order to infer how well nodes are predicted by other nodes in the network, i.e. akin to R^2 (Haslbeck & Fried, 2017; Haslbeck & Waldorp, 2018). These estimates were visualized as pie charts around the nodes.

Exploratory graph analysis

To reveal the factor structure of social-distancing behaviours, an Exploratory Graph Analysis (EGA) was conducted (Golino & Epskamp, 2017). The EGA works by estimating a network (in particular, a Gaussian Graphical Model (GGM) that represents the conditional associations between the social-distancing behaviours) and then applying the walktrap algorithm to reveal its factor structure. Notably, the stability and accuracy of the resulting factor structure can be assessed using bootstrapping procedures (see next section and [Supplementary Information III](#)).

Robustness and sensitivity analyses

Bootstrapping techniques, as implemented in the R-packages *bootnet* (Epskamp & Fried, 2018) and *EGAnet* (Christensen & Golino, 2021) were employed to assess the stability and accuracy of the estimated parameters. In particular, for the edge-weights, a non-parametric bootstrapping procedure was employed to assess their stability over 2500 bootstrapped samples. For the factor structure of the social-distancing network, the bootstrap EGA method was employed, as described in Christensen and Golino (2021). Using this procedure, a sampling distribution of 1000 replica networks was created and the frequency of occurrence of the main factor structure within this distribution was estimated. The results from these procedures briefly outlined in the Results section and are further detailed in [Supplementary Information III](#) and VI. Further sensitivity analyses are also detailed in the [Supplementary Information VII](#).

Results

Variable preparation and descriptive statistics

Descriptive statistics for COM-B and social distancing items are presented in [Tables 1](#) and [2](#). These ordinal items were measured on a 5-point Likert scale, with increasing scores being indicative of greater endorsement of COM-B and social distancing factors. The mean values of responses to COM-B items ([Table 1](#)) indicated that, on average, respondents agreed or strongly agreed that the psychological conditions of capability, opportunity and motivation, were sufficiently in place for them to potentially enact social distancing behaviour. Frequency statistics of self-reported social distancing behaviours, reported in [Table 2](#), illustrate that a large percentage of participants endorsed social distancing behaviours on most or every day of the week, with some exceptions (e.g. 'working from home'). For more details on these and other variables, refer to [Supplementary Information II](#).

Where the microscopic network model visualized the unique relations of the above raw items, the macroscopic network model visualized the unique interrelations of their factor scores. To compute the factor scores of the three COM-B components (that is, Opportunity; Motivation and Psychological Capability) and the 'broad' Social Distancing domain (i.e. the overall endorsement of all the individual behaviours), individual CFAs were employed. For further details on the CFA estimation procedure, variable preparation, as well as results, refer to [Supplementary Information I](#).

In the remainder of this section, we report the results of the primary and supplementary network models. These network models were stable and had accurately estimated parameters as revealed by the Robustness and Sensitivity analyses ([Supplementary Information VI](#) and [VII](#)).

Macroscopic network

The macroscopic network model visualizes the conditional associations among the macro-level components of the COM-B model (namely, Psychological Capability (PC), Opportunity (OP), and Motivation (MT)) and the broad social distancing factor, before (Model 1A, [Figure 1a](#)) and after (Model 1B, [Figure 1b](#)) covariate-adjustment. Predictability estimates (that is, variance explained) of the variables in this model are presented in [Table 3](#).

From Model 1A, it can be observed that only Psychological Capability (PC) exhibits a direct, positive association with social distancing (SD). Opportunity (OP) and Motivation (MT) did not directly predict SD behaviours; but did so indirectly through PC. The COM-B predictors themselves were highly interconnected (with predictability indices ranging from 0.59 for PC; to 0.65 for OP; and 0.69 for MT; [Table 2](#)). Overall, 7% of the variation in SD was explained by PC in Model 1A.

After covariate-adjustment ([Figure 1b](#)), the associations between the COM-B predictors and the SD were unaffected: Psychological Capability remained the only COM-B component associated with SD ($W_{PC-SD} = 0.12$). The inclusion of covariates in the network revealed informative associative patterns between the variables. For instance, some covariates predicted specific components of the COM-B model. In particular, 'older age' and 'living in city' were associated with greater Psychological Capability

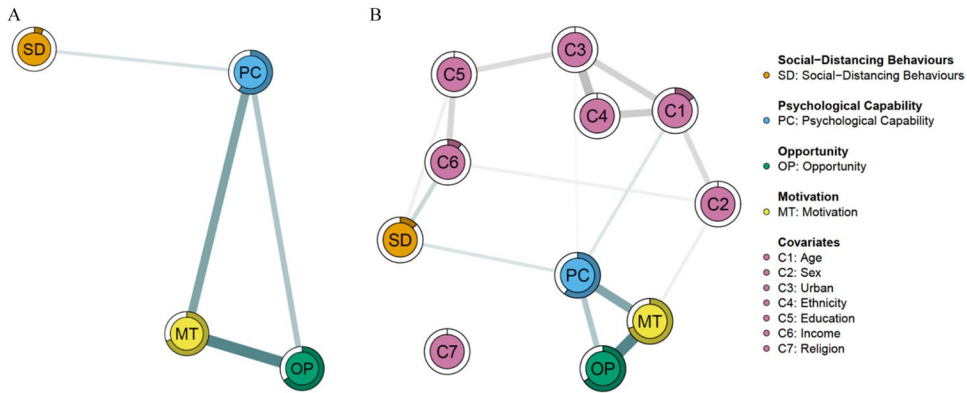


Figure 1. Macroscopic network, displaying the relations between the three macroscopic COM-B domains (Psychological Capability, Opportunity, and Motivation latent factors) and the social-distancing domain before (panel A) and after (panel B) covariate adjustment. Cadet blue edges represent positive conditional associations; red edges represent negative conditional associations between variables, while adjusting for all other variables. The thickness of the edges reflects the strength of the association (with thicker edges being stronger). The shaded aspect of the pie charts around the nodes represents the total amount of explained variance of a given node.

Table 3. Predictability estimates of Models 1 A and 1B.

Variable	Model 1A (Model 1B)
Psychological capability	0.591 (0.598)
Motivation	0.695 (0.699)
Opportunity	0.658 (0.656)
Social distancing behaviours	0.069 (0.130)

Note. Predictability refers to the amount of explained variance of a given variable by all other variables in the network (i.e., akin to R^2 in regression).

(PC), ($W_{PC-age} = 0.11$; $W_{PC-city} = 0.05$ respectively); whereas being female was associated with higher Motivation ($W_{MT-female} = 0.09$). It is worth noting that the former two covariates (that is, 'older age' and 'living in city') were uniquely predictive of Psychological Capability, and not of social distancing behaviour, suggesting that the effect of increasing age and city living on social distancing behaviours might be exerted through Psychological Capability. Conversely, higher levels of education and income were directly associated with adherence to social distancing behaviours, suggesting that these factors could exert a direct influence on social distancing behaviour ($W_{SDBs-education} = 0.1$; $W_{SDBs-income} = 0.17$).

Microscopic network

A network model at the microscopic level of analysis was estimated to assess the associations of all variables at a more refined level of analysis, before (Figure 2a) and after covariate adjustment (Figure 2b). These models included the individual items of all measures (see Tables 1 and 2), i.e. individual social distancing behaviours and responses to individual COM-B items. From this network model, a number of noteworthy observations can be made.

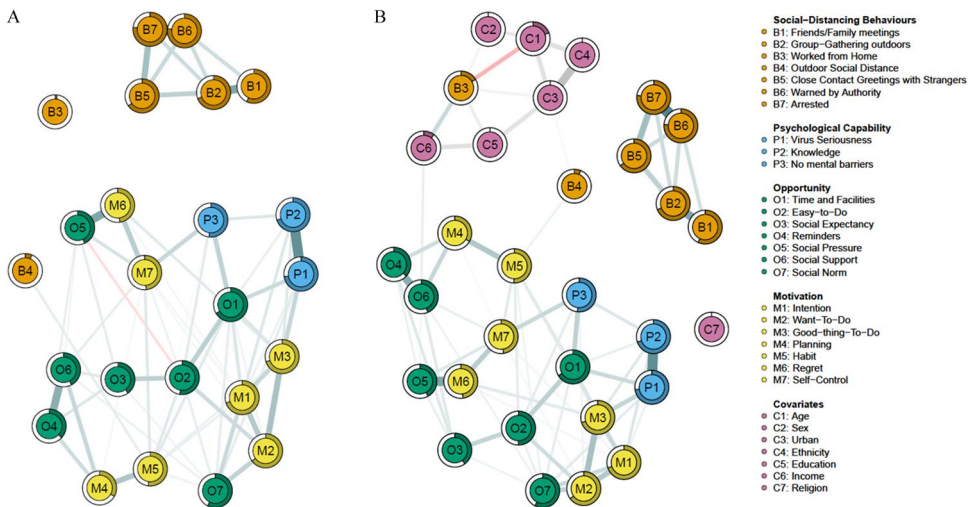


Figure 2. Microscopic network, displaying the conditional relations between COM-B indicators and the individual social distancing behaviours, before (panel A) and after (panel B) covariate adjustment. Cadet blue edges represent positive conditional relations; red edges represent negative conditional relations between variables, while adjusting for all other variables. The thickness of the edges reflects the strength of the association (with thicker edges being stronger). The shaded aspect of the pie charts around the nodes represents the total amount of explained variance of a given node.

First, the only association between social distancing behaviour and COM-B predictors was the one between ‘outdoor social distancing’ (B4) and M5 ‘habit’ (M5) ($W_{1B4-M5} = 0.06$), which remained after covariate-adjustment ($W_{2B4-M5} = 0.05$). Albeit weak, this association suggests that individuals who created habits around social distancing were more likely to enact them. Maintaining a 2-metre distance from others was also associated with age ($W_{B4-age} = 0.03$), suggesting that older adults are more likely to enact this social distancing behaviour.

Second, **Figure 2b** shows that sociodemographic variables ‘lower age’, ‘living in city’, ‘higher education’ and ‘higher income’ were all associated with ‘working from home’ (B3; $W_{B3-age} = 0.16$; $W_{B3-city} = 0.08$; $W_{B3-income} = 0.17$; $W_{B3-education} = 0.11$). These patterns suggest that more privileged and/or older members of society, for instance, those of higher socio-economic status, are more likely to maintain social distancing practices by working from home—most likely because they had the opportunity to do so (whereas younger participants would be more likely to be working in services, e.g. hospitality, on low incomes).

Finally, among the social distancing behaviours themselves, it is evident that they are more predictive of each other than they are predicted by any other predictor variable. Indeed, although the predictability of the broad social distancing factor was low in the previous models (e.g. 0.069), the predictability of its constituent elements (i.e. indicators) was high (e.g. $P_{B1} = 0.57$; $P_{B2} = 0.69$; $P_{B6} = 0.77$; **Table 4**). These results suggest that if one endorses a particular social distancing behaviour, there is an increased likelihood of them endorsing others as well. However, two exceptions to this rule were observed. In particular, ‘working from home’ and ‘outdoor social distancing’ did not form part of the main cluster of social distancing behaviours that

Table 4. Predictability estimates of social distancing behaviours.

Variable	Item description	Model 2A (Model 2B)
B1	'Met up with friend or extended family (outside your home).'	0.570 (0.570)
B2	'Gathered in a group of more than two people in a park or other public space?'	0.692 (0.692)
B3	'Worked from home?'	0.020 (0.166)
B4	'Stayed at least 2 metres (6ft) away from others when in public'	0.064 (0.063)
B5	'Engaged in close contact greetings with other people outside your family (e.g. shaking hands)?'	0.652 (0.652)
B6	'Been instructed to go home or to leave an area or been dispersed by the police?'	0.772 (0.763)
B7	'Been taken home, arrested, or fined by the police for breaking the social-distancing rules?'	0.769 (0.769)

Note. B3 is the only social distancing behaviour whose explained variance increased substantially after covariate-adjustment (suggesting it is mostly predicted by covariates).

were strongly predictive of each other and exhibited substantially lower predictability indices compared to them ($P_{B3} = 0.02$; $P_{B4} = 0.06$). To understand this associative dichotomy, the factor structure of social-distancing practices was explored.

Social distancing network

Given the mixed associations among the social distancing behaviours, the factor structure of social distancing practices was explored with an Exploratory Graph Analysis (EGA). Using EGA it is possible to reveal communities (or latent factors) in networks. An EGA on social distancing behaviours revealed that a one-factor solution was plausible. Additional bootstrapping procedures, however, revealed that a two-factor solution may be more appropriate since it is the most prevalent one within a distribution of 1000 replica networks (46% occurrence rate; see [Supplementary Information III](#)).

[Figure 3](#) displays the two-factor solution of the social distancing network. The first community comprised the set of social distancing behaviours that were highly predictive of one another. Because this cluster was reflective of social behaviours (e.g. 'having friends or family meetings'; or 'being arrested for breaking social distancing rules outdoor'), it was named 'interpersonal'. The second community was composed of the two remaining behaviours, that is, 'working from home' (B3) and '2-metre social distancing' (B4) and was labelled 'opportunity' as these behaviours were mostly a function of an individual's opportunity to enact them.

Discussion

In this study, we sought to investigate how psychological and sociodemographic factors influenced social distancing behaviour during the first weeks of the first national lockdown in the UK. Our Network Approach enabled us to gain insight into how these factors interacted with one other within the context of the COM-B model. Effects were explored at two levels of analysis (macro- and micro-levels), before and after covariate-adjustment. At the macro-level, the utility of the three macroscopic latent COM-B factors in predicting social distancing behaviour was assessed. At the micro-level, all variables were deconstructed to their constituent elements (that is, individual behaviours and beliefs) and their relations were assessed at the most refined

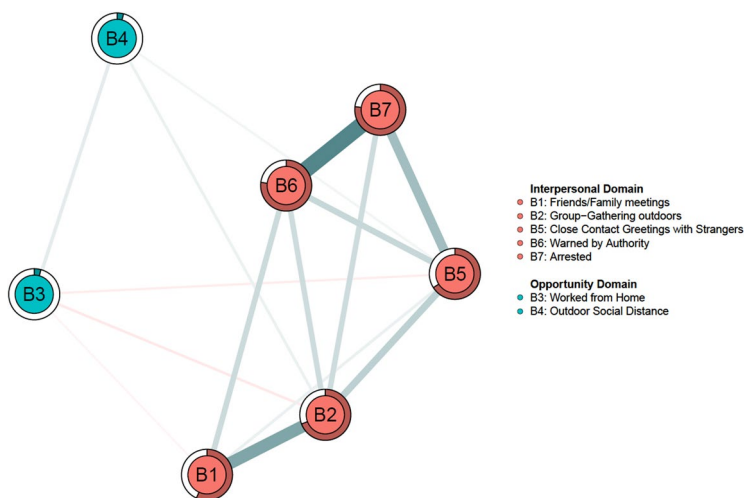


Figure 3. The final network structure of social distancing practices, as revealed through an Exploratory Graph Analysis. Interpretation of nodes, edges, and pie charts follows from previous figures. The colour of nodes reflects their community (or factor). Factor 1 refers to the ‘interpersonal’ domain of social distancing (for instance, ‘socialising’). Factor 2 refers to the ‘opportunity’ domain of social distancing (for instance, having the opportunity to ‘work from home’). For a more detailed explanation of this factor structure please see [Supplementary information III](#).

level of analysis. Our novel analyses offer insight into the components of the COM-B model that were most predictive of behaviour and illustrate how key socio-demographic variables strongly influence behaviour.

Overall, we derived four main findings: (1) Psychological Capability was the strongest COM-B predictor of social distancing behaviour at the macro-level; (2) Reflective Motivation (in particular, habit formation) was the strongest COM-B predictor of social distancing behaviour at the micro-level; (3) Social Distancing practices fell into two main ‘communities’ reflecting different behavioural patterns; and (4) higher levels of education and income were the strongest socio-demographic predictors of social distancing. These findings support urgent calls in the field of behavioural science for evidence to inform the development of effective interventions to increase adherence to ‘personal protective behaviours’ during the COVID-19 pandemic (see West et al., 2020). We offer insight into the complex influences involved in the enactment of such behaviour and show that those in socio-economically disadvantaged groups disproportionately struggle to enact protection behaviours and prevent disease, thus perpetuating existing health inequalities (Marmot, 2020).

In relation to COM-B predictors, the macroscopic network model revealed that Psychological Capability (i.e. having sufficient psychological knowledge, skills, strength or stamina to perform the behaviour) most strongly predicted social distancing. The COM-B predictors were highly interconnected with one another; however, motivation and opportunity were not directly associated with social distancing. This direction of influence is not typically predicted by the model, which postulates that although capability and opportunity may have direct effects on behaviour, a stronger pathway to behaviour would be via their influence on increasing motivation to act. In our analysis, we observed two patterns that may explain this contradiction. First, a

supplementary network without PC revealed that motivation can predict the broader social distancing factor. Since this prediction is no longer evident upon incorporating PC into the model, this could suggest that PC mediates the effect of motivation on social-distancing behaviour. Second, the microscopic network model revealed that a particular aspect of reflective motivation (namely, 'developing habits around social distancing in everyday routine', M5) was the only COM-B item that predicted a specific social distancing behaviour, namely, 'maintaining a 2-metre distance from others' (B4). This suggests a strong predictive role of motivation in the enactment of behaviour, over and above the influence of other psychological conditions specified in the model.

A key feature of our analysis was the addition of covariates into the network models, which revealed that sociodemographic characteristics can explain unique variation in social distancing behaviour, above and beyond that explained by COM-B factors. The macroscopic network model revealed that higher levels of education (C5) and income (C6) were strong predictors of social distancing, indicating that the extent to which social distancing practices are enacted successfully may partially be a function of one's privilege.

To scrutinize this pattern further, these relations were assessed at a more refined level of analysis by extricating individual behaviours from the merged social distancing factor. The network model at this micro-level revealed that the abovementioned effects of 'privilege' were unique to those individuals who 'worked from home.' In particular, higher levels of education (C5) and income (C6), being younger (C1) (as well as female, C2), and 'living in city' (C3) were predictive of 'working from home,' (B3) suggesting that the ability to work from home is a privilege that is reserved for individuals of higher socioeconomic status. This pattern highlights that some of the disparities in social distancing behaviour may be explained by the necessity of disadvantaged populations to work outside of the home, which inherently reduces opportunities for enacting social distancing. As we have suggested above, such 'structural' factors associated with economic disadvantage (in this case, the requirement to attend work) could impede the ability to comply with social distancing practices and expose disadvantaged groups to (risky) social contact and infection.

Socioeconomic disparities are not the only explanation of variation in social distancing behaviour. From the microscopic network model, we observed that individual social distancing behaviours formed two communities (or factors), suggesting that they are primarily a function of one another and are thus independent from the rest of the predictors in the network. The first community comprised the behaviours 'friends/family meetings' (B1), 'group gathering outdoors' (B2), 'close-contact greetings with strangers' (B5), 'warned by authority' (B6) and 'being arrested' because of breaking social distancing rules (B7). The second community comprised the behaviours 'working from home' (B3) and 'outdoor social distancing' (B4). A separate network of social distancing behaviours was constructed and its community (that is, factor) structure was assessed to explore this behavioural pattern further; the two-factor solution was replicated, suggesting that two clusters of social distancing behaviours may exist, reflecting different behavioural patterns (for further explanation, please see [Supplementary Information III](#)). We suggest that the first cluster of behaviours are of an interpersonal nature as they mostly reflect behaviours that relate to socializing (e.g. family- and group-gatherings). However, the second cluster mainly reflects the

abovementioned pattern of privilege since it comprises the two social distancing behaviours ('working from home' and 'outdoor social distancing') that can be interpreted to be a function of opportunity, rather than active choice (e.g. the opportunity to work from home or conduct social encounters in outdoor spaces so that all parties can observe the 'space' rule).

This separation of social distancing behaviours is interesting since it suggests that there may be distinct reasons for or influences on engaging in different types of social distancing behaviours. For instance, where the ability to shelter-in-place for prolonged periods of time may be a privilege reserved by those who have the ability to work from home, the choice to socialize (lawfully or unlawfully) may be more self-determined. If it is indeed the case that some behaviours are determined by opportunity alone (that is, having the necessary facilities to create such conditions and finding social distancing easy to enact), it is plausible that behaviours in the second cluster are indeed independent of the COM-B variables and other social distancing behaviours.

The stability of our finding across macro- and micro- models offers confidence in the patterns observed in our data. There are clear implications for intervention design and the development of policy in relation to promoting continued social distancing practices necessary to stem virus spread in this and future pandemics. At the first level of the behaviour change wheel (BCW) behaviour change interventions (BCIs) that target psychological capability will be effective in promoting social distancing. During the H1N1 pandemic, Bish and Michie (2010) reported that having a stronger belief in the effectiveness of recommended behaviours to protect against the disease was an important predictor of behaviour. Building on the preliminary work of West et al. (2020), who suggest that 'Understanding the importance of [social distancing] and ways of mitigating the adverse consequences [of COVID-19], both physical and psychological' may be effective in increasing Psychological capability, our findings suggest that, in the current context, interventions that increase psychological capability would involve educating individuals about why social distancing is important and how social contact transmits the virus; as well as defining the situations in which social distancing should be enacted and specifying exactly when, where and how to act.

The predictive association between reflective motivation and maintaining a 2-metre space from others provides good evidence that developing habits in everyday routine in relation to this behaviour would help cue appropriate behavioural responses—especially in men and where there are conflicting goals such as the desire to socialise, earn money, etc (West et al., 2020). Implementation intentions (or 'if-then' plans that specify exactly when, where and how to enact behaviour; Gollwitzer, 1999) have been shown to be effective in a range of other behavioural domains (Gollwitzer & Sheeran, 2006) and we suggest that employing these as a behaviour change technique in BCIs to promote 'space' would effectively increase reflective motivation to act, once conditions for psychological capability are in place.

Most importantly, BCIs should be specifically tailored to disadvantaged sociodemographic groups, that is, those with lower incomes and lower levels of education, for whom contextual factors may largely determine social distancing behaviours. The disproportionate impact of the COVID-19 pandemic on economically and socially disadvantaged groups on morbidity and mortality has been well-documented in

populations across the world (Mishra et al., 2021) to the extent that the role of COVID-19 in exposing and exacerbating existing and complex health inequalities has been described as a 'perfect storm' by the UK Local Government Association (2021). It is therefore imperative that appropriate interventions are tailored – and indeed targeted – towards disadvantaged groups in order to fulfil a 'moral imperative' to mitigate health inequity across social groups (British Medical Association (BMA), 2021). Marteau et al. (2021) argue that both behavioural causes *and* the wider determinants of ill health must be tackled in parallel to be effective in reducing inequality. Accordingly, in deprived groups, our findings show that psychological mediators may be weaker predictors of behaviour. Therefore, interventions that encompass wider layers of the behaviour change wheel may be more appropriate. For example, implementing appropriate economic and social policies can assist in overcoming practical or structural barriers that may prevent individuals who cannot work from home to social distance (e.g. ensuring COVID-safe work spaces). In parallel, the physical or psychological barriers to action (or inaction) must be addressed. In recognising individual barriers to action, it may be important to make a distinction between situations where the enactment of social distancing is driven by interpersonal factors or opportunity. Our findings suggest that if individuals engage in one social distancing practice, they are likely to generalise this behaviour to other social distancing practices, therefore interventions targeting key individual practices (e.g. 'space') may well be effective in also promoting adherence to a cluster of similar behaviours.

To our knowledge, this is the first study to explore social distancing practices and socio-demographic characteristics in relation to the COM-B model of behaviour change, within a UK representative sample. The present study is also among the first few that employ Network Analysis in a novel and theory-driven manner. By estimating network models at multiple levels of complexity, we were able to report associations among our constructs at global and local levels of analysis. Our results revealed several empirically important predictors of social distancing behaviour, including both COM-B model and demographic variables, and thereby advance knowledge in the field informing the content of interventions for promoting social distancing, as well as the target groups most in need of intervention. Future research can employ similar methodology when attempting to examine predictive effects through a network-analytic approach (see also Fried et al., 2020).

However, the current findings need to be interpreted with caution. First, the cross-sectional and observational nature of the current design limits the potency of the conclusions drawn. Although certain cause-and-effect relations can be intuited (for instance, being of higher socioeconomic status resulting in greater endorsement of social distancing behaviour), by and large, the reported associations must be interpreted as 'suggestive' and not 'conclusive.' Indeed, further in-depth qualitative work could be of value in identifying the barriers and enablers to social distancing behaviour, especially in younger and economically disadvantaged groups.

Second, although we have concluded that certain demographic factors are 'direct' predictors of social-distancing behaviour, it should be noted other psychological factors may mediate those predictions. For instance, the finding that females are more likely to social distance compared to males could be due to other sex differences in personality traits (e.g. impulsiveness; Wismans et al., 2021). Such traits were not

explicitly modelled in our networks and so it is unknown whether they mediate these sex-specific effects. Future work can thus expand our network systems by incorporating personality factors.

On the point of mediation, although we have attempted to address whether Psychological Capability mediates the effects of Opportunity and Motivation onto social distancing behaviour, it must be noted that conclusions about mediation cannot be made in cross-sectional designs. Although current network methodology does not allow for an explicit test of mediation, recent longitudinal network modelling procedures could be used (on panel and time-series data) to establish directionality of effects and thereby provide more evidence of the factors that directly predict social-distancing behaviour (see Epskamp, 2020).

Finally, our findings relate to a specific time period in the UK when social restrictions were tight. Nonetheless, given the efficacy of 'non-pharmacological interventions' in stemming the spread of viruses (Moore et al., 2021), we suggest that our findings might be applied to the development of approaches to promote social distancing in this and other pandemics for behavioural scientists as well as policy makers (e.g. in adopting appropriate 'light switch' or 'cluster' measures to stem local outbreaks; Hobbs, 2020).

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Data availability statement

The data used in this study is available at: <https://osf.io/9emvp/>

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