The impact of pandemic-related worry on cognitive functioning and risk-taking

Authors

Kevin da Silva Castanheira^{1*}, Madeleine Sharp², A. Ross Otto¹

Affiliations

1. Department of Psychology, McGill University
2. Department of Neurology and Neurosurgery, McGill University

* Corresponding author (Kevin.daSilvaCastanheira@mail.mcgill.ca)

Abstract

Here, we sought to quantify the effects of experienced fear and worry, engendered by the COVID-19 pandemic, on both cognitive abilities—speed of information processing, task-set shifting, and proactive control—as well as economic risk-taking. Leveraging a repeated-measures cross-sectional design, we examined the performance of 1517 participants, collected during the early phase of the pandemic in the US (April – June 2020), finding that self-reported pandemic-related worry predicted deficits in information processing speed and maintenance of goal-related context information. Cognitive performance was also impaired relative to pre-pandemic ‘baseline’ samples. In a classic economic risk-taking task, we also observed that more worried individuals’ choices were more sensitive to outcome probabilities of risky actions. Overall, these results elucidate the cognitive consequences of pandemic worry, which may play an important role in individuals’ understanding of—and adherence to—public health directives.

Introduction

The COVID-19 pandemic represents a significant threat to the physical, mental, and economic well-being of people globally. While a spate of recent work has documented the direct effects of the pandemic on mental health (Brooks et al., 2020; Di Blasi et al., 2021; Kachanoff et al., 2020; Taylor et al., 2020), less is known about the consequences it might hold for cognitive function. Identifying and understanding these cognitive and behavioural consequences is especially critical as governments continue to face the challenge of controlling the spread of the virus and mitigating its social, economic, and psychological consequences. More than ever, people are being asked to attend to a continuous stream of public health messages, to adhere to government directives and to control their impulses for the sake of the collective good (van Bavel et al., 2020). Seemingly simple decisions—like refraining from sharing a coffee with friends or registering for the vaccine—are the key elements of the global fight against COVID-19, yet concerning trends suggest declining adherence to these regulations and far-from-universal vaccine acceptance (Crane et al., 2021; Lazarus et al., 2021). Successful navigation of these situations is thought to rely on a key set of related cognitive processes often referred to as executive functions (Hinson et al., 2003; Peters & Büchel, 2011)—broadly defined as monitoring and selection of behaviours in accordance with internal goals (Diamond, 2013). Here, we elucidate the impact of the early stages of the COVID-19 pandemic on both executive function and risky decision-making.

At the same time, a body of work suggests that executive functioning is impaired under conditions of fear and anxiety (Moran, 2016; Wetherell et al., 2002) like those reported during the pandemic (Fitzpatrick et al., 2020; Heffner et al., 2020), possibly owing to the processing resources (e.g., working memory) displaced by excessive worry (Eysenck et al., 2007). For instance, anxiety is demonstrated to impair goal-directed cognitive processing thereby increasing the influence of

more reflexive responses (Yang et al., 2018). However, past work has also shown that some cognitive processes are preserved—or even facilitated—by anxiety (Robinson et al., 2013). Given the variability in the reported effects of emotional distress, pinpointing the locus of cognitive impairments brought about by pandemic-related worry may be particularly important.

Here, we provide an initial examination of the effects of pandemic-related worry upon cognitive functioning in a large, representative US-based sample, by measuring pandemic-related worry and assessing three distinct facets of cognitive functioning: 1) processing speed, measured with the digit-symbol coding task (Kail & Salthouse, 1994), 2) the ability to shift between multiple task sets, measured using a task-switching paradigm (Monsell, 2003) and 3) proactive cognitive control, the ability to utilize contextual, task-related information in accordance with internally maintained goals, measured by the AX- CPT (J. D. Cohen et al., 1999). We chose these three specific cognitive tasks because they index related yet disparate facets of cognitive ability (Miyake et al., 2000), all rely on anxiety-sensitive executive functions (e.g., working memory) (Braver, 2012; Burgess & Braver, 2010; Kail & Salthouse, 1994), and were previously administered online allowing for comparisons with pre-pandemic samples.

To do this, we administered an online task battery during the early phase of the COVID-19 pandemic in North America, across 3 waves, between April and June of 2020. We measured self-reported pandemic-related worry using the validated “Fear of Coronavirus” questionnaire (Mertens, Gerritsen, et al., 2020), and subsequently probed the relationship between pandemic worry and cognitive performance across these tasks, controlling for both financial and overall perceived stress levels. We also assessed the impact of pandemic progression by directly comparing task performance between waves, as well as performance on identical tasks of comparable online samples collected in years prior to the pandemic.

Finally, given the importance of risk assessments in a pandemic (Wise et al., 2020), we also examined the possibility that the effects of pandemic-related worry might also extend to individuals' risk-taking. Previous work has found that anxiety engenders an increased perceived likelihood of negative outcomes (Butler & Mathews, 1987; Eysenck & Derakshan, 1997; MacLeod et al., 1991), which can manifest as heightened risk aversion (Clark et al., 2012; Maner et al., 2007; Robinson et al., 2013). To evaluate this, we probed the effect of pandemic-related worry on decision-making by measuring individuals' risk attitudes in a traditional economic choice task (Ruggeri et al., 2020; Tversky & Kahneman, 1992)—specifically, whether pandemic-related worry is associated with an overall tendency towards risk aversion, or if this association was selective to choices pertaining to gains or losses (Hartley & Phelps, 2012; Porcelli & Delgado, 2009; Xu et al., 2013).

Results

We collected US-based online samples across three waves corresponding to the early phase of the COVID-19 pandemic in North America: April 2nd, 3rd, and 6th, April 17th and 20th -23rd, and June 19th and 22nd, 2020 (see Figure 1A). Within this period, many of the US states enacted strict regulations to mitigate the spread of the virus, including travel bans, limitations on gatherings, and stay-at-home directives, indicating that the pandemic was widespread at the time of data collection. Importantly, we also observed a strong relationship between the number of responses in each US state and that state's population in 2019 ($r = 0.976$, $p < .0001$; collapsed over waves), suggesting that the geographical distribution of participants was consistent with the state-level population distribution (Figure 1B). We measured participants' performance on three cognitive tasks, an economic choice task, pandemic-related worry (e.g., subjective worry, looking up pandemic

information) using the Fear of Coronavirus Questionnaire (FCQ) (Mertens, Gerritsen, et al., 2020), and both financial stress (Vinokur et al., 1996) and overall perceived stress (S. Cohen et al., 1994).

Experienced Fear, Worry and Stress

As depicted in Figures 1C&D, participants reported experiencing both moderate financial ($M_{FSS} = 8.35$; $SD_{FSS} = 3.22$) and overall perceived stress ($M_{PSS} = 18.63$; $SD_{PSS} = 7.42$) as measured by the FSS (Vinokur et al., 1996) and the PSS (S. Cohen et al., 1994) respectively. In addition, participants' self-reported pandemic worry—measured using the FCQ (Mertens, Gerritsen, et al., 2020) ($M_{April} = 29.81$; $SD_{April} = 6.40$; $M_{June} = 28.42$; $SD_{June} = 6.73$)—matched the levels reported by other work assessing worry in an international sample during the same time period (Mertens, Duijndam, et al., 2020). Next, we compared pandemic anxiety, perceived overall stress, and financial stress across waves (Figure 1E), finding that pandemic-related worry decreased linearly with wave ($\beta = -1.188$, $CI = [-1.642, -0.733]$, $p < .001$) mirroring previous observations taken during the North American pandemic onset (Cunningham et al., (in press); Mertens, Duijndam, et al., 2020). However, financial stress ($\beta = -0.232$, $CI = [-0.457, -0.007]$, $p = .042$), but not perceived stress levels were found to decrease as a function of pandemic progression (linear effect $\beta = -0.321$, $CI = [-0.841, 0.198]$, $p = .225$).

Processing Speed

We measured participants' ability to quickly process information (Kail & Salthouse, 1994), using the digit-symbol coding task, where participants were required to indicate, for as many stimuli as possible within 90 seconds, whether the digit-symbol pair matched according to a displayed digit-symbol key (Kail & Salthouse, 1994) (Figure 2A). Interestingly, we observed that higher levels of pandemic-related worry—indexed by the FCQ—predicted lower performance (Figure 2B). Statistically, this predictive effect was significant, controlling for age, gender, overall

stress, financial strain and a number of other demographic variables (FCQ $\beta = -0.940$, CI = [-1.591, -0.289], $p = .005$; Table S1). We also examined whether the predictive effect of worry on digit-symbol performance could be explained by a decrease in response caution, as indexed by faster correct RTs (Mathias et al., 2017). Instead, we found that increased FCQ scores were associated with slower correct response times (RTs; $\beta = 0.019$, CI = [0.005, 0.033], $p = .009$; see Figure 2C and Table S2), indicating that the onus of worry's predictive effect was a general slowing of information processing.

Next, we compared performance across waves (Figure 2D) and with a pre-pandemic sample taken in the US in 2018-2019 (see Table S3 sample information). We found that pandemic samples exhibited lower digit-symbol scores ($\beta = -5.470$, CI = [-7.640, -3.300], $p < 0.001$) and responded more slowly ($\beta = 0.105$, CI = [0.059, 0.151], $p < 0.001$) compared to the pre-pandemic sample, controlling for participants' age and gender. Across pandemic waves, we also observed a linear decline in processing speed as a function of pandemic progression ($\beta = -1.120$, CI = [-1.980, -0.259], $p = .011$; see Figure 2D): we found digit-symbol scores were lower in the second ($\beta = -2.295$, CI = [-3.863, -0.728], $p = .004$) and third waves ($\beta = -2.124$, CI = [-3.8492, -0.4000], $p = .0168$; see Table S1), relative to the first wave, controlling for FCQ scores. This pattern was echoed in RTs, where participants were slower in the latter two waves (e.g., Waves 2 and 3) in comparison to the first wave (p 's $< .05$, see Figure 2E & Table S2). In short, the observed impairments in processing speed, both in association with pandemic-related worry and pandemic progression, hint that a worry-induced reduction in basic information processing ability may be a cognitive consequence of the pandemic.

Task-Switching

Next, we examined individual's ability to reconfigure mental processes in response to a change in goals, indexed by switch costs—the slowing of responses following switches between tasks (Monsell, 2003; Otto & Daw, 2019). In the task-switching paradigm, participants are required to respond to a stimulus based on a subtask that varied from trial-to-trial (see Figure 3A). On half of the trials, the required subtask (COLOR versus PATTERN) repeated, while the other half of trials entailed a switch to the other subtask, yielding “repeat” and “switch” trials respectively. As is typical with task switching paradigms, we observed significantly slower RTs on switch trials compared to repeat trials ($\beta = 0.1037$, $CI = [0.0930, 0.1144]$, $p < 0.001$, see Figure 3B and Table S5), reflecting switch RT costs (Monsell, 2003).

Next, we examined whether pandemic-related worry predicted task performance, but failed to observe a statistically meaningful relationship between FCQ scores and RTs ($\beta = -0.0005$, $CI = [-0.0142, 0.0132]$, $p = 0.946$; see Table S4), nor switch costs ($\beta = -0.0015$, $CI = [-0.0080, 0.0050]$, $p = 0.647$; see Figure 3C & Table S4), suggesting that worry may not have affected the set-shifting ability. Mirroring these results, we did not find any differences in either RTs ($\beta = -0.0066$, $CI = [-0.0437, 0.0304]$, $p = .726$; see Table S5), or switch RT costs ($\beta = -0.0045$, $CI = [-0.0045, 0.0110]$, $p = .572$) between the pandemic and pre-pandemic ‘baseline’ sample collected in 2019. Similarly, comparing across waves, we did not observe an effect of pandemic wave upon RTs when comparing between waves (all p 's $\geq .05$; see Table S5).

Examining task-switching accuracy, we observed a typical decrease in accuracy on task switches compared to task repetitions ($\beta = -0.5719$, $CI = [-0.6531, -0.4907]$, $p < 0.001$; see Table S10) (Monsell, 2003). As depicted in Figure 3D, we failed to find a relationship between either pandemic-related worry (FCQ) and overall accuracy ($\beta = -0.0385$, $CI = [-0.0865, 0.0096]$, $p =$

.117; See Table S10) or switch-costs expressed in terms of accuracy ($\beta = 0.0066$, $CI = [-0.0415, 0.0547]$, $p = .788$; see Table S6). However, we did find that the pandemic samples were generally less accurate compared to the pre-pandemic sample ($\beta = -0.2443$, $CI = [-0.3835, -0.1051]$, $p = 0.001$; see Figure 3B and Table S7), controlling for age and gender. Overall, accuracy was lower in the second and third waves compared to the first (p 's $< .05$; see Table S6), after controlling for age, gender, and worry. Together, these results suggest that, unlike processing speed, general task-set shifting abilities—indexed by task switch costs—were unrelated to pandemic-related worry.

Proactive cognitive control

Next, we probed whether pandemic-related worry had any predictive bearing on proactive cognitive control, assessed with the Dot Pattern Expectancy task (DPX) (MacDonald, 2008). In the DPX task (Figure 4A), a cue stimulus (blue dot pattern; A or B) is presented briefly, followed by a delay and a probe stimulus (white dot pattern; X or Y). Participants were instructed to make a ‘target’ response only to a valid cue-probe pair (denoted AX), and a ‘non-target’ response for all other invalid cue-probe pairs: BX , AY , and BY . Importantly, target (AX) trials are far more frequent than non-target trials (approximately 2/3 of trials), engendering a preparatory context triggered by the A cue, and a bias for target responses triggered by the X probe.

The relative performance on BX versus AY trials is used as a measure of proactive control, because the cue-driven expectancy set by the B context can be utilized to inhibit the incorrect, but prepotent target response to the X probe (Braver & Cohen, 2000). Accordingly, engaging in the use of proactive control supports performance on BX trials, but at the same time, can impair performance on non-target AY trials. Conversely, reactive control relies more on the probe, which is thought to impair performance on non-target BX trials but improve AY performance. Overall, DPX RTs and accuracies in the pandemic sample mirrored typically observed patterns (Henderson

et al., 2012; Otto et al., 2015): subjects made faster and more accurate responses to target *AX* trials and non-target *BY* trials compared to *AY* and *BX* (RT cue $\times$ probe interaction $F=254.7$, $p < .001$; Accuracy interaction $F=905.57$, $p < .001$; see Table S8).

We next examined whether pandemic-related worry predicted deficits in the proactive behavioural index (PBI)(Braver et al., 2009)—an RT-based measure of proactive control, calculated as $(RT_{AY} - RT_{BX}) / (RT_{AY} + RT_{BX})$ —finding that individuals with higher FCQ scores had lower PBIs (Figure 4B; $\beta = -0.0020$, CI = $[-0.0034, -0.0005]$, $p = 0.010$; see Table S9), controlling for gender, age and self-reported stress. That is, individuals reporting more pandemic-related worry had greater difficulty inhibiting stimulus-driven responding. Additionally, we observed a negative relationship between reported chronic stress (measured with the PSS) and PBIs ($\beta = -0.0108$, CI = $[-0.0200, -0.0015]$, $p = 0.023$, see Figure 4C).

Relative to a pre-pandemic sample collected in 2013, the pandemic sample exhibited significantly—albeit slightly—reduced PBIs ($\beta = -0.0353$, CI = $[-0.0674, -0.0032]$, $p = 0.031$; Figure 4B), but no pandemic progression effect (linear effect of wave: $\beta = -0.0075$, $[-0.0204, 0.0054]$, $p = .254$; see Figure 4D) nor any significant PBI differences between the first wave and the latter two waves (p 's > 0.20 & Table S8). Importantly, overall response accuracy did not vary as a function of wave or FCQ (p 's $> .05$; see Figure 4E & Table S10). In summary, these results suggest that pandemic-related worry is associated with deficits in proactive cognitive control.

Risky Decision-Making

Finally, we examined how pandemic-related worry relates to risk preferences as a function of gain-loss decision framing (Tversky & Kahneman, 1981), outcome probability, and their possible interactions (Tversky & Kahneman, 1992). To do this, we measured risk preferences using a classic economic choice task (Figure 5A), wherein participants made a series of

hypothetical choices between a ‘certain’ option e.g., a sure win of \$75, and a ‘risky’ option e.g. a 25% chance of winning \$0 and a 75% chance of winning \$100 (see Table S11 for full list of stimuli used). These choices varied both in terms of the decision frame (i.e., losses versus gain outcomes) and the probability of the non-zero risky outcome, which varied from unlikely (1-10%) to likely (90-99%).

Overall, we observed participants were sensitive to the decision frame in accordance with the framing effect (Ruggeri et al., 2020; Tversky & Kahneman, 1992): participants’ choices were risk-averse for gains and risk-seeking for losses (gain/loss frame $\beta = -1.3200$, CI = [-1.4430 – -1.1969], $p < 0.001$; see Table S12 and Figure 5B). We next examined if pandemic-related worry predicted risk preferences, finding that FCQ did not relate to individuals’ overall risk-taking (FCQ main effect; $\beta = -0.0450$, CI [-0.1250, 0.0350], $p = .270$; see Table S12), nor susceptibility to the framing effect (FCQ x Frame interaction; $\beta = 0.0226$, CI = [-0.0977, 0.1429], $p = 0.713$; see Table S12). Participants were also sensitive to described risk level (Frame x Probability interaction $\beta = 0.2560$, CI = [0.1744, 0.3375], $p < 0.001$; see Figure 2C), in accordance with the ‘Fourfold pattern’ of risk preferences: choices were relatively more risk-seeking in situations of unlikely gains and likely losses compared to situations of likely gains and unlikely losses (Tversky & Kahneman, 1992). This pattern of preference is thought to arise from the underweighting of likely probabilities and overweighting of unlikely probabilities. Individuals reporting greater pandemic-related worry appeared more sensitive to described risk level (Figure 5D): FCQ scores predicted participants’ tendency to exhibit this fourfold pattern in choice (visualized more continuously in Figure 5E) as indicated by a significant three-way interaction between frame, outcome probability and worry ($\beta = 0.1720$, CI = [0.0929, 0.2511], $p < 0.001$; see Table S12).

Comparing the 2019 pre-pandemic sample, to the pandemic samples, we observed a decrease in overall risk-taking (Sample main effect $\beta = -0.3490$, CI = [-0.6417, -0.0563], $p = .019$; see Table S13) and a decrease in sensitivity to gain/loss framing (Frame x Sample interaction $\beta = 0.7465$, CI = [0.3242, 1.1688], $p = .001$; see Table S13) after controlling for age and gender. Participants in the pandemic sample, compared to the pre-pandemic sample, also exhibited increased sensitivity to described risk level, i.e. greater expression of the fourfold pattern described above (Figure 5C), which was supported statistically by an interaction between frame, outcome probability, and sample (baseline versus pandemic; $\beta = 0.4723$, CI = [0.1925, 0.7522], $p = .001$, see Table S13). We did not observe an effect of pandemic progression on overall risk preferences (linear effect of wave $\beta = -0.0884$, CI = [-0.1819, 0.0123], $p = .085$), but we did find that overall sensitivity to the gain/loss decision frame decreased as a function of wave (linear effect of wave x Frame interaction $\beta = 0.1949$, CI = [0.0440, 0.3458], $p = .011$)—participants in the third wave were found to be less sensitive to decision frame when compared to the first wave (Wave x Frame interaction $\beta = 0.4281$, CI = [0.1256 – 0.7306], $p = .006$; see Table S14). We also found participants in the third wave showed greater expression of the fourfold pattern in comparison to the first wave (Wave x Frame x Probability interaction $\beta = 0.6322$, CI = [0.4278 – 0.8366], $p < .001$, see Table S14). In summary, we found that both pandemic-related worry and pandemic progression were associated with a greater sensitivity to described risk level, but only pandemic progression impacted framing effects.

Discussion

Here, we sought to delineate the cognitive and behavioural consequences of the COVID-19 global pandemic in a representative US sample. Consistent with our predictions, we observed a marked decrease in individual's executive functioning as a function of individual differences in experienced fear/worry. Together, the results outlined above buttress previously observed anxiety-induced impairments in executive functioning (Fales et al., 2008; Moran, 2016; Yang et al., 2018), and extend this literature by replicating declining performance in response to the threats posed by the COVID-19 pandemic (Fitzpatrick et al., 2020; Heffner et al., 2020)—a naturalistic stressor.

Pervious accounts of anxiety posit that excessive worrying impairs executive functioning by displacing the cognitive resources (i.e., working memory) necessary for successful goal-directed control (Eysenck et al., 2007). Supporting this view, we found higher levels of pandemic-related worry predicted impairments in proactive cognitive control and the speed of information processing but not task-switching ability. We believe that this uneven effect of worry across cognitive tasks reflects the extent to which each task relies on working memory resources. On this view, we found that self-reported coronavirus anxiety measured by FCQ, hindered the use of goal-driven (i.e. proactive) control (Krug & Carter, 2012; Lamm et al., 2013; Yang et al., 2018)—which is thought to rely more strongly on working-memory capacity than reactive control (Braver, 2012; Burgess & Braver, 2010). Similarly, declines in processing speed are thought to reflect both the slowing of basic mental operations, and limitations to the amount of simultaneously available information (Kail & Salthouse, 1994). Surprisingly, we failed to find a relationship between pandemic worry and task-switching. However, the effects negative affective states on task-switching ability has revealed mixed findings (Plessow et al., 2012, 2011). Perhaps working-memory demands play a key role in anxiety-induced impairments in set shifting ability, as both

task complexity (Derakshan et al., 2009), and response preparation (Steinhauser et al., 2007) have been found to mediate these effects. Together, these results highlight how executive functioning reflects a related, yet distinct set of cognitive abilities (Miyake et al., 2000), and suggest that the effects of worry are not commensurate across domains.

Whether poorer cognitive control is a function of, or a consequence of anxiety remains unclear, as previous work suggests that worrying interferes with cognitive ability (Beckwé et al., 2014), and that lower cognitive ability contributes to worrying through an inability to inhibit negative thoughts (De Lissnyder et al., 2012). Furthermore, other work has proposed that engaging in demanding cognitive tasks can reduce anxiety (Balderston et al., 2016; Vytal et al., 2012), highlighting the hypothesized shared resources between worrying and goal-directed behaviour. Critically, as anxiety-induced deficits in task performance were not general, we believe it is unlikely that our results are exclusively explained by effort-induced reductions in anxiety. However, future work is needed to disentangle these possibilities.

In the context of a pandemic, individuals' risk assessments are equally crucial as they predict compliance with social-distancing measures (Wise et al., 2020). Extant accounts suggest that anxiety shapes decision-making via an increased tendency to interpret uncertain information more negatively, though there are some inconsistencies (Hartley & Phelps, 2012). Anxious individuals are thought to overestimate the likelihood of negative outcomes (Butler & Mathews, 1987; Eysenck & Derakshan, 1997; MacLeod et al., 1991), leading to greater risk aversion (Clark et al., 2012; Maner et al., 2007; Robinson et al., 2013). However, we failed to find any evidence that greater worry was associated with risk aversion, nor loss aversion. Instead, we found that pandemic worry predicted individuals' tendency to distort described risk levels: underweighting likely probabilities and overweighting unlikely probabilities regardless of valence (Tversky &

Kahneman, 1992). Perhaps, this disparity across studies in the observed effect of anxiety on choice reflects the use of different strategies to manage risk and/or worry (Starcke & Brand, 2012).

One possible explanation for anxious individuals' greater sensitivity to described risk is an increase in information seeking, resulting in greater exposure to discussions of risk, which are the current focus of media coverage. On this view, intolerance of uncertainty has been associated both with greater pandemic worry (Mertens, Duijndam, et al., 2020), and greater information seeking—particularly when the uncertainty is related to one's health (Norr et al., 2015; Rosen & Knäuper, 2009). Indeed, among individuals experiencing elevated levels of anxiety, there have been increases in searches for pandemic-related information (Chao et al., 2020). While the risk attitudes measured here were unrelated to one's health, we believe this increased contemplation of risks, particularly for those experiencing anxiety, reflects an overall greater saliency of described risks on behaviour.

Beyond anxiety, we also probed whether the pandemic had an effect on task performance, finding that, in comparison to our pre-pandemic samples, those tested during the pandemic exhibited slower processing speed (Kail & Salthouse, 1994; Mathias et al., 2017; Salthouse, 1985), decreased task-switching accuracy (Monsell, 2003; Otto & Daw, 2019), less proactive control (Braver et al., 2009; Gonthier et al., 2016), and greater sensitivity to described risk (Tversky & Kahneman, 1992). We further probed the effect of longer exposure to the stressor i.e., pandemic progression, controlling for anxiety, financial and overall stress. While proactive control remained stable, we found that participants in the third wave, compared to the first, had slower processing speed, lower task-switching accuracy, and were more sensitive to risk. We can only speculate as to the mechanisms underlying the decline in cognitive performance across this 2-month period in the early stages of the pandemic. In keeping with other research (Cunningham et al., (in press);

Mertens, Duijndam, et al., 2020), we observed a decline in pandemic worry whereas task performance remained largely impaired—suggesting there may be factors contributing to impaired executive functioning. Of note, despite controlling for possible demographic differences between samples (e.g., age, gender, years on AMT; see Supplemental Materials), we cannot rule out the possibility that our groups (collected in years prior to the pandemic) sampled different populations, as the pandemic was associated with a marked increase in financial hardships and remote work.

We believe the results outlined here have broader implications for human behaviour, as intact executive control is cornerstone to healthy daily living (e.g., economic productivity), workplace performance (Schilbach et al., 2016), and the delay of gratification. Indeed, recent work has observed a positive relationship between working-memory, and one’s decision to comply with government sanctioned social-distancing directives (Xie et al., 2020). However, given the putative role of coronavirus anxiety in successful goal-directed behaviour observed here, it is likely that individual worry serves as a crucial mediator. Given the declining adherence to government directives and the far-from-universal acceptance of vaccination (Crane et al., 2021; Lazarus et al., 2021), more work is needed to understand the factors underlying adaptive behaviour and decision-making in order to mitigate the effects of the pandemic. More broadly, these results highlight the importance of considering the individual (i.e., worry) and the circumstantial (i.e., the pandemic) factors outside experimental control which may contribute to measured behaviour—hereafter it may be unreasonable to assume that human participants enter experiments in a neutral state (Goldfarb, 2020). Going forward, we believe that future research should consider these individual differences when interpreting any behaviour relying on executive functioning—particularly for research conducted during and immediately following the pandemic.

Materials and Methods

Participants

We recruited three samples of 509, 501 and 507 human participants residing in the US for waves 1 (April 2nd, 3rd & 6th) 2 (April 17th, 20th -23rd) and 3 (June 19th, 22nd) respectively (1517 total), via Mechanical Turk (Crump et al., 2013). Participants provided informed consent and were paid \$5 USD for completing the task battery. Our experimental protocol was approved by the McGill Research Ethics Board. We employed several exclusion criteria on a task-by-task basis to ensure the quality of the data collected (see Supplemental Material). Crucially, exclusion from our sample was not found to covary with the key variable of interest—pandemic worry (see Supplemental Results). Given the cross-sectional design of the study, it is essential to establish that the samples recruited are comparable in terms of demographic variables. To determine the similarity of the samples, we compared the three recruited samples both to each other and to the collapsed pre-pandemic samples on several demographic variables (see Supplemental Materials S15-S16). Overall, participants had comparable ages across waves 1 ($M_{\text{age}} = 36.2$, $SD_{\text{age}}=9.87$), 2 ($M_{\text{age}} = 36.5$, $SD_{\text{age}}=10.4$), and 3 ($M_{\text{age}} = 36.6$, $SD_{\text{age}}=10.4$), and in comparison to the collapsed baseline sample ($M_{\text{age}} = 37.8$, $SD_{\text{age}}=14.6$, $F_{(3, 1753)}=1.655$, $p = 0.175$). In terms of reported gender, the third wave (females= 138, males=327, other=0) contained proportionally more male participants than the first wave (females= 172, males=275, other=4), second wave (females= 166, males=287, other=2), and collapsed baseline sample (females= 164, males=224, other=4).

Procedure and Materials

To assess the extent of the COVID-19 pandemic's impact on individuals' cognitive functioning and behaviour, we asked participants to complete a battery of 4 different tasks in a counterbalanced order.

Digit-Symbol Coding Task

To measure processing speed, participants were asked to complete a computerized version of the Digit-Symbol Coding task (Mathias et al., 2017; Salthouse, 1985). During this task, participants are shown a static list of 9 digit-symbol pairs at the top of screen (see Figure 2A). On each trial, participants are asked to respond whether the digit-symbol pair presented in the centre of the screen matches one of the 9 pairs depicted at the top of the screen. Responses were made using the left and right arrow keys, with the response-key mappings counterbalanced between participants. Following prior work (Mathias et al., 2017), participants were asked to respond correctly to as many trials as they could within 90 seconds. We asked participants who did not achieve 70% accuracy to complete the task a second time and analyzed data from the last run only. Data was compared to a pre-pandemic sample, previously collected in the lab (da Silva Castanheira & Otto, submitted).

Task-Switching Paradigm

To measure task-set shifting ability, we asked participants to complete a task switching paradigm (Monsell, 2003; Otto & Daw, 2019) in which participants were shown a square either on the top or bottom half of the screen (see Figure 3A). Depending on the position of the square, participants were asked to indicate the colour (i.e. orange or blue) or the pattern of the box (i.e. solid or striped) using either the 'E' or 'I' buttons on the keyboard (e.g. blue = "E", orange = "I"; solid = "E", striped= "I") within the 1500ms time limit. Critically, both the position-task mappings, and the key-response mappings were counterbalanced between participants. Participants completed 80 task-switching trials, in which half switched between subtasks and the other half repeated the previous subtask. These data were compared to the "preliminary phase" data of previously collected data in the lab (Otto & Vassena, 2020).

Dot Pattern Expectancy task (DPX)

We assessed proactive cognitive control by using the DPX dot-pattern expectancy task (MacDonald, 2008). During this task, participants were first shown a dot pattern which served as the cue for 500ms, followed by a fixation cross for 2000ms (the delay period), and finally the probe stimulus for 500ms. Participants were instructed to respond using the “1” key when presented the “target” cue-probe pair—which we refer to as the AX trial—and respond with the “2” key with all other non-target combinations—AY, BX, BY. Participants completed a total of 128 trials, where the majority were target trials (AX, 68.75%), to establish the prepotency of the “target” response. The remaining trials were equally distributed among the three other trial types (BX, BY, AY). Using participant’s RTs, we calculated the proactive behavioural index (Braver et al., 2009) (PBI) which reflects the relative inference on AY and BX trials—calculated as $(RT_{AY} - RT_{BX}) / (RT_{AY} + RT_{BX})$, where a larger PBI reflect more utilization of cue-based contextual information (and less probe-driven behavior) (Braver et al., 2009; Gonthier et al., 2016). Note that our baseline DPX sample (Otto et al., 2015) lacked self-reported age or gender, and accordingly these variables they were not included in the linear model comparing across baseline and pandemic samples.

Risky Decision-Making Task

Participants’ risk preferences were assessed using a simple risky decision-making task in which they were presented with 120 binary choices and 5 practice trials between a risky and a certain option. For half of the choices, options were framed as losses (i.e., either -\$200 or -\$100) and the remaining half were framed as gains (i.e., either \$200 or \$100). All risky options were associated with both a chance of winning (or losing) a non-zero amount of hypothetical money

and a chance of winning (or losing) nothing at all. For the risky options, the probability of the non-zero outcome varied between likely (0.90, 0.95 or 0.99) or unlikely (0.10, 0.05, 0.01) outcomes (Tversky & Kahneman, 1992). All choices were between options of equal expected value (EV), except for fifteen “catch” trials in which the expected value greatly favored an option (expected value = +/- 90), ensuring that participants understood the task (see Table S11 for full list of stimuli used). Participants were asked to select an option within a 2500ms limit by responding with either the left or right arrow key. Data was compared to a pre-pandemic sample, previously collected in the lab, where participants completed the same risky decision-making task under two deadlines (2500ms and 3500ms) (da Silva Castanheira & Otto, submitted).

Questionnaires

First participants completed all four behavioural tasks in a counterbalanced order, then the PSS, FSS, and the FCQ questionnaire in a randomized order. Finally, participants were asked to complete a final questionnaire assessing demographic variables and rated their ability to focus.

Fear of Coronavirus Questionnaire – (FCQ)–To assess anxiety related to the pandemic, we administered an 8-item questionnaire assessing beliefs and behaviours relating to the COVID-19 pandemic (Mertens, Gerritsen, et al., 2020). Participants were asked to rate on a 5-point scale, the extent to which they endorsed statements relating to fear of the virus (e.g. “I am very worried about the corona virus outbreak.”) or engaging in certain behaviours (e.g. “I am constantly following all news updates regarding the virus.”). Scores on this questionnaire ranged from 8 to 40, where larger numbers reflect greater fear.

Perceived Stress Scale – The Perceived Stress Scale is a 10-item instrument which measures an individual’s perceived level of stress over the last month (S. Cohen et al., 1994). Participants were asked to rate how often they felt overwhelmed (e.g. “In the last month, how often have you felt

nervous and ‘stressed’?)” or in control (e.g. “In the last month, how often have you felt that you were on top of things?”) on a scale from 1 “very often” to 5 “never”. Responses to the negatively framed questions were reversed-scored, such that larger scores reflect more stress, and range from 10 to 50.

Financial Strain Scale (FSS) – We used a 3-item measure of financial strain which asks participants to rate, on a 5 point scale, how much they endorse statements conveying financial hardships (e.g., “in the next two months, how much do you anticipate that you or your family will experience actual hardships such as inadequate housing, food, or medical attention?”) (Vinokur et al., 1996). Scores ranged from 3 to 15, where larger numbers reflect more strain.

Self-reported ability to focus – At the end of the cognitive tasks, participants were asked to rate their ability to focus during the experiment using a 9-item scale which assessed the degree of understanding (e.g., “all instructions were clear”), motivation (e.g., “I did my best on the task at hand”), and distraction (e.g., “I was distracted during the experiment”)(Zwaan et al., 2018). Ratings were taken on a 11-point scale, resulting in a range of possible scores from 0 to 90, where lower scores reflect less focus.

Demographic Variables – In addition to the above measures, participants were asked to indicate several demographic variables to be included as covariates in the regressions. We asked participants to indicate their age, gender, highest level of education achieved, their household income, and the number of adults and children currently living with them. Additionally, we asked participants to specify if English was their first language, and if not, what age did they first start learning English. To account for the possibility that the pandemic could have attracted new people to Mturk, we asked participants to indicate how long have they been a worker on Mturk. Finally, participants were asked to indicate if they felt sick with any COVID-19 symptoms and to determine

if they believed themselves to be at an elevated risk of contracting a more severe case of COVID-19.

Data Analysis

We evaluated whether the individual measures of stress and anxiety varied as a function of pandemic progression (i.e., between waves) using simple linear regressions. Next, we ran separate linear (logistic) mixed-effect models for each task to assess the extent to which response-times (response accuracy) related to the pandemic worry, controlling for various covariates (see Supplemental Methods). We also ran separate linear (logistic) mixed-effect models for each task comparing all the pandemic samples collapsed, to the pre-pandemic sample with a dummy coded variable (i.e. Pre-Pandemic: 0 vs Pandemic: 1). For the multi-level models, we included the within-participant variables as both random and fixed effects (i.e. task switch, response congruency, decision frame, outcome probability). All analyses were conducted using the *lme4* package (version 1.1-21) for the R programming language

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Figures and Tables

Figure 1: Summary of participant responses across waves of data collection. **A.** Map of the U.S. depicting the distribution of participants collected during the three samples. **B.** Correlation between the number of responses per state and the state population. **C.** Participants reported moderate levels of overall perceived stress which did not vary as a function of ($\beta = -0.321$, $CI = -0.841 — 0.198$, $p = .255$); plotted here with 95% bootstrapped confidence intervals. **D.** Mean self-reported financial strain also decreased with pandemic progression (wave $\beta = -0.232$, $CI = -0.457 — -0.007$, $p = .042$); again, plotted with 95% bootstrapped confidence intervals. **E.** Mean self-reported coronavirus fear/worry (FCQ) decreased as a function of wave ($\beta = -1.188$, $CI = -1.64 — -0.733$, $p < .001$); again plotted with 95% bootstrapped confidence intervals.

Figure 2: Participants' performance on the digit-symbol coding task. **A.** Screenshot of the Digit symbol-coding task. **B.** We observed a relationship between FCQ scores and Digit Symbol-Score ($\beta = -0.940$, $CI = [-1.591, -0.289]$, $p = .005$); here plotted with the marginal distribution of the ordinate and abscissa. **C.** We also observed a relationship between FCQ scores and log correct RTs ($\beta = 0.019$, $CI = [0.005, 0.033]$, $p = .009$); again plotted with the marginal distribution of the ordinate and abscissa. **D.** Processing Speed decreased in comparison to the pre-pandemic sample and by wave (p 's $< .05$); here plotted by wave with 95% bootstrapped confidence interval. **E.** Participants' response times increased in comparison to the pre-pandemic sample and by wave (p 's $< .05$); again, plotted here with 95% bootstrapped confidence intervals.

Figure 3: Participants' performance on the Task-Switching paradigm. *A.* Schematic of task-switching paradigm. *B.* Accuracy (top; p 's < .05) but not response-times (bottom) decreased by wave (p 's $\geq$.05); variables plotted with 95% bootstrapped confidence interval. *C.* There was no relationship observed between FCQ scores and switch costs expressed in RT ($\beta = -0.0005$, $CI = [-0.0142, 0.0132]$, $p = .946$); here, plotted with marginal distributions for the ordinate and abscissa and *D.* There was no relationship observed between FCQ scores and switch trial accuracy ($\beta = -0.0385$, $CI = [-0.0865, 0.0096]$, $p = .117$); again plotted with marginal distributions plotted for the ordinate and abscissa.

Figure 4: Participants' performance on the Dot Pattern Expectancy task. **A.** Schematic of the dot pattern expectancy task. **B.** We observed a negative relationship between FCQ scores PBI ($\beta = -0.0020$, $CI = [-0.0034, -0.0005]$, $p = .010$); here plotted with marginal distributions plotted for the ordinate and abscissa. **C.** We observed a negative relationship between perceived stress scores and PBI ($\beta = -0.0108$, $CI = [-0.0200 - -0.0015]$, $p = .023$); again, plotted with marginal distributions plotted for the ordinate and abscissa. **D.** Proactive behavioural index (PBI) decreased in comparison to the pre-pandemic sample ($\beta = -0.0353$, $CI = [-0.0674, -0.0032]$, $p = .031$) but not with pandemic progression (p 's $> .20$); error bars represent the 95% bootstrap confidence interval. **E.** Overall accuracy was not found to decrease as a function of pandemic progression ($p > .05$).

Figure 5: Participants' performance on the risky decision-making task. *A.* Schematic of the economic decision-making task used to assess risk preferences. *B.* Overall, participants were loss averse, as demonstrated by their sensitivity to the framing of problems as either losses or gains ($\beta = -1.3200$, $CI = [-1.4430, -1.1969]$, $p < .001$) which also varied as a function of pandemic wave ($\beta = 0.1949$, $CI = [0.0440, 0.3458]$, $p = .011$). *C.* Average proportion of risky choice by frame, outcome probability and sample. Participants in the third wave, compared to the first and the pre-pandemic sample, were more likely to distort outcome probability ($p \leq .001$). *D.* Average proportion of risky choice by frame, outcome probability and fear of coronavirus questionnaire (FCQ) scores median split. *E.* We observed a positive relationship between fear of coronavirus and one's tendency to distort outcome probability ($\beta = 0.1720$, $CI = [0.0929, 0.2511]$, $p < 0.001$)—indexed as the magnitude of the fourfold pattern ($(P(risky))_{Likely Losses} -$

$P(risky)_{Unlikely\ Losses}) + (P(risky)_{Unlikely\ Losses} - P(risky)_{Likely\ Gains}))$; plotted here with marginal distributions plotted for the ordinate and abscissa.