EHPS HEALTHPSYCHOLOGY BULLETIN

# Socioeconomic Status, Crowding, COVID-19 Perceptions, and Protective Behavior

EMPIRICAL PAPER

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## ABSTRACT

Crowding, a key factor that catalyzes the transmission of infectious diseases, disproportionately affects individuals from lower socioeconomic groups. The purpose of the current study was to assess whether socioeconomic status (SES) and crowding are related to differences in COVID-19 risk and efficacy perceptions and whether these perceptions explain protective behaviors. We specifically focused on household income and education as indicators of SES, and household crowding and public transportation use as indicators of crowding. Results from an online survey of 387 working adults, collected during the second peak of the pandemic in Turkey, showed that SES and public transportation use were negatively related to COVID-19 risk perceptions. On the other hand, SES, household crowding, and COVID-19 risk and efficacy perceptions were positively related to hygiene-related protective behavior and physical distancing. Moreover, the association between COVID-19 perceived protective norms and physical distancing was moderated by household crowding such that the positive relationship between protective norms and physical distancing was stronger at higher levels of domestic crowding. Yet, robustness checks suggest that further evidence is needed before to make any definitive conclusions about the interaction effect.

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**KEYWORDS:**

socioeconomic status; public transportation use; domestic crowding; risk; efficacy; COVID-19; protective behavior

**TO CITE THIS ARTICLE:**

Özden, M., Baruh, L., Cemalcilar, Z., & Kuru, O. (2023). Socioeconomic Status, Crowding, COVID-19 Perceptions, and Protective Behavior. *Health Psychology Bulletin,* 7(1), pp. 1–16. DOI: https://doi.org/10.5334/hpb.40

# 1. INTRODUCTION

## 1.1. COVID-19 AS A SYNDEMIC

The biopsychosocial model (Engel, 1977) postulates that the social structure surrounding the individual may exert an influence on individual behaviors and experiences, in turn, which may modify biological processes. Thus, considering deeply entrenched adverse conditions associated with lower socioeconomic status (SES), lower SES individuals are expected to be under more COVID-19 related threat due to their higher likelihood of having COVID-19 risk factors. Moreover, health risk factors do not operate independently from each other. Syndemic refers to the synergistic interaction of various epidemics or health adversities that are often embedded within harmful social conditions (Singer & Clair, 2003). Based on historical evidence from previous pandemics and the current state of COVID-19, Bambra et al. (2020) argue that COVID-19 can be considered another example of a syndemic.

Living in poorer neighborhoods has been associated with comorbidities, such as cardiovascular diseases (Abdalla et al., 2020; Rosengren et al., 2019), diabetes (Ross et al., 2010), and respiratory diseases (Chen et al., 2006), which, according to the World Health Organization (WHO, 2020a) and the U.S. Centers for Disease Control and Prevention (2021), increase the severity of COVID-19. Discrepancies in those health outcomes may be due to several structural factors, such as inequalities in access to medical care (Fiscella et al., 2000), health illiteracy (Sørensen et al., 2015), and access to financial and material resources (Groffen et al., 2008; Urbanos-Garrido, 2012). Due to its importance to airborne diseases, the disproportionate amount of crowding that lower SES individuals are exposed to, as explained below in detail, is one of the major health adversities for this syndemic.

## 1.2. SOCIOECONOMIC DIFFERENCES IN CROWDING, AND ITS IMPACT ON COVID-19 RISK

The WHO (2020b) underlines that COVID-19 is mainly transmitted through droplets and aerosols, which can occur while coughing, sneezing or talking. To avoid becoming infected, it suggests precautions such as physical distancing and avoiding places with crowds or poor ventilation (World Health Organization, 2020b). Since indoor crowding reduces the ability to maintain enough physical distancing from cohabitants, residing in a crowded household (Almagro et al., 2020; Maroko et al., 2020), living unit (e.g., apartment; Almagro et al., 2020) or neighborhood with a high proportion of crowded households (Oishi et al., 2021) are associated with a higher likelihood of being infected with COVID-19. In that sense, lower SES individuals are under more threat from a potential transmission in the household, considering that the poor are more likely to reside in overcrowded living spaces (e.g., Sauli & Törmälehto, 2010; Lopoo & London, 2016).

Lower SES individuals do not only experience crowding in their private spaces. Unlike those with higher SES, who have higher control over their mode of transportation and can switch to private vehicles when needed (Boisjoly et al., 2020; Lucas, 2012), lower SES individuals do not have the means to reduce the crowding that they are exposed to outside their houses. Similarly, during the pandemic, higher SES individuals could more easily switch to working remotely and use private transportation to commute to work when needed (Durand et al., 2021; Irigoyen-Camacho et al., 2020; Jaspal et al., 2020). Hence, during the pandemic, the largest reduction in human mobility has been observed in high-income areas (Kissler et al., 2020; Lee et al., 2021; Mena et al., 2021). Since the restriction of human mobility was essential to mitigate COVID-19 morbidity (Kraemer et al., 2020; Tian et al., 2020) and mortality (Hadjidemetriou et al., 2020), higher SES individuals could be accepted to be more privileged in their security from COVID-19 infection as a result of their ease in mobility.

Consequently, partly due to the differences in SES-related structural inequalities including crowding, the COVID-19 incidence rate has been higher at the lower echelons of society (Oberndorfer et al., 2021). Furthermore, possibly due to higher comorbidities, lower SES individuals were more likely to be hospitalized (Azar et al., 2020) and had a higher infection fatality rate (Mena et al., 2021).

## 1.3. CROWDING AND COVID-19 RELATED PERCEPTIONS

The implementation of nonpharmaceutical interventions is indispensable for managing COVID-19 (for a review, see Perra, 2021). However, as proposed in the research summarized above, not all sociodemographic groups could yield the benefits of those interventions. Moreover, the success of nonpharmaceutical interventions is inherently tied to human behavior (West et al., 2020), and adherence to those measures can be intercepted or facilitated by structural inequalities (Abel & Frohlich, 2012; Andersen, 1995; Ding et al., 2021). In addition to its impact on individuals' ability to reduce their susceptibility to COVID-19, crowding may also influence their risk perceptions and efficacy beliefs, which, in turn, influence individuals' behavioral patterns. Behavioral change models (e.g., theory of planned behavior, Ajzen, 2002; protection motivation theory, Maddux & Rogers, 1983; extended parallel process model, Witte, 1992) point to three mechanisms that may be particularly pertinent to how crowding may have a bearing on individuals' perceptions and behavioral inclinations: (1) risk perceptions, (2) efficacy perceptions, (3) social norms.

First, an important driver of protective behavior is individuals' risk perceptions. Recent literature demonstrates that higher risk perceptions are associated with higher intention to engage in protective behavior against COVID-19 (Ezati Rad et al., 2021; Mahmood et al., 2021; Šurina et al., 2021). Especially, COVID-19 perceived severity is an important factor that explains adherence during the pandemic (González-Castro et al., 2021; Okuhara et al., 2020; Pilch et al., 2021). That being said, health behavior models applied in COVID-19 and other health crises typically utilized cognitive risk perceptions. However, as Slovic et al. (2005) argue, affect is a more convenient source of information than cognitive risk perceptions suggested in expectancy-value models; and health behaviors might be based on more affective thinking (e.g., worry, fear). Therefore, some studies (Dryhurst et al., 2020) incorporated cognitive and affective components of individuals' risk perceptions for themselves and for close others (e.g., family, friends). Such an approach may capture the multidimensional nature of risk perceptions in omnipresent infectious diseases like COVID-19 and better explain individual behaviors in those health crises. For example, one's own risk of becoming infected with COVID-19 will also lead to increased concern for the well-being of other household members. With respect to COVID-19, then, it would be reasonable to assume that lower SES and crowding (i.e., household crowding, commuting with public transportation), which increase objective risk, will also increase individuals' risk perceptions for themselves and their close others (e.g., Pagnini et al., 2020; Schweda et al., 2021).

Second, individuals' perceived efficacy to engage in a behavior is a consistent predictor of health-protective behavior (e.g., Luszczynska, 2004; Williams & French, 2011). In an earlier study regarding an influenza pandemic, Teasdale et al. (2012) showed that efficacy perceptions were positively related to intentions of staying at home. Likewise, concerning COVID-19, high efficacy perceptions are necessary for engaging in protective behavior (Ezati Rad et al., 2021; Mahmood et al., 2021; Okuhara et al., 2020), such as developing coping and action strategies to reduce exposure to COVID-19 (Lin et al., 2020). However, efficacy perceptions are not formed in a vacuum; rather, they are influenced by social-structural factors that impede or facilitate mastery of certain actions (e.g., Businelle et al., 2010; Sen et al., 2016; Xie et al., 2020). With respect to crowding in physical environments and individual protection from COVID-19, this would imply that factors that diminish individuals' ability to control their exposure to risk may also influence their perceived self-efficacy. For example, individuals who must take public transportation to/from work may become more defeatist about the extent to which they can realistically protect themselves from exposure to COVID-19.

Third, and in contrast to its potential negative impact on efficacy perceptions, household crowding may indeed motivate individuals to engage in protective behavior to reduce their cohabitants' exposure to COVID-19 as the normative behavior. For example, social norms communicated by individuals cohabiting a house will have a stronger bearing on protective behavior because cohabitants, typically close family members, are more likely to be affected negatively by COVID-19 (Wolff, 2021). We expect that this relationship would be stronger when individuals are in crowded living arrangements that make it harder for them to isolate themselves from other household members (e.g., because they do not have a separate restroom or cannot effectively self-isolate from other household members).

## 1.4. THE CURRENT STUDY

In the present study, we investigate crowding and lower socioeconomic status (SES) as risk factors that might influence perceptions (i.e., risk perceptions, efficacy perceptions, and perceived protective norms) and protective behavior in the context of COVID-19 (for a conceptual map, see Figure 1). The specific hypotheses are listed below:

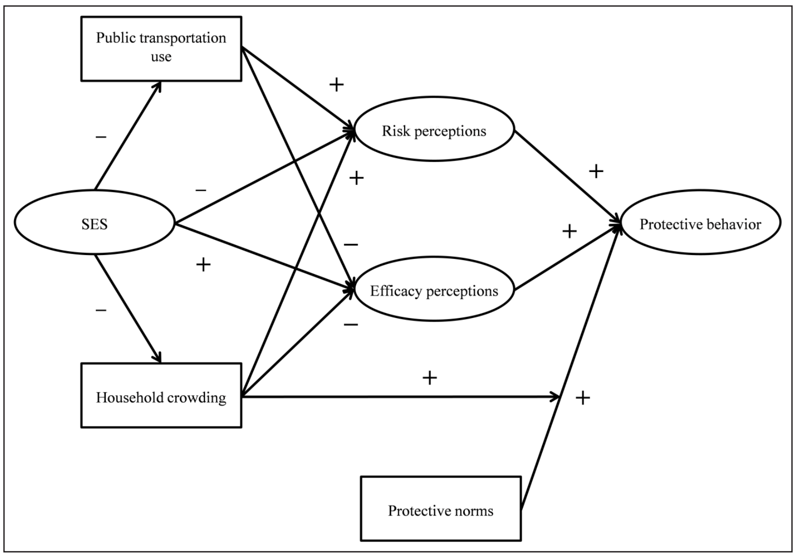


**Figure 1** Conceptual Map of the Study.

H1: SES will be negatively associated with exposure to crowding in different contexts (i.e., public transportation use, and household crowding).
H2: SES will be negatively, and crowding will be positively associated with COVID-19 related risk perceptions.
H3: SES will be positively, and crowding will be negatively associated with COVID-19 efficacy perceptions.
H4: Risk and efficacy perceptions will be positively associated with protective behavior.
H5: The positive relationship between perceived protective norms and protective behavior will be moderated by household crowding such that the relationship will be stronger in more crowded domestic spaces.

Through these hypotheses, this study aims to contribute to the literature on the role human environments (i.e., SES and crowding) play in influencing individuals' risk and efficacy perceptions and their tendency to comply with recommended health/safety measures in relation to COVID-19. These findings have the potential to provide further insights for the appraisal of SES-related crowding about infectious diseases in future health crises.

## 2. METHODS

### 2.1. SAMPLE AND PROCEDURE

The data for this study come from the first wave of a larger multi-wave project on COVID-19 and health-protective behavior conducted online (Baruh et al., 2020). The project received ethical approval by the Koç University Committee on Human Research (IRB number: 2020.261.IRB3.102).

We used a quota sample to reflect the demographic characteristics of the general Turkish population in terms of age, education, and sex as well as NUTS 2[1] (Nomenclature of Territorial Units for Statistics) regions in Turkey (48 provinces, 93.3% of the participants coming from metropolises). Respondents were recruited from an online panel provided by Qualtrics Panel (Qualtrics, UT, USA), and the survey was distributed through their software. Participants received monetary compensation for completing the study. Data collection started in late-August 2020 and took 15 days to be completed, which coincided with the beginning of the second wave of COVID-19 in Turkey. Following a brief period of loosening in the COVID-19 restrictions in the early summer of 2020 (e.g., tourism incentives, working time adjustments), the government announced the highest number of symptomatic patients in the last two months.

In the current wave, where data for this study is collected, a total of 759 adults participated in the online survey. Because one of the central variables of concern was commuting to work by public transportation, only currently employed individuals were included in the dataset for this study. In addition, those who used taxis in their commute ($n = 3$) were excluded from the analysis. Whether a taxicab is a mode of public transportation is a debated topic (e.g., Aarhaug, 2016; Nelson et al., 2010). While taxi cabs contain relatively less risk of COVID-19 than other modes of public transportation (e.g., more control over ventilation, mandatory mask use for taxi drivers), in comparison to private transportation, taxi cabs nonetheless require exposure to potential COVID-19-infected individuals (i.e., drivers). Due to this unique position of taxi cabs and the very low number of taxi use in the current sample, we decided not to include commuters with taxi cabs in our analyses. There are no further omissions from the original dataset, and the final sample used in this study included 387 participants. Respondents were allowed to skip questions in the survey (missing rate for all questions; *Min* = 0%, *Max* = 9.3%, which is the item for income).

### 2.2. MEASURES

**Socioeconomic Status (SES).** Education and household income were used as indicators of SES. Education was assessed with an ordinal variable ranging from *primary school* to *doctorate*. Based on the International Standards Classification of Education (ISCED; UNESCO Institute for Statistics, 2012). Majority of the participants reported completing a level of education equivalent to ISCED 3 or ISCED 5. Therefore, we coded education as a two-level ordinal variable with *lower* (i.e., ISCED 0–3) and *higher education* (i.e., ISCED 4–8). As an assessment of income, respondents indicated their monthly household income from all monetary sources. Household income was coded as *low-* (i.e., less or equal to 5000 Turkish liras; roughly corresponds to two minimum wages at the time of the data collection), *middle-* (i.e., 5001–9500 Turkish Lira), and *higher-income* (i.e., more than 9500 Turkish Lira).

**Crowding Factors.** We assessed crowding in relation to two contexts; one for transportation and the second for housing. In assessing exposure to crowds while using transportation, we had the respondents first indicate whether they worked remotely from home or commuted to work, then indicate which commuting mode they used. We constructed a variable for crowding in commute called *public transportation use*, which has two levels: (0) non-public transportation users (i.e., those who go to work by private motor vehicle, bicycle, walking, or are working remotely from home), (1) public transportation users (i.e., those who go to work by bus, train, or work shuttle). Public transportation users would be exposed to other passengers who might have been infected with COVID-19 in a closed space, meanwhile both remote workers and commuters with private means do not encounter such situations while going to work in a similar setting. One could still argue that remote workers and private transportation users are two distinct groups. Insofar as access to private space is limited to people employed in higher management positions (e.g., directors), it is possible that individuals reporting using private transportation to go to work during the pandemic would also be more likely to have access to a private office at work. This possibility implies that both people working remotely and those using private transportation enjoy more control over their working conditions than those who use public transportation. In addition, our analyses confirmed that, in the current sample, participants working remotely and participants using private transportation were indeed comparable in terms of their education and income; thus, we grouped them as non-public transportation users.

As a second crowding factor, we assessed the extent to which individuals were exposed to crowding in their homes during the pandemic. Following the definition by the United Nations Statistics Division (2001), *household crowding* was assessed as the number of occupants per room calculated by dividing the number of occupants by the number of rooms (excluding kitchen and bathrooms). We believe that, in comparison to household size, occupants per room captures the individual experience of crowding in terms of COVID-19 more accurately, as the person living in a bigger household, if the housing unit is spacious enough, may still enjoy the means to self-isolate in case of a COVID-19 diagnosis among the cohabitants. On the contrary, it is possible that those living in a small housing unit would still lack adequate space to self-isolate, even if the household did not have too many members.

**COVID-19 Risk Perceptions.** Unlike most health conditions (e.g., lung cancer) and protective behaviors (e.g., smoking cessation), which are analyzed using behavioral change models, COVID-19 is characterized by a rapid spread among close contacts, and cannot be prevented with only solitary actions. Therefore, individuals have a high risk of carrying the disease to their close others if they do not adhere to preventive measures. For this reason, we assessed a multidimensional risk perception for individuals and their close others including their affective and cognitive appraisal of the disease.

*Susceptibility* and *severity perceptions* were assessed using items adopted from susceptibility measures utilized for protection motivation theory (Maddux & Rogers, 1983) (e.g., "How likely is it that you would become infected with coronavirus within the next month.", 0 = *not at all* to 5 = *very likely*; "If I were infected with coronavirus, it would have an everlasting negative impact on my health.", 0 = *strongly disagree* to 4 = *strongly agree*). Additionally, we added a single-item measuring *worry* about COVID-19 (i.e., "How much do you worry about being infected with coronavirus?", 0 = *not at all* to 4 = *very much*). All three measures were repeated to assess participants' perceptions about their cohabitants' risk (e.g., "How likely is it that other household members would become infected with coronavirus within the next month," 0 = *not at all* to 5 = *very likely*). These items were combined to create a composite score with a reliability of Cronbach's $\alpha = .79$.

**COVID-19 Efficacy Perceptions.** Efficacy perceptions were measured with two items adapted from (Sen et al., 2016) that tap into self- and response-efficacy (e.g., "If I want, I can perform measures necessary for protection from coronavirus.", 0 = *strongly disagree* to 4 = *strongly agree*). The inter-item correlation was strong ($r = .62$, $p < .001$).

**COVID-19 Perceived Protective Norms.** Perceived protective norms about COVID-19 were assessed with a single-item, "People I care about encourage me to take precautions against coronavirus." on a 0–4 Likert scale.

**COVID-19 Protective Behavior.** We created items that asked respondents to indicate the extent to which they performed 16 COVID-19 related protective behaviors (0 = *not at all* to 4 = *very much*). Those actions were grouped under two categories, namely hygiene, and physical distancing. See Supplementary Information S1 for specific items. Whereas hygiene includes personal hygiene-related measures such as washing hands or disinfecting items that concern fomite transmission, physical distancing includes measures such as mask use or online shopping that concern airborne transmission of the disease. Cronbach's $\alpha$ was .77 for hygiene, and .78 for physical distancing. Factor loadings for the items are presented in Supplementary Information S2.

## 2.3. ANALYTIC PROCEDURE

All variables concerning demographic information and COVID-19 related social cognitive constructs were included in the analyses. Variables present in the larger project that were not theoretically relevant to the hypotheses listed above (e.g., political orientation, trust, personality) were excluded.

To test the study hypotheses, factor analyses and structural equation modeling were performed using *lavaan* package (Rosseel, 2012) on R. For correlation analyses, we used the mean scores of the constructs. SEM analyses were conducted with the latent variables for the constructs with multi-item scales (e.g., SES, social cognitions, and protective behavior) and with the total scores for the measured variables (i.e., household crowding, and public transportation use). COVID-19 risk perceptions were treated as a second-order construct comprising other factors (i.e., severity, susceptibility, and worry for self and others). Considering that some of our variables (i.e., education, commuting) were not continuous, structural equation models were estimated with diagonally weighted least squares (DWLS) which yields less biased parameter estimates in ordinal and multivariate non-normal data (Finney & DiStefano, 2006; Mîndrilă, 2010). All continuous variables used in an interaction term were mean-centered prior to the analysis. A posthoc power analysis was conducted with *semPower* package (Moshagen & Erdfelder, 2016) on R, and it showed that, for a model with *df* = 462, the sample size had a 99.99% statistical power to detect a misfit model identified by RMSEA equal to .05 at $\alpha$ = .05. A one-tailed p-value of .05 was determined to indicate statistical significance. See Supplementary Information S3 & S4 on alternative models for robustness checks that considered different models and statistical analysis. Finally, as we have covered a broad spectrum of COVID-19 protective behaviors in this study, we argue that it respects potential individual differences in one's daily life that prioritize some preventive measures over others, and it enables us to assess overall behavioral tendencies. Instead of single-item measurements of distinct physical distancing and hygiene-related protective behaviors (e.g., mask use, physical distancing, hygiene), treating them as a construct comprising different but related behaviors may help reduce measurement error (Diamantopoulos et al., 2012). However, we also acknowledge that the adoption of each protective behavior (e.g., mask use and physical distancing) may follow different patterns with respect to the study variables. Specifically, household crowding may be more relevant for hygienic measures related to the use of communal spaces in one's house than personal hygiene, and public transportation use may reduce the motivation to avoid other crowded spaces while at the same time increasing adherence to recommendations about mask use. Then, these distinct behaviors may need to be addressed by different policies or persuasion strategies depending on those patterns. Therefore, we ran additional regression models (see Supplementary Information S5) to check the extent to which the independent variables can predict basic protective behaviors advised by the World Health Organization (2022).

## 3. RESULTS

### 3.1. DESCRIPTIVE RESULTS

Table 1 summarizes descriptive statistics and includes the correlation matrix. More than half of the participants did not have higher education (*N* = 201), and approximately a third of the participants had low income (*N* = 123). Most of the participants were not exposed to high levels of crowding, indicated by the fact that they mostly did not use public transportation in their commute (*N* = 123) and lived in households with moderate crowding (*Median* = 1). Regarding COVID-19 perceptions, on average, participants perceived high efficacy and protective norms; however, their COVID-19 risk perceptions were relatively lower. Participants moderately adhered to COVID-19 hygiene and physical distancing measures.

Women had higher COVID-19 risk perceptions ($\bar{X}_{diff}$ = .28, $t(384) = 3.62$, $p < .001$) and COVID-19 protective norms ($\bar{X}_{diff}$ = .14, $t(381) = 1.80$, $p < .05$). Likewise, they reported engaging in hygiene-related COVID-19 measures more ($\bar{X}_{diff}$= .41, $t(384) = 5.63$, $p < .001$). Hence, in the inferential SEM analyses, we entered sex as a covariate.

### 3.2. MODEL TESTING

We explored three structural equation models to test our hypotheses. In the first model, we tested the full model summarized in Figure 1. In the second model, we

| | M (SD) | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| **1.** SES[a] | 1.68 (.49) | .79*** | .74*** | –.16** | –.25*** | –.10* | –.01 | .00 | .11* | .02 |
| **2.** Income[b] | 2 (.83) | – | .16** | –.09† | –.25*** | –.11* | .01 | .03 | .14** | .09* |
| **3.** Education = 1[c] | 48.1% | | – | –.12* | –.13** | –.07† | –.05 | –.03 | .02 | –.06 |
| **4.** Household crowding | 1.04 (.39) | | | – | –.02 | .02 | –.09* | –.06 | .05 | .07† |
| **5.** Public transportation use | 33.8% | | | | – | –.06 | –.08* | –.06 | –.19*** | –.17** |
| **6.** Risk perceptions | 2.66 (.77) | | | | | – | –.20*** | .17*** | .22*** | .27*** |
| **7.** Efficacy perceptions | 3.10 (.77) | | | | | | – | .18*** | .23*** | .23*** |
| **8.** Perceived protective norms | 3.35 (.77) | | | | | | | – | .31*** | .22*** |
| **9.** Hygiene-related measures | 2.97 (.74) | | | | | | | | – | .70*** |
| **10.** Physical distancing | 2.67 (.63) | | | | | | | | | – |

**Table 1** Descriptive Statistics and Zero-Order Correlations Among Variables of Interest.

*Notes*: [a] A weighted arithmetic mean of household income and education was computed only for correlation matrix. The SEM model treats SES as a latent variable with income and education as predictors.

[b] 1 = *low*, 2 = *middle*, 3 = *high*.

[c] Education was coded as 0 = *high school or less*; 1 = *more than high school*.

† *p* < .10, * *p* < .05, ** *p* < .01, *** *p* < .001.

simplified this model by removing COVID-19 perceived protective norms. This allowed us to focus only on risk and efficacy perceptions, proposed by the protection motivation theory, as mediators between structural factors and COVID-19 protective behavior. Nevertheless, it is also plausible that the relationship between structural factors and COVID-19 protective behavior is mediated by other unobserved variables (e.g., habits, behavioral control), and a less complex model may have better prediction accuracy for unobserved cases in other samples. Therefore, in the third model, we included SES-related demographic factors without the mediating variables (i.e., COVID-19 risk and efficacy perceptions) to check whether the inclusion of COVID-19 related perceptions was necessary to understand the relationship between SES and protective behavior through crowding in different contexts. The summary of the models can be found in Table 2.

Model 1 showed an adequate fit (Kline, 2016), and it explained 50.9% of the variance in hygiene-related protective behavior and 49.3% in physical distancing. Path coefficients are shown in Table 3, and they are illustrated in Figure 2. The results partially confirmed H1 in that SES was negatively associated with public transportation use ($\beta = -.47$, $p = .002$), but it was not significantly associated with household crowding ($\beta = -.05$, $p = .08$). Regarding H2; SES and public transportation use were negatively associated with risk perceptions ($\beta = -.30$, $p = .02$; $\beta = -.20$, $p = .01$; respectively). In other words, in contrast to our hypothesis, public transportation users perceived less COVID-19 risk. Meanwhile, as expected, SES was a negative predictor of COVID-19 perceptions. On the other hand, there was not a significant relationship between household crowding and COVID-19 risk perceptions. Similarly, neither SES nor crowding contexts were significantly associated with self-efficacy, not providing support for H3.

As for the relationship between risk factors (i.e., SES and crowding contexts) and protective behavior, confirming H4; risk perceptions, efficacy perceptions, and perceived protective norms were all positively associated with both hygiene-related protective behavior ($\beta = .42$; $\beta = .45$; $\beta = .43$; $ps < .001$; respectively) and physical distancing ($\beta = .47$; $\beta = .50$; $\beta = .36$; $ps < .001$; respectively). Controlling for social cognitions and normative differences, SES was positively associated with hygiene-related protective behavior ($\beta = .31$, $p < .05$), but the relationship between SES and physical distancing did not reach statistical significance ($\beta = .26$, $p = .08$). Household crowding positively predicted both hygiene-related protective behavior ($\beta = .35$, $p = .001$) and physical distancing ($\beta = .49$, $p < .001$). No significant direct association between public transport use and protective behavior was observed. Finally, household crowding did not moderate the relationship between perceived protective norms and hygiene-related protective behavior. Meanwhile, partially confirming H5, the positive relationship between perceived protective norms and physical distancing was significantly moderated by household crowding ($\beta = .12$; $p = .02$) such that the positive effect of perceived protective norms on physical distancing was stronger for individuals living in households with high crowding than with moderate ($\beta = .05$; $p = .02$) and low crowding ($\beta = .09$; $p = .02$). That being said, some models tested in robustness checks did not show supporting evidence for this finding (see Supplementary Information S3).

Considering that structural equation models using different estimation techniques for non-normal data may vary in their goodness-of-fit (DiStefano & Morgan, 2014), and DWLS (as used in this study) tend to inflate fit indices in some cases (Nye & Drasgow, 2011), the rule of thumbs for fit indices (e.g., Kline, 2016) may not always be applicable. Therefore, another reason for exploring different models other than those stated above was to see which model fitted the data better and whether the relationship patterns between key variables were similar across the models.

The second model, which only included mediational paths, showed a similar fit with the previous model, albeit having a larger CFI. As can be seen in Table 3, there were not any major differences between those models in their parameter estimates for the same relationships.

Finally, the third model focused on the relationship between SES-related crowding factors and protective behavior without risk and efficacy perceptions as mediating variables. This model also showed a similar fit with the other models while having fewer variables. However, its predictive power for protective behavior

| | $\chi^2$ | *df* | $\chi^2/df$ | $\Delta\chi^2$ | $\Delta df$ | CFI | RMSEA[a] [90% CI] | SRMR |
|---|---|---|---|---|---|---|---|---|
| Model 1 | 1218.47*** | 462 | 2.64 | 317.68*** | 58[b] | .89 | .07*** [.061 –.070] | .07 |
| Model 2 | 900.79*** | 404 | 2.23 | 580.82*** | 265 | .92 | .06* [.052 –.061] | .07 |
| Model 3 | 319.97*** | 139 | 2.30 | – | – | .95 | .06† [.050 –.066] | .07 |

**Table 2** Summary of the Fit Indices of the Structural Equation Models.

*Notes*: [a] Asterisks used for RMSEA indicate whether the value is significantly different than .05.

[b] Using likelihood ratio test, each model is compared to the following model.

† $p < .10$, * $p < .05$, *** $p < .001$.

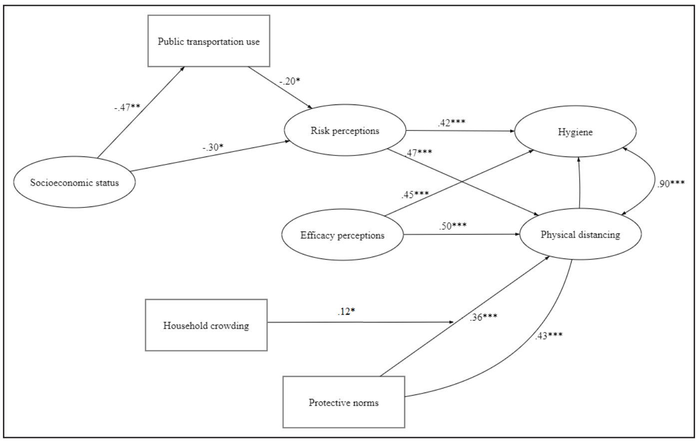


**Figure 2** Standardized Parameter Estimates of Model 1.
*Notes*: Only significant paths are demonstrated in the diagram.
* $p < .05$. ** $p < .01$. *** $p < .001$.

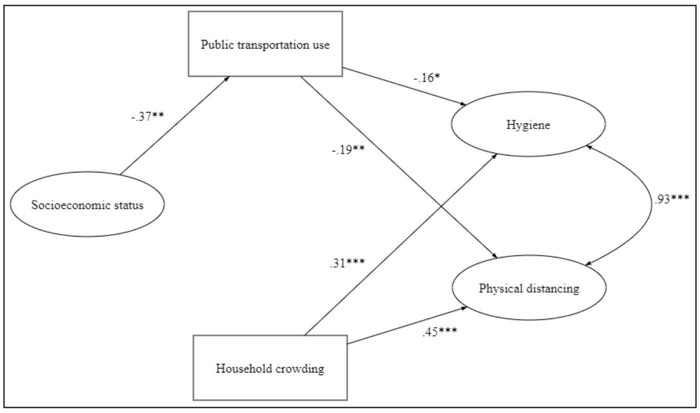


**Figure 3** Standardized Parameter Estimates of Model 3.
*Notes*: Only significant paths are demonstrated in the diagram.
* $p < .05$. ** $p < .01$. *** $p < .001$.

decreased since 15.5%, and 11.9% of the total variability in respectively hygiene-related protective behavior and physical distancing were explained by SES and crowding alone (i.e., household crowding and public transportation use). The relationships in the model are illustrated in Figure 3. The third model differed from previous models such that, without controlling for COVID-19 risk and efficacy perceptions, public transportation users reported less hygiene-related protective behaviors ($\beta = -.16$, $p = .02$) and physical distancing ($\beta = -.19$, $p = .004$). On the contrary, SES was no longer a significant predictor of hygiene-related protective behaviors when COVID-19 perceptions were not included in the model.

In sum, Model 1 was the model that explained the most variability in protective behavioral tendencies for this sample, whereas Model 3 was the most parsimonious one as suggested by a closer fit. All models tested in the study converged on the results that household crowding was not significantly associated with COVID-19 risk and efficacy perceptions. However, when SES was controlled, household crowding was a factor that increased protective behavior as well as increasing the strength of the relationship between COVID-19 protective norms and physical distancing. On the other hand, crowding in another context (i.e., public transportation use) was negatively related to both risk perceptions and protective behavior. In both cases, the magnitude of the relationship between crowding factors (i.e., household crowding and public transportation use) and protective behavior tended to be small to moderate.

## 4. DISCUSSION

How do socioeconomic disparities contribute to individuals' sense of and actual self-protection efforts against the pandemic? This study tested the relation between household crowding and public transportation use (among employed individuals) as characteristics shared mainly by lower SES individuals, COVID-19 related perceptions and a diverse set of protective behaviors including physical distancing and hygiene measures. The findings underscore SES differences in exposure to crowding and COVID-19 risk perceptions.

| | MODEL 1 | MODEL 2 | MODEL 3 |
|---|---|---|---|
| | ***B* (*SE*)** | | |
| Public transportation use | | | |
| Woman | −0.19 (.13) | −0.17 (.14) | −0.17 (.14) |
| SES | −1.42*** (.47) | −1.43*** (.47) | −1.56*** (.54) |
| Household crowding | | | |
| Woman | 0.00 (.04) | 0.01 (.04) | 0.01 (.04) |
| SES | −0.14† (.08) | −0.14† (.08) | −0.16† (.10) |
| Risk perceptions | | | |
| Woman | 0.44*** (.07) | 0.37*** (.07) | |
| SES | −0.82* (.34) | −0.83* (.34) | |
| Public transportation use | −0.18* (.07) | −0.19* (.07) | |
| Household crowding | 0.09 (.08) | 0.09 (.08) | |
| Efficacy perceptions | | | |
| Woman | 0.02 (.07) | −0.09 (.07) | |
| SES | −0.15 (.19) | −0.16 (.20) | |
| Public transportation use | −0.09 (.06) | −0.09 (.06) | |
| Household crowding | −0.10 (.07) | −0.10 (.07) | |
| Hygiene-related COVID-19 measures | | | |
| Woman | 0.09* (.04) | 0.18*** (.04) | 0.23*** (.03) |
| SES | 0.38* (.19) | 0.36* (.18) | 0.18† (.10) |
| Public transportation use | 0.01 (.05) | 0.01 (.05) | −0.06* (.03) |
| Household crowding | 0.14** (.04) | 0.13** (.04) | 0.12** (.03) |
| Risk perceptions | 0.18*** (.04) | 0.18*** (.03) | |
| Efficacy perceptions | 0.26*** (.04) | 0.25*** (.04) | |
| Perceived protective norms | 0.17*** (.02) | | |
| Perceived protective norms X Household crowding | −0.01 (.02) | | |
| Physical distancing | | | |
| Woman | 0.03 (.06) | 0.17** (.06) | 0.24*** (.05) |
| SES | 0.46† (.26) | 0.46† (.25) | 0.19 (.15) |
| Public transportation use | 0.00 (.07) | .00 (.07) | −.11** (.04) |
| Household crowding | 0.29*** (.06) | 0.29*** (.06) | 0.27*** (.05) |
| Risk perceptions | 0.31*** (.05) | 0.30*** (.05) | |
| Efficacy perceptions | 0.42*** (.07) | 0.42*** (.07) | |
| Perceived protective norms | 0.22*** (.03) | | |
| Perceived protective norms X Household crowding | 0.07* (.03) | | |

**Table 3** Unstandardized Parameter Estimates of the Structural Equation Models for the Association Between SES and COVID-19 Protective Behavior Through Crowding and COVID-19 Perceptions.

† $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$.

In general, lower SES individuals were exposed to more crowding than those of higher socioeconomic status. SES was a stronger predictor of public transportation use than household crowding. The availability of switching to remote work in the current pandemic might have contributed to existing discrepancies in commuting modes. This finding is in line with prior research observing that people from higher SES had more flexibility in terms of switching to working remotely and using private transportation during the pandemic (Durand et al., 2021; Jaspal et al., 2020). However, unlike preliminary correlational analyses and contrary to findings from prior research (e.g., Sauli & Törmälehto, 2010; Lopoo & London, 2016), we found that the association between SES and household crowding in SEM was small enough to be considered insignificant.

Albeit mostly having small effect sizes, crowding was observed to be an important factor for adherence to hygiene- and social distancing-related COVID-19 measures. It should also be noted that the relationship between crowding and protective behavior may be complex since public transportation use and household crowding were found to be related to protective behaviors in different directions. Unlike public transportation use, household crowding was a factor that was positively related to protective behavioral tendencies. This difference might stem from the fact that the accountability of one's choices, and the social pressure induced by closer bonds can be expected to be higher in the spaces shared with close others (e.g., household) than in public spaces (e.g., public transportation).

### 4.1. IMPLICATIONS FOR PROTECTION MOTIVATION AGAINST COVID-19 IN REGARDS TO SES AND CROWDING

We hypothesized that individuals would perceive a higher risk for themselves and their close others when their objective risk of being infected was higher due to their socioeconomic conditions. This hypothesis was confirmed such that having a lower SES was associated with higher COVID-19 risk perceptions. This relationship may, in part, be explained by one's realistic appraisal of the risk in their surroundings. Furthermore, as risk perceptions in this study involve other household members, higher empathic concern (Kraus et al., 2012; Varnum et al., 2015) and more compassion (Piff & Moskowitz, 2018; Stellar et al., 2012) toward others, observed among lower SES individuals, may also further explain SES differences in COVID-19 risk perceptions.

In addition, a key factor that this study explored as a potential mediator between SES and risk perceptions was crowding. In contrast to our predictions, transportation-related crowding was negatively associated with risk perceptions. One possible explanation for this finding is that individuals using public transportation might have tried to downplay the importance of risk concerning crowding as a coping mechanism. This would be in line with models like the extended parallel process model, which suggests that when threat levels exceed one's efficacy to cope with the threat, fear control (i.e., finding ways to reduce one's fear) rather than danger control (i.e., finding ways to reduce risk) will dominate decision making (Witte, 1992). One alternative explanation could be the presence of a circular causality such that those who perceived more risk switched to private means of commuting. However, automobile ownership is considerably low in Turkey (21.4% of the adult population; TURKSTAT, 2020a). Thus, switches to private means would have been limited. Similar to risk perceptions, public transportation users reported less adherence to hygienic measures, which can be explained by a potential spillover effect from being unable to satisfy physical distancing requirements to a general decrease in protective behavioral tendencies.

Household crowding was not found to be related to risk perceptions. It is important to note that in the current study, we only focused on individuals who were currently employed. Hence, it is possible that among lower SES individuals who are not working, household crowding may be a stronger predictor of risk perceptions. Indeed, while household crowding did not significantly affect risk perceptions, it nevertheless was positively related to protective behavior against COVID-19, suggesting that being in crowded domestic environments prompted individuals to pay more attention to safety precautions, including both hygienic and physical distancing measures. This finding is in line with recent research (e.g., Liotta et al., 2020), suggesting that individuals may try to take more responsibility to reduce the risk for others when facing structural constraints, such as household crowding.

In relation to efficacy perceptions, we predicted that lower SES, and consequently, crowding would be an obstacle to implementing physical distancing. This would, in turn, decrease the perceived ability to perform protective behaviors. On a bivariate level, both household crowding and public transportation were negatively correlated with COVID-19 efficacy perceptions. However, they did not have statistically significant relationships in the structural equation model.

For H4, the results confirmed previous studies (e.g., Ezati Rad et al., 2021; Okuhara et al., 2020) concerning the association between health perceptions and protective behaviors. Specifically, in line with the predictions of the theory of planned behavior (Ajzen, 2002) and the protection motivation theory (Maddux & Rogers, 1983), risk, efficacy, and normative perceptions were all positively related to COVID-19 protective behaviors. Furthermore, in H5, we predicted that the motivation to comply with social norms about protective behavior would be more pronounced among individuals who have less domestic space to shield cohabitants from COVID-19. In addition to the direct association between household crowding and physical distancing, the interaction between protective norms and household crowding confirmed this expectation. The lack of interaction effect for more hygiene-related protective behavior can stem from the lower visibility of hygiene-related measures than physical distancing, making the former less susceptible to social pressure. In addition, more evidence is necessary about this interaction effect since it did not persist in all robustness checks.

### 4.2. LIMITATIONS AND FUTURE DIRECTIONS

Our research has some important caveats. Firstly, it was a cross-sectional study that could not capture changes in perceptions and behaviors. The first peak of the pandemic took place four months before data collection, and a second wave was in its initial stages during data collection. As such, the dynamics we are observing may have been different if the data were collected during different stages of the pandemic. Secondly, given the digital divide in Turkey in terms of internet access (TURKSTAT, 2021), the online survey might have resulted in an underrepresentation of demographic groups from lower SES. This may explain the high prevalence, in our sample, of potentially white-collar individuals who reported working remotely. However, no alternative data collection procedures were available at the time, considering potential physical and psychological safety risks in face-to-face data collection. We also observed that an overwhelming majority of participants lived in urban environments (93%), much higher than the actual urban population in Turkey (78%; TURKSTAT, 2020b). Therefore, the results may not be generalizable to a more rural and less dense population. This problem in generalizability is especially important for crowding, because rural and urban populations are most likely to experience crowding in different patterns. Whereas households are more crowded in rural settlements, urbanites are exposed to more crowding in public spaces, which might change their risk and efficacy perceptions for the adherence to physical distancing measures. Finally, the applicability of path analysis models, especially in nonexperimental studies, can be questioned (e.g., Spencer et al., 2005; Rohrer et al., 2022). However, the predictors of COVID-19 perceptions and protective behavior analyzed in this study are relatively stable sociodemographic factors (i.e., SES, and crowding) that are unlikely to have associations with reverse causality in regard to mediators included in the model (i.e., COVID-19 perceptions). Thus, this study proceeded with a structural equation model. In other words, individuals are not likely to experience changes in their SES and household crowding as an outcome of their COVID-19 perceptions and behavioral tendencies. As argued above, even if it is plausible that some individuals might switch to private means in their commute or remote working because of their risk perceptions, their numbers are expected to be marginal as public transportation use is more likely to be determined by SES than cognitive appraisals. Nonetheless, considering the possibility of multiple paths from omitted variables (Coenen, 2022), we additionally tested our hypotheses with another statistical technique (i.e., hierarchical linear regression) which does not assume any structural mechanism among the variables, and this analysis available at Supplementary Information S4 also yielded similar results.

Future research may assess crowding in more detail by using more fine-tuned operationalization of crowding, such as frequency of contact with non-household members, time spent in public transportation, and access to private office space. Likewise, a combination of the number of rooms, number of bathrooms, and total floor area may help better assess the consequences of household crowding. In addition to cross-sectional studies, experience sampling methods might be employed to uncover crowding effects in other contexts (e.g., work, leisure).

### 4.3. CONCLUSION

This study extends previous research on understanding the impact of SES and crowding on the experiences of individuals during COVID-19. To date, most research on crowding and COVID-19 has focused on the impact of city-and neighborhood-level estimations of population density and its impact on the spread of COVID-19. Our study supplements this prior work by explaining how these ecological conditions are experienced by individuals in ways that may affect their risk perceptions and, in turn, their proclivity to engage in protective behavior. In the case of COVID-19, the findings show that any effects of SES and crowding on protective behavior tend to be small. We postulate that this difference stems from the fact that risk factors such as lower SES and crowding in different contexts (i.e., household, and public transportation) may influence COVID-19 perceptions in different directions.

## DATA ACCESSIBILITY STATEMENT

All data and codes are available on OSF: https://osf.io/8bj3h/.

## NOTE

1 NUTS (Nomenclature of Territorial Units for Statistics) is a three-level classification system for dividing up the economic territory of the European Union. NUTS 2 divides the EU countries into basic socioeconomic regions and is the most widely used classification for comparative purposes. See https://ec.europa.eu/eurostat/web/nuts/background for a detailed description.

## FUNDING INFORMATION

This work was conducted as part of a larger research project supported by The Scientific and Technological Research Council of Turkey (TÜBİTAK) [grant number 120K438].

## COMPETING INTERESTS

The authors have no competing interests to declare.

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**TO CITE THIS ARTICLE:**
Özden, M., Baruh, L., Cemalcilar, Z., & Kuru, O. (2023). Socioeconomic Status, Crowding, COVID-19 Perceptions, and Protective Behavior. *Health Psychology Bulletin,* 17(1), pp. 1–16. DOI: https://doi.org/10.5334/hpb.40

**Submitted:** 06 September 2022 **Accepted:** 15 March 2023 **Published:** 24 March 2023



*Health Psychology Bulletin* is a peer-reviewed open access journal published by Ubiquity Press.