Personality and Individual Differences 187 (2022) 111404

Contents lists available at ScienceDirect

Personality and Individual Differences

journal homepage: www.elsevier.com/locate/paid

Fear of being near: Fear supersedes sociability when interacting amid a pandemic

Ran Amram[a,*], Inbal Ravreby[a,b], Nitzan Trainin[c], Yaara Yeshurun[a,c]

[a] *School of Psychological Sciences, Tel Aviv University, Tel Aviv, Israel*
[b] *Department of Neurobiology, Weizmann Institute of Science, Rehovot, Israel*
[c] *Sagol School of Neuroscience, Tel Aviv University, Tel Aviv, Israel*

ARTICLE INFO

Keywords:
Social interactions
COVID-19
Sociability
Fear
Disease avoidance

ABSTRACT

In the COVID-19 era, physical interactions ubiquitously pose a disease threat. Using a novel online paradigm, this study tested whether under such unique circumstances, the fundamental motivation to avoid disease-related threats interacts with individual differences in sociability, such that: (i) responses to others are slowed down, particularly among sociable individuals, reflecting motivational tension; (ii) the role of sociability in predicting interaction likelihood is diminished. Participants (Israeli young adults, $N = 207$) listened to auditory descriptions of everyday social situations, taking place in either the physical or virtual space, and decided quickly whether to interact. Participants also completed the Sociability Scale (Cheek & Buss, 1981). Responses were slower in the physical compared to virtual space, regardless of sociability. The association between interaction likelihood and sociability was stronger in the virtual space, with sociability mirrored by self-reported fear of COVID-19 in predicting interaction likelihood. We propose that when physical contact with others poses a threat to safety, fear supersedes sociability in guiding behavior in physical interactions.

1. Introduction

The coronavirus (COVID-19) pandemic has had, and continues to have, an overwhelming impact on everyday social life. Nowadays, physical interactions ubiquitously pose a threat of disease infection, necessitating adaptation of social behavior (Townsend et al., 2020). Such adaptation may be particularly stark for sociable individuals: the fundamental drive to *avoid* disease-related threats (Schaller, 2015) seems to collide with their tendencies to *approach* social interactions (Poole & Schmidt, 2020), engendering a motivational tension. This study thus tested whether during pandemic times, opportunities to interact physically with others bring about an *approach-avoidance conflict* among sociable individuals, dampening the association between sociability and decisions to interact.

In the wake of the COVID-19 era, physical distancing – which involves avoiding close physical contact with others, a core component of human sociality (Townsend et al., 2020) – emerged as a primary protection measure. This prompted inquiries into the relationship between distancing behavior and individual differences in social dispositions. Consider, for example, an individual who, when strolling around the neighborhood during a lockdown, spots a neighbor from afar. How might the novel virus threat combine with that individual's social inclinations in determining whether she would go over and greet her neighbor? Thus far, studies addressing this issue have been largely observational, employed extraversion as a marker of sociality, and reported conflicting results: extraversion has been found to be positively (e.g., Shook et al., 2020), negatively (e.g., Carvalho et al., 2020), and not (e.g., Bogg & Milad, 2020) associated with self-reported distancing. Thus, the interplay between social dispositions and avoidance of physical contact during the pandemic has not been made clear, particularly when contemplating any potential underlying motivational mechanism.

Focusing on the distinct sociability trait (Cheek & Buss, 1981) may be conducive to this effort. Sociability refers to an individual tendency, rooted in *approach* motivation, to engage and affiliate with others in the social environment (Poole & Schmidt, 2020). Critically, in the COVID-19 era, individuals might also be motivated to *avoid* close physical contact with others. This could emanate from needs to comply with distancing norms but may also originate in the primal motivation to avoid disease-related threats (Schaller, 2015). Regardless, this suggests that when sociable individuals decide whether to physically interact with others in everyday situations during the pandemic, they experience *approach-avoidance conflict.* A sociable individual, in the above example, might

* Corresponding author at: School of Psychological Sciences, Tel Aviv University, Ramat Aviv, 6997801, Tel Aviv, Israel.
E-mail address: ranamram@mail.tau.ac.il (R. Amram).

https://doi.org/10.1016/j.paid.2021.111404
Received 17 May 2021; Received in revised form 3 October 2021; Accepted 14 November 2021
Available online 23 November 2021

struggle to decide whether to interact with her neighbor. The resulting behavior in this and similar conflictual situations should be determined by the relative strengths of approach and avoidance motivations (Corr & Krupić, 2017). To the extent that the pandemic has rendered sociable individuals more likely than before to avoid close physical contact, sociability could be further dissociated from interaction decisions. In contrast, in the online realm of social interactions – where offline motivational tendencies broadly apply (Orchard & Fullwood, 2010) – disease-related conflict should not emerge regardless of sociability, because interactions pose no direct virus threat. Accordingly, sociability should indicate decisions to interact.

These hypotheses were tested in an online study conducted amid the first COVID-19 lockdown imposed in Israel. At the time, there were around 6000 present cases of infection, 10,000 cases of recovery, and 235 deaths reported in the country (Halon, 2020). Data were collected over a 23-day period (4/30/2020–5/22/2020), during which strict movement restrictions were gradually lifted. Small outdoor gatherings became permitted, with some public spaces (e.g., parks, malls) reopening. Importantly, however, physical interactions still took place under mandatory distancing restrictions (TOI Staff, 2020). These conditions were ideal for the study, given the goal to examine behavior in *common everyday situations* under the continued threat and restrictions imposed by the pandemic.

The study employed a novel choice reaction time (RT) task. Slow responses can be held to reflect approach-avoidance conflict, as manifested in motivational difficulties in decision-making (e.g., Diederich, 2003). Participants listened to pre-recorded descriptions of everyday social situations typical to the COVID-19 era, taking place in either the physical or virtual space, and were required to decide quickly whether to interact with others. Participants also completed the Sociability Scale (Cheek & Buss, 1981). We predicted that RT would rise with sociability, particularly in the physical space. We further predicted that the likelihood to decide to interact would also rise with sociability, but less so in the physical space.

2. Method

2.1. Participants

Given the unique context within which this novel study was conducted, performing an informed a-priori power analysis was not an option. However, established RT effects can be obtained in online experiments using sample sizes around 50 and below (e.g., Crump et al., 2013). To err on the side of over- rather than under-sampling, the sample size was set at 150–250, with the option of halting recruitment when within that range in case of an intersection between low participation rate and near-complete lifting of major COVID-19 restrictions in Israel.

Two-hundred and eight native Hebrew speakers ended up participating in the study. One participant was excluded due to inattentiveness to the task (see Section 1.2 of the Supplementary method in the Supplementary material available online). Thus, the final sample consisted of 207 participants (148 females, 180 university students). The study focused on young adults (ages 21–34, $M = 25.0$, $SD = 2.8$), because they were expected to be more accustomed to online interactions compared to their older counterparts. One-hundred and forty-two participants were recruited via social networks, 10 of which were chosen in a random lottery to each receive a payment of 100 NIS ($31.3). The remaining participants were Tel Aviv University students who received academic credit points as compensation. The study adhered to legal requirements in Israel and was approved by the Tel Aviv University ethics committee. All participants granted informed consent prior to participation.

At the time of participation, and based on self-report, no participants were diagnosed as carriers of COVID-19, 27 participants were required to self-isolate at some point, 14 participants were at high risk for COVID-19 complications, and 71 participants have worked during lockdown period, with 38 participants defined as essential workers. These variables were not associated with any of our measures of interest (see Fig. S1 in the Supplementary method).

2.2. Materials

The study was designed using PsychoPy (Peirce, 2007) and hosted on Pavlovia (https://pavlovia.org).

2.2.1. Social Interaction Task

Participants performed a task developed specifically for this study. In the task, participants listened to recordings that depicted everyday scenarios typical, though not necessarily exclusive, to the COVID-19 era. All scenarios were recorded by the same male experimenter. Each recording concluded with a question that required participants to decide how to act within the scenario and respond accordingly with a keyboard press. Participants had two response options, labeled on the screen as *Yes* and *No*. They were instructed to respond as quickly as possible and in accordance with how they would have behaved had the scenario taken place at the day of participation. The recording was played only once and responding was made possible immediately after it had ended, as the required decision was made clear. The mean duration of recordings was 7.51 s (SD = 1.28). Participants performed 66 pseudorandomly ordered trials, each presenting a different scenario (for the full list, see Section 1 of the Full materials in the Supplementary material):

2.2.1.1. Physical and virtual scenarios. Forty scenarios, split evenly between the physical and virtual spaces, presented opportunities to interact with others in common everyday situations, which people were generally expected to have experienced both before and during the pandemic. Among virtual scenarios, this included eight Zoom-based interactions that came to replace equivalent physical interactions ever since the outbreak (e.g., attending a virtual birthday party; for analyses that compared these interactions to non-video virtual interactions, see Section 2 of the Supplementary results in the Supplementary material). Potential interaction partners were mostly either strangers or far acquaintances, and interactions were generally suggested to involve low levels of direct communication. Scenarios alternately required decisions to either *opt in to* or *opt out of* the interactions. However, across scenarios, the decision-making process, as operationalized by RT, was held to be sensitive to both approach and avoidance motivations. Responses were held to reflect the resulting decisions to either interact (*close*) or not (*far*). In turn, this indicated either predominantly approach-driven or predominantly avoidance-driven behavior, respectively, as determined by the relative strengths of approach and avoidance motivations (e.g., *Physical*: “You walk down the street near your home. You spot someone heading your way on the sidewalk. Would you move across to the other side of the street?”; *Virtual*: “A friend of a friend started following you on Twitter after one of your tweets got a lot of replies. Would you follow her back?”).

2.2.1.2. Non-social scenarios. Twenty recordings depicted everyday non-social scenarios (e.g., “You wake up thirsty in the middle of the night, with no water next to you. Would you go to the kitchen and pour yourself a glass of water?”). These scenarios served two purposes: providing individual RT baselines (Fazio, 1990), and obscuring the purpose of the study to alleviate concerns for both habitual responding and social desirability effects.

2.2.1.3. Catch scenarios. The remaining six trials were catch trials. For these scenarios, one response was held to be consensual (e.g., “You drive your car and there is a crosswalk ahead of you. You notice a little child crossing the road. Would you stop the car?”). Thus, responses in these trials served as markers for participants' attentiveness to the task (see Section 1.2 of the Supplementary method).

2.2.2. Self-report measures

Participants completed back-translated Hebrew versions of the Sociability Scale (Cheek & Buss, 1981) and the Revised Cheek and Buss Shyness Scale (RCBS; as reported in Hopko et al., 2005). The RCBS is a measure of shyness, an *avoidance*-driven tendency associated with social withdrawal (Cheek & Buss, 1981). This measure was included given the well-established notion that individuals who are both sociable and shy experience *social*, rather than disease-related, approach-avoidance conflict (Poole & Schmidt, 2020). Participants also completed COVID-19-related measures designed specifically for this study, including use of both social networking sites (SNSs; e.g., Facebook) and instant messaging applications (IMAs; e.g., WhatsApp) in both the past month (i.e., lockdown period) and past year, fear of contracting COVID-19, and fear of infecting both close others and strangers with COVID-19 (for the full list, see Section 2 of the Full Materials). Responses to all measures were provided on a visual analog scale ranging from 0 ("Not at All") to 100 ("Very Much").

2.3. Procedure

After granting consent, participants were directed via a link to the online environment. They first performed the task, then completed the Sociability and Shyness scales, and finally answered the COVID-19-related questions. The median participation time was 14.6 min.

2.4. Data analysis

All analyses were carried out using R (4.0.2; R Core Team, 2020). The data and code are available online at https://osf.io/a8r4y/.

2.4.1. Preliminary analyses

2.4.1.1. Self-report measures. Pearson correlations between pairs of measures included in the study were computed (see Fig. S1 in the Supplementary method). Following this descriptive analysis, the following sets of self-report measures were merged by averaging across individual measures: (a) fear of COVID-19 for self, close others, and strangers ($\alpha = 0.84$); (b) use of SNSs in the past month and past year ($\alpha = 0.95$); (c) use of IMAs in the past month and past year ($\alpha = 0.96$). This yielded three single variables – Fear of COVID-19 Infection (Fear), SNS Use (SNS), and IMA Use (IMA), respectively – which were selected for the modeling phase.

2.4.1.2. Reaction time. Across both outcome variables, all trials with RT lower than 100 ms were excluded (Whelan, 2008). Because stimuli in the task were dynamic, and responses were provided only after presentation had ended, a high upper exclusion cutoff of 5 s was selected. With the novelty of the task in mind, this cutoff was raised to 10 s after observing the RT distribution (Fig. 1a); responses in the 5–10 s range were held to reflect genuine attempts to comply with task demands, in contrast to responses slower than 10 s (see Fig. S2a in the Supplementary method). After exclusions were made, the median and mean absolute deviation from the median (MAD) were computed for each scenario type. These statistics were preferred over the mean and standard deviation for their robustness (Leys et al., 2013; Whelan, 2008). RTs (ms) were both the slowest and most variable in Physical scenarios ($Mdn = 753$, $MAD = 645$), followed by Virtual scenarios ($Mdn = 639$, $MAD = 592$), and then Non-Social scenarios ($Mdn = 620$, $MAD = 532$). Relative RT differences between scenario types remained stable when lowering gradually the upper cutoff to 5 s (see Fig. S2b in the Supplementary method).

Next, each participant's RTs in Physical and Virtual scenarios were standardized against the median and MAD of that participant's Non-Social RTs (Fig. 1b). The resulting standard RT scores were thus relative to individual baselines, broadly exempt from noise originating in non-relevant differences in reaction tendencies (Fazio, 1990). Then, distribution fitting was conducted using the maximum likelihood method, revealing the lognormal distribution to be a good fit (see Section 4.2 of the Supplementary method). Thus, RT scores were log-transformed and submitted to a model that assumes normality. Due to both the employment of standardized RT scores rather than raw RTs and the drawbacks of back-transforming log-transformed RT data (Lo & Andrews, 2015), results are reported on the logarithmic scale.

2.4.2. Main analysis strategy

Using the *lme4* package (Bates et al., 2015), two separate processes of model fitting were conducted for RT scores (across interaction decisions) and *close/far* decisions within a linear and logistic mixed model framework, respectively, with random effects for participants and scenarios. All self-report measures were scaled before analysis. For each outcome variable, unconditional models were fitted first, with sequential addition of effects for Scenario (Physical/Virtual), Sociability, and the remaining self-report measures (i.e., Shyness, Fear, SNS, and IMA). Initial model comparison was based on information criteria and guided selection of a final model. This model was then compared to a nested null model using a likelihood ratio test. Only a subset of the fitted models is reported here, with a focus on fixed effects (excluding intercepts; for specifications of all the fitted models, see Section 3 of the Supplementary results). Accordingly, the marginal R^2 statistic for mixed models (Nakagawa & Schielzeth, 2013) is reported for global effect sizes. In interpreting the results, primacy is given to fit statistics (Vrieze, 2012) and local effect sizes (Cumming, 2014).

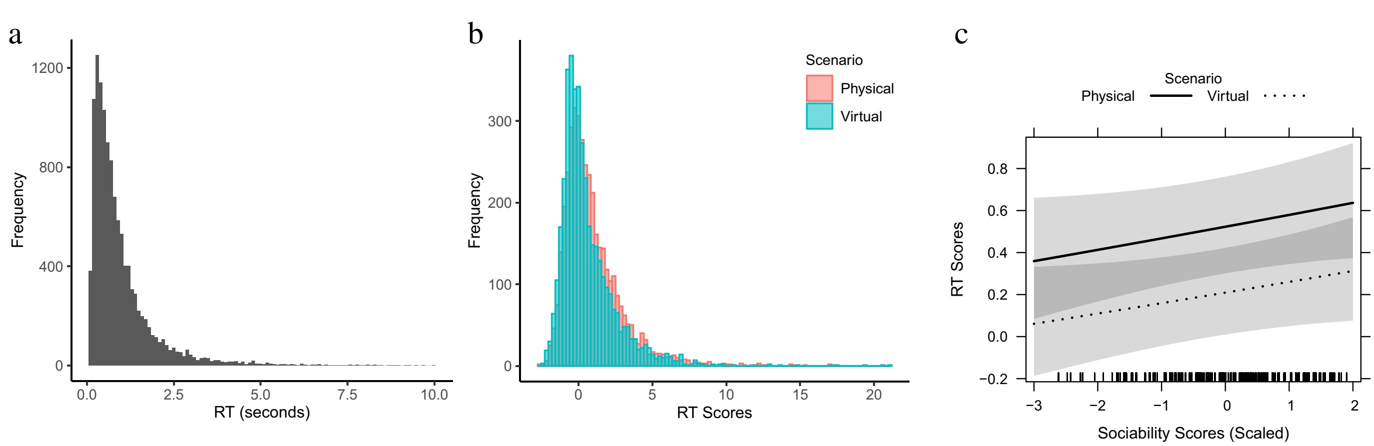

Fig. 1. Reaction time (RT) data and analysis. Across-participant distributions of (a) raw RT after exclusions (Physical/Virtual/Non-Social) and of (b) RT standardized against Non-Social trials (Physical/Virtual), and (c) standardized RT as predicted by Scenario and Sociability (shaded areas denote 95% pointwise confidence bands).

3. Results

3.1. Reaction time

The final model included effects for Scenario and Sociability, but not their interaction. The null model omitted the Scenario term. The final model fitted better, $\chi^2(1) = 4.04$, $p = .044$ (Table 1). Responses were slower in Physical compared to Virtual scenarios, $\beta = 0.098$, $t(40.3) = 2.06$, $p = .046$. Controlling for all other variables, moving from Virtual to Physical scenarios increased RT scores by 10.3% on average (Fig. 1c). RT scores rose with Sociability, although not significantly, $\beta = 0.017$, $t(206.2) = 1.67$, $p = .097$. Controlling for all other variables, a 1 SD increase in Sociability scores predicted an average increase of 1.7% in RT scores (Fig. 1c). Importantly, these effects were not qualified by an interaction, $\beta = -0.003$, $t(206.8) = -0.33$, $p = .746$ (Table 1).

3.2. Close/far decisions

The final model included effects for Scenario, Sociability, and their interaction, along with Fear and its interaction with Scenario. The null model omitted the Sociability interaction term. The final model fitted better, although not significantly, $\chi^2(1) = 2.89$, $p = .089$ (Table 2). The likelihood to respond *close* rose with Sociability, $OR = 1.20$, $Z = 4.31$, $p < .001$. This effect was broadly qualified by an interaction with Scenario that approached significance, $OR = 0.87$, $Z = -1.71$, $p = .087$. Controlling for all other variables, a 1 SD increase in Sociability scores predicted average increases of 11.9% and 28.6% in the likelihood to respond *close* in Physical and Virtual scenarios, respectively (Fig. 2a). A distinct interaction pattern between Fear and Scenario also emerged, $OR = 0.76$, $Z = -3.35$, $p = .001$. Controlling for all other variables, a 1 SD increase in Fear scores predicted average decreases of 25.0% and 1.6% in the likelihood to respond *close* in Physical and Virtual scenarios, respectively (Fig. 2b).

These effects were explored further by adding to the final model the three-way interaction term of Scenario, Sociability, and Fear. The resulting model did not fit much better, $\chi^2(2) = 3.09$, $p = .213$ (Table 2). However, a distinct three-way pattern emerged approaching significance, $OR = 0.88$, $Z = -1.76$, $p = .078$. Controlling for all other variables, a 1 SD increase in Sociability scores predicted, among individuals low (at Q_1), medium (at Q_2), and high (at Q_3) in Fear, average increases of 18.3%, 10.3%, and 4.9% in Physical scenarios, and 24.1%, 30.1%, and 34.5% in Virtual scenarios, respectively, in the likelihood to respond *close* (Fig. 2c).

Table 2
Fixed effects and fit statistics for close/far models.

	Null model		Final model		Three-way interaction model	
	OR	[95% CI]	*OR*	[95% CI]	*OR*	[95% CI]
Fixed effects						
Scenario	1.01	[0.52, 1.96]	1.01	[0.52, 1.95]	1.01	[0.52, 1.96]
Sociability	1.22***	[1.13, 1.33]	1.20***	[1.10, 1.30]	1.20***	[1.10, 1.30]
Scenario × Sociability	–	–	0.87†	[0.74, 1.02]	0.87†	[0.74, 1.01]
Fear	0.86***	[0.80, 0.93]	0.86***	[0.80, 0.93]	0.86***	[0.80, 0.93]
Scenario × Fear	0.76***	[0.65, 0.89]	0.76***	[0.65, 0.89]	0.77**	[0.66, 0.90]
Sociability × Fear	–	–	–	–	0.99	[0.92, 1.06]
Scenario × Sociability × Fear	–	–	–	–	0.88†	[0.75, 1.02]
Shyness	0.90**	[0.83, 0.97]	0.90**	[0.83, 0.97]	0.90*	[0.83, 0.98]
SNS	1.16***	[1.08, 1.25]	1.16***	[1.08, 1.25]	1.16***	[1.08, 1.25]
Fit statistics						
Deviance	9435.1		9432.2		9429.1	
AIC	9457.1		9456.2		9457.1	
BIC	9534.0		9540.1		9555.0	
$R^2_{GLMM(m)}$	0.03		0.03		0.03	

† $p < .1$.
* $p < .05$.
** $p < .01$.
*** $p < .001$.

4. Discussion

This study investigated the interplay between sociability and disease avoidance during a global pandemic. When facing opportunities to interact with others, participants responded more slowly, relative to themselves, in the physical compared to virtual space. Slower responses also emerged among sociable individuals. However, contrary to predictions, the association between RT and sociability was similar in the physical and virtual spaces. In contrast, the association between interaction likelihood and sociability was, as hypothesized, stronger in the virtual compared to physical space. Simultaneously, a mirroring pattern emerged whereby the association between interaction likelihood and explicit fear of infection was stronger in the physical space. Furthermore, as fear rose, the association between interaction likelihood and sociability weakened and strengthened in the physical and virtual spaces, respectively. It is important to note, however, that the sociability effects were only marginally significant.

We propose that RT differences between the physical and virtual spaces indicate that in the COVID-19 era, the virus threat evokes, across the board, an innate fear response in the form of *freezing* behavior within

Table 1
Fixed effects and fit statistics for reaction time models.

	Null model		Final model		Interaction model	
	β	[95% CI]	β	[95% CI]	β	[95% CI]
Fixed effects						
Scenario	–	–	0.098*	[0.003, 0.193]	0.098*	[0.003, 0.193]
Sociability	0.017†	[−0.003, 0.036]	0.017†	[−0.003, 0.036]	0.016	[−0.004, 0.036]
Scenario × Sociability	–	–	–	–	−0.003	[−0.023, 0.017]
Trial number	−0.030***	[−0.040, −0.021]	−0.030***	[−0.040, −0.021]	−0.030***	[−0.040, −0.021]
Fit statistics						
Deviance	9810.5		9806.5		9806.4	
AIC	9826.5		9824.5		9826.4	
BIC	9882.4		9887.4		9896.3	
$R^2_{LMM(m)}$	0.01		0.02		0.02	

† $p < .1$.
* $p < .05$.
*** $p < .001$.

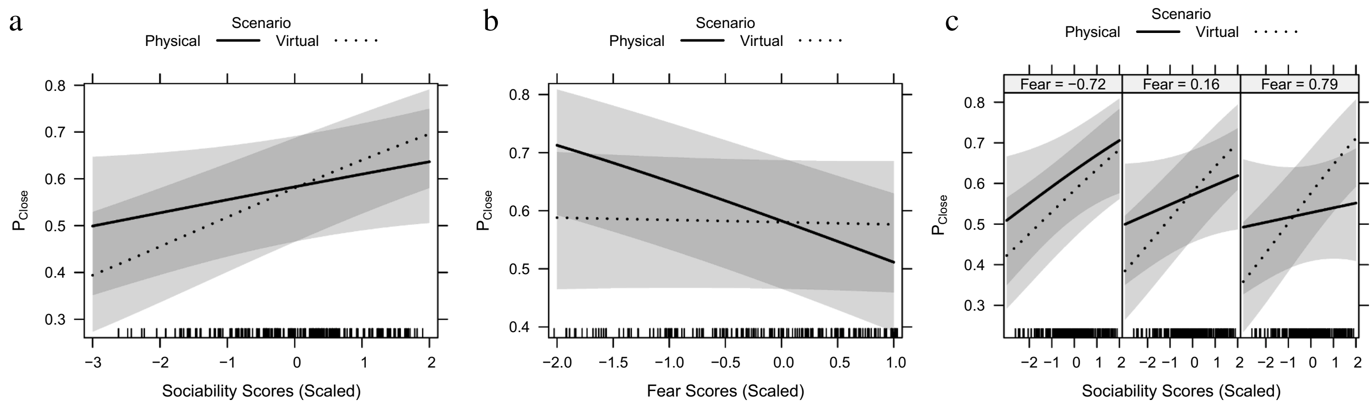

Fig. 2. Probability to respond *close* as predicted by Scenario and (a) Sociability, (b) Fear of COVID-19 Infection (Fear), and (c) Sociability at different levels of Fear (note that the Fear values presented in this panel correspond, from left to right, to Q_1, Q_2, and Q_3 of the scaled Fear scores distribution). Shaded areas denote 95% pointwise confidence bands.

the immediate experience of everyday physical interactions. Specifically, facing this novel threat should necessitate action preparation that subsequently leads to either approaching or avoiding the interaction. Such preparation could be facilitated by freezing at the initial stage of the decision-making process, extending interaction decision time; conflicted individuals might require additional time to further evaluate rewards and punishments associated with interacting (Livermore et al., 2021; Roelofs, 2017). Thus, it might be that differences in *social* conflict levels persist during the pandemic, with the virus threat eliciting a fundamental fear response that precedes individual reaction tendencies rooted in differences in social dispositions. The nature, as well as weakness and insignificance, of the RT-sociability association might be explained by the more nuanced relationship between sociability and shyness (see Section 1 of the Supplementary results).

Two findings indicate indirectly that the difference in decision time between the physical and virtual spaces is unique to the circumstances of interacting under infection threats: first, within the virtual space, reactions were faster for video (e.g., Zoom) compared to non-video (e.g., SNS/IMA) interactions, which suggests that exposure to physical properties of others does not delay responses in and of itself (see Section 2 of the Supplementary results. Note that this effect did not reach significance, $p = .084$). Second, the strong association between interaction likelihood and self-reported fear of COVID-19 infection in the physical space, which suggests that representations of physical interactions accounted for the virus threat. Note that the fact that self-reported fear did not predict RT is consistent with this interpretation, as explicit-implicit dissociations are common in threat perception (e.g., Robinson et al., 2005).

Results suggest that the virus threat further alters social behavior in the physical space by attenuating the role of the distinct sociability trait as an indicator of the actual decisions to interact. This finding is consistent with existing evidence for a motivational tradeoff between social approach and lab-activated disease avoidance (e.g., Sacco et al., 2014; Sawada et al., 2018), extending it to the real-life everyday settings of interacting amid a global pandemic. Moreover, results suggest that explicit fear of infection mechanistically supplants sociability in guiding behavior. In particular, the fact that sociability's role in predicting physical interactions diminished as fear rose indicates that it was indeed disease avoidance, rather than compliance with external norms of physical distancing, that directed interaction decisions. Furthermore, the fact that the opposite pattern was found for online interactions implies that to some extent, the COVID-19 threat has shifted the weight of sociability's predictive role to the virtual space. Whereas the study focused on young adults for methodological reasons, this notion may apply across the age spectrum (e.g., Drouin et al., 2020). Taken together, these findings illustrate how some individuals, given their behavioral inclinations, adapt to the unique social circumstances imposed by a global pandemic (Townsend et al., 2020). This interpretation should be treated with caution, however, considering that the relevant effects only reached marginal significance.

In conclusion, this study outlines a potential motivational mechanism that integrates disease avoidance and social dispositions to guide individuals in their social environments when physical contact with others poses a ubiquitous threat to safety, as is currently the case with the COVID-19 pandemic. By examining motivated decision-making as it unfolded within the context of everyday opportunities to interact, this study has shown that the virus threat alters the motivational scheme throughout the decision-making process. This may be driven primarily by fear of infection, which transcends stable differences in propensities to interact: first, by manifesting in pervasive freezing behavior, delaying individual reaction tendencies to allow for immediate action preparation in face of the virus threat. Then, by superseding sociability in guiding the actual decisions. In drawing these conclusions, however, it is critical to note that this study only measured intended behaviors across hypothetical situations rather than actual behaviors in more ecological settings. With this important limitation in mind, we hope this study could aid in further understanding of the social challenges introduced by the pandemic and the potential means to overcome them.

CRediT authorship contribution statement

Ran Amram: Conceptualization, Methodology, Investigation, Formal analysis, Writing – original draft, Writing – review & editing, Visualization. **Inbal Ravreby:** Methodology, Investigation. **Nitzan Trainin:** Methodology, Software, Data curation. **Yaara Yeshurun:** Supervision, Methodology, Writing – review & editing.

Declaration of competing interest

None.

Acknowledgements

The study was funded by Israel Science Foundation, Grant No. 2434/19.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.paid.2021.111404.

References

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software, 67*(1), 1–48. https://doi.org/10.18637/jss.v067.i01

Bogg, T., & Milad, E. (2020). Demographic, personality, and social cognition correlates of coronavirus guideline adherence in a U.S.sample. *Health Psychology, 39*(12), 1026–1036. https://doi.org/10.1037/hea0000891

Carvalho, L.d. F., Pianowski, G., & Gonçalves, A. P. (2020). Personality differences and COVID-19: Are extroversion and conscientiousness personality traits associated with engagement with containment measures? *Trends in Psychiatry and Psychotherapy, 42* (2), 179–184. https://doi.org/10.1590/2237-6089-2020-0029

Cheek, J. M., & Buss, A. H. (1981). Shyness and sociability. *Journal of Personality and Social Psychology, 41*(2), 330–339. https://doi.org/10.1037/0022-3514.41.2.330

Corr, P. J., & Krupić, D. (2017). Motivating personality: Approach, avoidance, and their conflict. In A. J. Elliot (Ed.), *Advances in motivation science* (Vol. 4, pp. 39–90). Academic Press. https://doi.org/10.1016/bs.adms.2017.02.003.

Crump, M. J. C., McDonnell, J. V., & Gureckis, T. M. (2013). Evaluating Amazon's Mechanical Turk as a tool for experimental behavioral research. *PLoS ONE, 8*(3). https://doi.org/10.1371/journal.pone.0057410

Cumming, G. (2014). The new statistics: Why and how. *Psychological Science, 25*(1), 7–29. https://doi.org/10.1177/0956797613504966

Diederich, A. (2003). Decision making under conflict: Decision time as a measure of conflict strength. *Psychonomic Bulletin & Review, 10*(1), 167–176. https://doi.org/10.3758/BF03196481

Drouin, M., McDaniel, B. T., Pater, J., & Toscos, T. (2020). How parents and their children used social media and technology at the beginning of the COVID-19 pandemic and associations with anxiety. *Cyberpsychology, Behavior, and Social Networking, 23*(11), 727–736. https://doi.org/10.1089/cyber.2020.0284

Fazio, R. H. (1990). *A practical guide to the use of response latency in social psychological research*. In C. Hendrick, & M. S. Clark (Eds.) (Vol. 11, pp. 74–97). SAGE Publications.

Halon, E. (2020, May 6). Rolling out exit plan, Netanyahu unveils easing of lockdown restrictions. In *The Jerusalem Post*. https://www.jpost.com/breaking-news/government-to-allow-malls-libraries-gyms-water-sports-starting-friday-626828.

Hopko, D. R., Stowell, J., Jones, W. H., Armento, M. E. A., & Cheek, J. M. (2005). Psychometric properties of the revised Cheek and Buss shyness scale. *Journal of Personality Assessment, 84*(2), 185–192. https://doi.org/10.1207/s15327752jpa8402_08

Leys, C., Ley, C., Klein, O., Bernard, P., & Licata, L. (2013). Detecting outliers: Do not use standard deviation around the mean, use absolute deviation around the median. *Journal of Experimental Social Psychology, 49*(4), 764–766. https://doi.org/10.1016/j.jesp.2013.03.013

Livermore, J. J. A., Klaassen, F. H., Bramson, B., Hulsman, A. M., Meijer, S. W., Held, L., Klumpers, F., de Voogd, L. D., & Roelofs, K. (2021). Approach-avoidance decisions under threat: The role of autonomic psychophysiological states. *Frontiers in Neuroscience, 15*. https://doi.org/10.3389/fnins.2021.621517

Lo, S., & Andrews, S. (2015). To transform or not to transform: Using generalized linear mixed models to analyse reaction time data. *Frontiers in Psychology, 6*. https://doi.org/10.3389/fpsyg.2015.01171

Nakagawa, S., & Schielzeth, H. (2013). A general and simple method for obtaining R2 from generalized linear mixed-effects models. *Methods in Ecology and Evolution, 4*(2), 133–142. https://doi.org/10.1111/j.2041-210x.2012.00261.x

Orchard, L. J., & Fullwood, C. (2010). Current perspectives on personality and internet use. *Social Science Computer Review, 28*(2), 155–169. https://doi.org/10.1177/0894439309335115

Peirce, J. W. (2007). PsychoPy—Psychophysics software in Python. *Journal of Neuroscience Methods, 162*(1–2), 8–13. https://doi.org/10.1016/j.jneumeth.2006.11.017

Poole, K. L., & Schmidt, L. A. (2020). Shyness and sociability revisited. In L. A. Schmidt, & K. L. Poole (Eds.), *Adaptive shyness*. Cham: Springer. https://doi.org/10.1007/978-3-030-38877-5_9.

R Core Team. (2020). *R: A language and environment for statistical computing*. R foundation for statistical computing.

Robinson, M. D., Meier, B. P., & Vargas, P. T. (2005). Extraversion, threat categorizations, and negative affect: A reaction time approach to avoidance motivation. *Journal of Personality, 73*(5), 1397–1436. https://doi.org/10.1111/j.1467-6494.2005.00353.x

Roelofs, K. (2017). Freeze for action: Neurobiological mechanisms in animal and human freezing. *Philosophical Transactions of the Royal Society B: Biological Sciences, 372* (1718). https://doi.org/10.1098/rstb.2016.0206

Sacco, D. F., Young, S. G., & Hugenberg, K. (2014). Balancing competing motives: Adaptive trade-offs are necessary to satisfy disease avoidance and interpersonal affiliation goals. *Personality and Social Psychology Bulletin, 40*(12), 1611–1623. https://doi.org/10.1177/0146167214552790

Sawada, N., Auger, E., & Lydon, J. E. (2018). Activation of the behavioral immune system: Putting the brakes on affiliation. *Personality and Social Psychology Bulletin, 44* (2), 224–237. https://doi.org/10.1177/0146167217736046

Schaller, M. (2015). The behavioral immune system. In D. M. Buss (Ed.), *The handbook of evolutionary psychology* (pp. 206–224). John Wiley & Sons, Inc.. https://doi.org/10.1002/9781119125563.evpsych107

Shook, N. J., Sevi, B., Lee, J., Oosterhoff, B., & Fitzgerald, H. N. (2020). Disease avoidance in the time of COVID-19: The behavioral immune system is associated with concern and preventative health behaviors. *PLoS ONE, 15*(8). https://doi.org/10.1371/journal.pone.0238015

TOI Staff. (2020, May 5). No more 100-meter limit; malls, libraries to reopen: All the eased regulations. In *The Times of Israel*. https://www.timesofisrael.com/malls-libraries-gyms-and-zoos-the-businesses-that-can-reopen-under-new-rules/.

Townsend, A. K., Hawley, D. M., Stephenson, J. F., & Williams, K. E. G. (2020). Emerging infectious disease and the challenges of social distancing in human and non-human animals. *Proceedings of the Royal Society B: Biological Sciences, 287*(1932). https://doi.org/10.1098/rspb.2020.1039

Vrieze, S. I. (2012). Model selection and psychological theory: A discussion of the differences between the Akaike information criterion (AIC) and the Bayesian information criterion (BIC). *Psychological Methods, 17*(2), 228–243. https://doi.org/10.1037/a0027127

Whelan, R. (2008). Effective analysis of reaction time data. *The Psychological Record, 58* (3), 475–482. https://doi.org/10.1007/BF03395630