

Original quantitative research

A person-centred approach to COVID-19 pandemic-related stressors

Ann-Renee Blais, PhD; Ève-Marie Blouin Hudon, PhD; Matthew Lymburner, MA

This article has been peer reviewed.

(Published online May 11, 2022)

 [Tweet this article](#)

Abstract

Introduction: The COVID-19 pandemic and resultant containment effects has had a detrimental effect on individuals' social, occupational and financial circumstances. Taking a person-centred approach to inquiry and data analysis, we sought to identify classes (or segments) of employees with distinct configurations of responses across several pandemic-related stressors. We also investigated purported risk and resilience factors of membership in these classes.

Methods: We analyzed data from 4277 employees who completed a pulse survey in August 2020, using latent class analysis to identify classes of employees with unique patterns of responses across six pandemic-related stressors. We also conducted a multinomial logistic regression analysis to explore the associations between several risk and resilience factors (e.g. age, gender, perceived organizational support) and class membership, and we compared the emergent classes' levels of self-reported mental health.

Results: The data revealed four unique classes of employees: "adapting," "conflicted," "insecure" and "stressed" (30%, 35%, 21% and 14% of the sample, respectively). All of the risk and resilience factors were associated with being in the adapting class versus the other classes. The adapting employees also showed the most positive self-reported mental health relative to their counterparts.

Conclusion: By identifying classes of employees with distinct configurations of pandemic-related stressors, as well as differential risk factors and levels of self-reported mental health, the present study offers a starting point for informing work-related interventions with the goal of helping employees most vulnerable to pandemic-related stressors effectively cope with these stressors.

Keywords: *latent class analysis, mental health, risk factors, resilience, perceived organizational support, adapting, stress*

Introduction

The COVID-19 pandemic has had a pivotal impact on individuals, organizations and governments around the world.^{1,2} Many individuals had to quickly transition to a fully remote work environment, with little time to adapt to the new tools and processes of their work, all while learning to navigate an entirely novel social landscape.³ Arguably, increased demands in

both personal and professional domains likely had a largely negative influence on working individuals' psychological health and safety related to work.

In the Canadian population, anxiety has quadrupled and depression more than doubled since the onset of the pandemic.⁴ Furthermore, one-third of Canadians with depression and anxiety have reported an increase in alcohol and cannabis use

Highlights

- Only 30% of employees reported low levels of stress in response to six pandemic-related stressors, whereas 70% reported at least moderate levels of stress in response to one or more of these stressors.
- Several risk factors (i.e. being younger, being a woman, being a visible minority) were related to employee's responses to stressors.
- Conversely, perceived organizational support emerged as a reliable promotive factor that appears to counteract exposure to risk.
- These results can help guide work-related interventions to support employees most vulnerable to pandemic-related stressors cope with these stressors and improve their mental health.

during this time.⁴ These findings demonstrate that the pandemic is likely to have lasting effects on Canadians' mental health. As for working professionals, literature reviews of the impact of COVID-19 on employee mental health have revealed that main pandemic-related stressors include self-threat (defined as threat to one's well-being), financial insecurity, occupational insecurity, social isolation and work-life imbalance.^{1,5-8}

Risk factors: socioeconomic and sociocultural considerations

Although these findings demonstrate a clear need for organizations to support

Author reference:

Statistics Canada, Ottawa, Ontario, Canada

Correspondence: Ann-Renee Blais, Statistics Canada, R.H. Coats Building, 100 Tunney's Pasture Driveway, Ottawa, ON K1A 0T6; Tel: 613-799-0921; Email: ann-renee.blais@statcan.gc.ca

their employees in coping with the realities (and aftermath) of the pandemic, COVID-19 stressors may not affect all employees in the same way.^{9,10} In order for organizations to successfully support a diverse workforce, it is important to explore how these stressors relate to the sociocultural and socioeconomic (e.g. employment equity groups, age, income, job characteristics) implications of the pandemic.⁸ For example, longitudinal studies examining the mental health impact of stressors during the pandemic in a North American context showed that, relative to their older counterparts, younger adults are more likely to develop psychological distress, depressive symptoms and negative health behaviours, as well as to suffer financial impacts (perhaps in part because of their greater likelihood of working precarious jobs).^{8,11,12}

Recent studies have also found that, compared to men, women report increased family demands and work–family conflict, job loss, depression and psychological distress as a result of the pandemic.^{8,11,12} Furthermore, sharing a household with a larger number of dependents is related to poorer mental health—and this is especially true for women.¹³ Similarly, visible minorities expressed greater socioeconomic concerns relative to their White counterparts.^{11,14,15} Finally, persons living with a disability experience greater financial insecurity, loneliness, fear of contracting COVID-19 and sleep disturbances as well as decreased feelings of belonging and overall mental health than their counterparts without disabilities.^{16–18}

Resilience factor: perceived organizational support

Resilience factors can have direct positive effects on mental health, independently of the levels of exposure to risk factors such as the socioeconomic and sociocultural characteristics described above, or they can buffer the negative effects of these risk factors on mental health.¹⁹ In particular, research has shown that perceived organizational support, defined as employees' perceptions that their employer cares for their well-being and recognizes their contributions,^{20,21} is one of the most consistent resilience factors among working professionals.^{2,5,22–29} Organizations can bolster these perceptions by, for instance, providing their employees with resources to cope with work-related demands.^{25,30} Research has also demonstrated that

perceived organizational support constitutes a protective factor for burnout,^{25,31} and that it is positively associated with performance and negatively associated with absenteeism and turnover.^{20,27,32}

Research questions

The potential associations of risk and resilience factors with COVID-19-related stressors, and the relationships between these stressors and employee mental health are unclear. The situation is still evolving, and the long-term or sustained psychological effects of the current crisis remain unknown. To gain a more precise understanding of these phenomena, we first sought to identify configurations, or patterns, of responses across several COVID-related stressors through a person-centred strategy. Then, we examined the relationships between these nascent configurations of responses, the risk and resilience factors, and self-reported mental health. To our knowledge, this study is the first to apply a person-centred lens to pandemic-related stressors in general and in a work setting more specifically.

Marketing researchers often use person-centred techniques to reduce several variables to a few easily interpretable classes, or segments, of individuals.³³ Of these techniques (e.g. median split, cluster analysis), methodologists have identified latent class analysis as the most flexible and, arguably, the most psychometrically robust.³⁴ Examining the complex interplay of multiple stressors in an organization can offer a more detailed picture of the environment than that afforded by studying these dimensions in isolation.^{35,36} Not only are employee classes easy to communicate to managers, through the use of personas, for example,³⁷ but they can also guide the development of differential intervention strategies targeting specific subgroups.³⁸ In turn, matching appropriate strategies to the different employee segments or dedicating resources to the most exposed subgroups will likely yield the greatest benefit to both employees and the organization.³⁹

In summary, we posed the following research questions:

1. How many distinct configurations of pandemic-related stressors exist for employees, and what form do they take?

2. Are the aforementioned risk and resilience factors related to membership in these emergent employee classes?
3. Do the employee classes differ in their levels of self-reported mental health?

Methods

Participants

We conducted secondary analyses on data collected via a pulse survey on COVID-19 and its impacts on the work and well-being in a public service organization. This medium-to-large-size organization, with a little less than 7500 employees at the time of data collection, is in the science and professional services domain of the public service. Employees are distributed across occupational groups and levels with pay and benefit structures commensurate with the work performed in the organization, from entry level to senior executive positions, and from clerical and general administrative positions to highly specialized technical positions.

The majority of the respondents worked at the organization's headquarters in Canada's National Capital Region (71.1%; 95% confidence interval [CI]: 69.7–72.4) and the remainder were scattered across the country. The respondents engaged in research and analytical activities, clerical and administrative activities, project and program management activities, and a variety of corporate services (such as human resources and finance). Many were economics and social science professionals (42.7%; 95% CI: 41.2–44.2). Almost all were teleworking at the time of the study (93.9%; 95% CI: 93.1–94.6).

Data collection

The survey covered topics such as employee engagement, leadership, workforce, workplace, compensation and workplace well-being. Data collection took place from 10 to 28 August 2020. The data were collected anonymously, with access to the electronic survey made available to all staff via email; the response rate was approximately 57%, for a total of 4277 respondents.

In an attempt to reduce sampling bias,⁴⁰ the collected data were benchmarked to known population totals. We applied this benchmark factor to all subsequent analyses.

Measures

Pandemic-related stressors

We focussed on six pandemic-related stressors, each assessed with a single survey item beginning with the stem “Thinking of right now, to what extent do the following factors cause you stress?” These stressors were “being sick”; “financial hardships”; “lack of job security”; “impact on my workload”; “being isolated from my family and friends;” and “balancing work and personal life.” Respondents rated all items on 5-point scales from 1 (“Not at all”) to 5 (“To a very large extent”).

Risk and resilience factors

We selected the following risk factors for analysis in the present study: a younger age (we included age as a continuous variable in the multinomial logistic regression analysis; see Table 1); a larger household size (also a continuous variable and a proxy for a larger number of dependents in the household; with a median of 3, ranging from 1 to 20); self-identifying as female, a visible minority or living with a disability (all binary variables recoded as 1 [“yes”] or 0 [“no”]); and employment status (also a binary variable recoded as 1 [“contract”] or 0 [“indeterminate”]).

We included having a supervisory role (another binary variable recoded as 1 [“yes”] or 0 [“no”]) for exploratory purposes because the relationship between having a supervisory role and pandemic-related stressors was unclear.

We assessed perceived organizational support by averaging respondents’ ratings across three items: “My department or agency regularly shares accurate information with employees about COVID-19 and its impact on the organization”; “I have the materials and equipment I need to do my job;” and “My department or agency shares support services, resources, and information on mental health such as the Employee Assistance Program regularly, and encourages employees to get help if they need it” (4.31; 95% CI: 4.29–4.33; $\alpha = 0.62$). Respondents rated these items on 5-point scales from 1 (“Strongly agree”) to 5 (“Strongly disagree”; reverse coded).

Self-reported mental health

We created a self-reported mental health score by averaging respondents’ ratings across three items: “In general, how is

TABLE 1
Characteristics of survey sample^a

Characteristic	%	95% CI
Age group (years)		
≤ 24	3.14	2.66–3.71
25–29	9.52	8.65–10.45
30–34	8.64	7.80–9.55
35–39	12.95	11.94–14.03
40–44	14.88	13.80–16.02
45–49	15.33	14.23–16.50
50–54	15.46	14.35–16.64
55–59	10.49	9.56–11.50
≥ 60	9.60	8.70–10.58
Gender^b		
Female	57.73	56.19–59.25
Male	42.27	40.75–43.81
Living with a disability		
Yes	6.92	6.17–7.76
No	93.08	92.24–93.83
Visible minority		
Yes	19.34	18.15–20.58
No	80.66	79.42–81.85
Contract employee		
Yes	13.73	12.70–14.83
No	86.27	85.17–87.30
Non-supervisory role		
Yes	66.65	65.20–68.07
No	33.35	31.93–34.80

^a The collected data were benchmarked to known population totals.

^b The survey questionnaire asked for respondents’ gender, with the response options being “female” or “male.”

your mental health?”; “Compared to the pre-COVID period, how has your mental health been affected?”; and “Overall, my level of work-related stress is...” (3.02; 95% CI: 2.99–3.04; $\alpha = 0.71$). Respondents rated these items (reverse coded where necessary) on 5-point scales from 1 (e.g. “Poor”) to 5 (e.g. “Excellent”).

Analytical approach

Stressor classes

We estimated latent class solutions including one to eight classes with Mplus software version 7.4 (Muthen & Muthen, Los Angeles, CA, US) by means of its robust maximum likelihood estimator and complex survey design functionalities to account for the benchmarking factor.^{41,42}

To handle the small amount of missing data present at the item level (mean = 7.8%; range: 1.4% to 14.2%), we relied on full information maximum likelihood,⁴³ the default option with maximum likelihood estimator in Mplus.⁴¹ Each model used 10 000 sets of starting values, with the best 500 sets retained for final stage optimization.⁴⁴

We used the Bayesian information criterion (BIC),⁴⁵ the sample-size adjusted BIC⁴⁶ and the consistent Akaike information criterion (CAIC)⁴⁷ as primary indicators of model fit, with lower values signifying a better fit to the data. For completeness, we also report the Akaike information criterion (AIC),⁴⁸ the adjusted

Lo–Mendell–Rubin likelihood ratio test (aLMR)⁴⁹ and the entropy, which ranges from 0 to 1, with a higher value reflecting a greater model classification accuracy.⁵⁰ The aLMR test provides a *p* value to compare models with a model with one less class.

To aid in interpretation and establish the gains in fit for each additional class estimated, we relied on a scree plot of the BIC, adjusted BIC and CAIC values, inspecting the point at which the slope of the plot flattens (Figure 1).⁵¹ Finally, we also paid attention to the parsimony and stability (i.e. including the relative sizes of the emergent classes) of the different solutions prior to choosing a final model.^{52,53}

Risk and resilience factors and self-reported mental health

We added the risk and resilience variables and the self-reported mental health score to the final model with the automatic three-step procedure and the R3STEP and BCH commands, respectively.⁵⁴ The R3STEP command uses multinomial logistic regression to evaluate if, for example, being a woman increases the likelihood of an employee belonging to one class relative to another class, whereas the BCH command tests the estimated mean differences between the classes on the self-reported mental health score. R3STEP and BCH analyses handle missing data via listwise

deletion (*n* = 3849) and full information maximum likelihood estimation (*n* = 4262), respectively.

Results

Stressor classes

For the BIC, the five-class solution exhibited the best fit compared to all other solutions, with the BIC reaching its lowest value at five classes (Table 2 and Figure 1). The adjusted BIC and CAIC, on the other end, attained their lowest value at seven and four classes, respectively. Because the four-class solution was associated with both the lowest CAIC value and the first non-significant aLMR test, and because the relative sizes of the emergent classes were all greater than 8%, we used it as the basis for further modelling.⁵³

Configurations of pandemic-related stressors and their forms

Employees in the “adapting” class, with a prevalence of 30%, had very low probabilities of choosing “to a large extent” or “to a very large extent” when evaluating the extent to which the pandemic-related stressors caused them stress (Table 3). In contrast, employees in the smallest class (“stressed,” making up 14% of the sample) had consistently moderate probabilities of endorsing “to a large extent” or “to

a very large extent” in reaction to the stressors.

The most frequent class of employees (“conflicted,” 35%) showed very low probabilities of selecting “to a large extent” or “to a very large extent” in response to self-threat, financial and job insecurity and workload, but a higher probability of these responses in reaction to work–life imbalance (with social isolation a close second). The third-largest class (“insecure”; 21%) had fairly low probabilities of choosing “to a large extent” or “to a very large extent” in response to five of the stressors, but a higher probability of selecting these options in reaction to job insecurity (with self-threat as a close second).

Risk and resilience factors

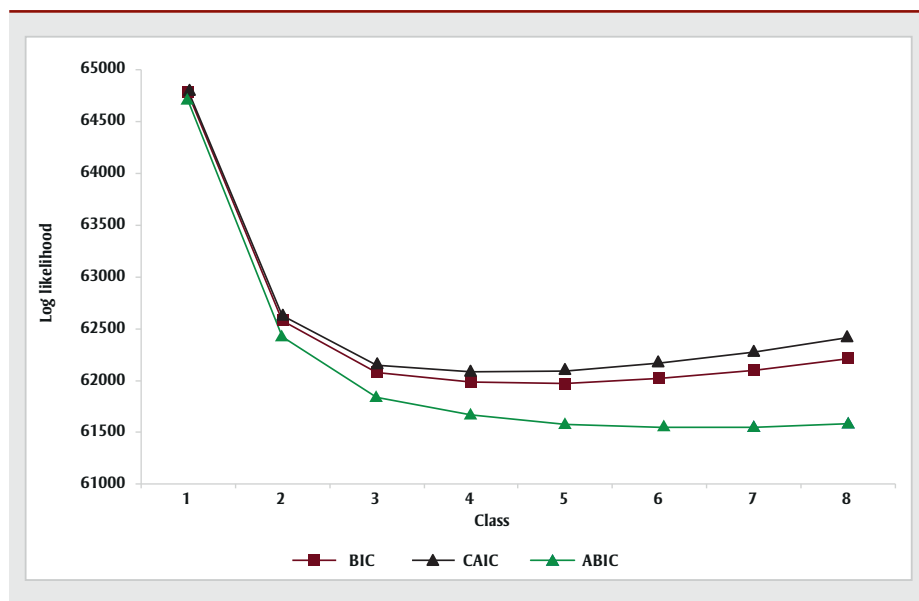
A logical target for workplace interventions would be to transition those employees who are most vulnerable to pandemic-related stressors (“stressed”) into the most favourable configuration of these stressors. To aid in interpretation, we used the adapting class as the referent (Table 4). In terms of the resilience factor specifically, lower perceived organizational support was related to belonging in the conflicted, insecure or stressed class relative to the adapting class (Table 4).

In terms of risk factors, women and supervisors were more likely to belong to the conflicted class than the adapting class, whereas the opposite was true for contract employees. Age was negatively associated with membership in the conflicted class compared to the adapting class.

Visible minorities, persons living with a disability and contract employees had a higher likelihood of belonging to the insecure class than the adapting class, whereas the opposite was true for supervisors. Age was positively associated with membership in the insecure class versus the adapting class.

Women, visible minorities, persons living with a disability and contract employees were more likely to belong to the stressed class than the adapting class. Age was negatively associated with belonging in the stressed class relative to the adapting class, whereas the opposite was true for household size.

FIGURE 1
Scree plot of the fit indices of the latent class analyses^a



Abbreviations: ABIC, adjusted BIC; BIC, Bayesian information criterion; CAIC, consistent Akaike information criterion.

^a The collected data were benchmarked to known population totals; after deleting cases with missing data on all variables, unweighted *n* = 4262.

TABLE 2
Latent class enumeration fit indicators^a

Number of classes	LL	FP	AIC	BIC	Adjusted BIC	CAIC	aLMR	Entropy
1	-32 290.139	24	64 628.279	64 780.858	64 704.596	64 804.858	–	–
2	-31 085.250	49	62 268.500	62 580.017	62 424.315	62 629.017	< 0.001	0.622
3	-30 728.692	74	61 605.384	62 075.839	61 840.697	62 149.839	< 0.001	0.636
4	-30 579.668	99	61 357.336	61 986.728	61 672.147	62 085.728	0.558	0.609
5	-30 467.652	124	61 183.303	61 971.632	61 577.612	62 095.632	0.591	0.604
6	-30 388.191	149	61 074.383	62 021.650	61 548.189	62 170.650	0.703	0.617
7	-30 323.355	174	60 994.711	62 100.915	61 548.015	62 274.915	0.764	0.637
8	-30 275.892	199	60 949.783	62 214.925	61 582.585	62 413.925	0.784	0.651

Abbreviations: AIC, Akaike information criterion; aLMR, adjusted Lo–Mendell–Rubin likelihood ratio test; BIC, Bayesian information criterion; CAIC, consistent Akaike information criterion; FP, free parameters; LL, log likelihood.

^a The collected data were benchmarked to known population totals; after deleting cases with missing data on all variables, unweighted n = 4262.

TABLE 3
Pandemic-related stressors and item-response probabilities^a

Latent class indicator	Item-response probability				
	Not at all	To a small extent	To a moderate extent	To a large extent	To a very large extent
Adapting class (30%)					
Self-threat	.845	.094	.037	.014	.010
Financial insecurity	.843	.111	.028	.015	.002
Job insecurity	.750	.146	.069	.013	.022
Workload	.814	.129	.042	.013	.003
Social isolation	.521	.325	.123	.031	.000
Work–life imbalance	.468	.277	.155	.058	.041
Conflicted class (35%)					
Self-threat	.489	.275	.138	.062	.036
Financial insecurity	.685	.240	.064	.011	.000
Job insecurity	.638	.280	.074	.008	.000
Workload	.434	.341	.169	.042	.013
Social isolation	.052	.369	.371	.133	.075
Work–life imbalance	.090	.325	.322	.169	.094
Insecure class (21%)					
Self-threat	.224	.354	.218	.145	.058
Financial insecurity	.117	.462	.296	.090	.035
Job insecurity	.000	.411	.318	.157	.114
Workload	.146	.445	.324	.079	.005
Social isolation	.110	.405	.322	.117	.046
Work–life imbalance	.095	.366	.384	.141	.014
Stressed class (14%)					
Self-threat	.373	.149	.136	.109	.233
Financial insecurity	.219	.208	.180	.142	.251
Job insecurity	.200	.151	.143	.136	.371
Workload	.193	.117	.221	.179	.289
Social isolation	.179	.151	.177	.231	.263
Work–life imbalance	.098	.089	.164	.191	.458

^a The collected data were benchmarked to known population totals; after deleting cases with missing data on all variables, unweighted n = 4262.

TABLE 4
Three-step results for risk and resilience covariates^{a,b}

Factor	Adapting vs. conflicted			Adapting vs. insecure			Adapting vs. stressed			Conflicted vs. insecure			Conflicted vs. stressed			Insecure vs. stressed		
	Coef.	SE	OR	Coef.	SE	OR	Coef.	SE	OR	Coef.	SE	OR	Coef.	SE	OR	Coef.	SE	OR
Age	-0.185***	0.037	0.831	0.060*	0.030	1.062	-0.146***	0.037	0.864	0.245***	0.037	1.278	0.039	0.036	1.040	-0.207***	0.038	0.813
Female gender ^c	0.305*	0.144	1.357	0.232	0.137	1.261	0.452*	0.174	1.571	-0.073	0.162	0.930	0.147	0.170	1.158	0.220	0.191	1.246
Living with a disability	0.651	0.339	1.917	0.723*	0.303	2.061	1.589***	0.318	4.899	0.072	0.321	1.075	0.939**	0.277	2.557	0.866**	0.303	2.377
Visible minority	-0.060	0.184	0.942	0.677***	0.158	1.968	0.585**	0.197	1.795	0.737***	0.201	2.090	0.645**	0.211	1.906	-0.092	0.211	0.912
No. of people in the household	-0.067	0.054	0.935	0.008	0.052	1.008	0.167**	0.063	1.182	0.075	0.060	1.078	0.234***	0.061	1.264	0.159*	0.068	1.172
Contract employee	-1.698***	0.368	0.183	0.712***	0.160	2.038	0.567*	0.227	1.763	2.410***	0.353	11.134	2.265***	0.363	9.631	-0.145	0.228	0.865
Non-supervisory role	-0.747***	0.152	0.474	0.880***	0.195	2.411	0.174	0.202	1.190	1.627***	0.220	5.089	0.921***	0.191	2.512	-0.706**	0.260	0.494
POS	-1.317***	0.198	0.268	-1.440***	0.172	0.237	-2.237***	0.200	0.107	-0.123	0.122	0.884	-0.921***	0.116	0.398	-0.797***	0.125	0.451

Abbreviations: Coef., coefficient; OR, odds ratio; POS, perceived organizational support; SE, standard error (of the coefficient).

^a The collected data were benchmarked to known population totals; after listwise deletion, unweighted n = 3848.

^b Coefficient (coef.) is the estimate from the R3STEP multinomial logistic regression analysis, which uses listwise deletion. The coefficient and OR reflect the effects of the covariates on the likelihood of membership into the second listed profile relative to the first listed profile.

^c The survey questionnaire asked for respondents' gender, with the response options being "female" or "male."

* p < 0.05.

** p < 0.01.

*** p < 0.001.

Self-reported mental health

Employees self-reported the most positive mental health when they belonged to the adapting class (mean [SE] = 3.734 [0.028]), followed by the conflicted (3.034 [0.035]), insecure (2.712 [0.028]) and stressed (2.197 [0.049]) classes (all at $p < 0.05$, based on a modified Bonferroni adjustment).

Discussion

The results of the present study shed light on the ways COVID-19-related stressors combine, particularly in a work setting. We identified four classes of employees from a medium-to-large public service organization, each with a distinct configuration of stressors. Adapting employees conveyed low probability of response to the six studied stressors, whereas stressed employees reported consistently high levels of stress in reaction to these stressors. Reinforcing the notion that the adapting class was the most resilient, employees in this class reported the most positive mental health of all employees. Two additional classes—the conflicted and insecure classes—highlighted the fact that one or two stressor(s) (i.e. work-family imbalance and job insecurity, respectively) can be a driving force(s) in the current COVID-19 crisis situation. Thus, the present study illustrates the advantages of taking a person-centred approach to exploring patterns of stressors in this context rather than looking at these stressors in isolation.

Perceived organizational support emerged as a reliable promotive factor for being in the adapting class compared to each of the other classes. Although we recognize that testing for the presence of buffering effects would be a valuable next step in future studies, at the very least this finding provides preliminary support for a compensatory model, that is, a process in which perceived organizational support appears to counteract exposure to risk.⁵⁵ This result also aligns with research findings on the direct effects of social support on post-disaster psychological distress.⁵⁶

The first class comparison identified being younger, a woman, a supervisor and a permanent employee as risk factors for membership in the conflicted class versus the adapting class. That supervisors were more likely to belong to the conflicted class than the adapting class is not surprising in light of the evidence linking job authority to work-related pressures and

strains in the work–family interface.⁵⁷ Future research could further explore these links.

The second comparison distinguished being a visible minority, living with a disability and being a contract employee as risk factors for membership in the insecure class compared to the adapting class, substantiating topical research recognizing these characteristics as risk factors for adverse pandemic-related outcomes.^{11,14–18} Being older and occupying a non-supervisory role also emerged as risk factors when comparing these groupings of employees, factors future research could delve into. For example, older employees may be rethinking their retirement as a result of the current COVID-19 crisis situation.⁵⁸

Last, being younger, a woman or a visible minority, living with a disability, having precarious employment and living in larger households all emerged as risk factors when comparing the stressed to the adapting employees. These results align with recent work identifying these socioeconomic and sociocultural characteristics as risk factors for detrimental outcomes during the ongoing COVID-19 pandemic.^{8,11–18}

Limitations and future directions

A drawback of the present study is that the findings rely exclusively on self-reported data and a cross-sectional design. This kind of study design makes it impossible to reach clear conclusions regarding the probable causal links between the risk and resilience factors, class membership and self-reported mental health. Future research would benefit from examining the directionality of these relationships through a longitudinal design. Furthermore, because consistency is an important criterion in evaluating the validity of classes emerging from person-centred research, future work should demonstrate that our nascent class structure remains consistent across samples drawn from the same population of employees.^{38,59} In addition, because our findings resulted from crowd-sourced data, they do not generalize to the entire population of employees. Nonetheless, given the large number of respondents, they should offer valuable insights on the employees' attitudes and perceptions.

Another limitation of the present study lies in its limited investigation of the notion of work-related social support.

Sources of support can include an employee's organization, but it can also comprise their supervisor or co-workers.⁶⁰ Research has identified different types of support (i.e. emotional, instrumental, appraisal and informational),⁶¹ a dimension we were unable to explore in this study because the survey items pertaining to perceived organizational support only reflected instrumental and informational forms of support. Future research could investigate whether certain types of organizational support are most beneficial in lessening specific kinds of stressors among employees. For instance, Cutrona and Russell⁶² identified emotional support as one of the best predictors of positive outcomes in the context of uncontrollable events.

Future work could also give meaningful consideration to supervisor mental health, an area of inquiry that remains largely unexplored.⁶³ Supervisors are not impervious to mental health problems,⁶⁴ and there are several reasons (e.g. cognitive complexity, responsibility, social isolation and loneliness) why high-quality leadership might come at a high cost.⁶³ Future research could explore how supervisors experience stressors such as work–life imbalance in order to inform workplace interventions tailored to their specific needs.

Practical implications

Organizational policies and interventions are often based on the average-population approach.⁶⁵ However, identifying the stressors specific to distinct segments of employees can greatly help in designing and implementing effective workplace interventions for employees most vulnerable to these stressors. The present study shows that a one-size-fits-all approach cannot accurately cater to gender differences, sociocultural practices, employment status and cultural backgrounds, among others. Adopting a person-centered lens is essential in order to effectively support diverse groups of employees through the use of targeted and adapted information, engagement efforts and interventions.

Our findings suggest that all employees would probably benefit from increased provision of instrumental and informational organizational support during the COVID-19 pandemic crisis, irrespective of their configurations of pandemic-related stressors. However, offering the type(s) of

organizational support that best address specific employees' challenges would likely be most effective. Such an undertaking would also go a long way in showing employees that their organization values their unique circumstances. For instance, employees who are particularly concerned about work–life imbalance might best profit from the implementation of adaptive organizational practices such as flexible work-hours, telework and paid pandemic leave.⁶⁶ In contrast, such practices might not be as helpful to precarious workers who might best benefit from transparent communication about personnel decisions pertinent to their job security.⁶⁶

Conclusion

The COVID-19 pandemic has bolstered, and at times created, important risk factors for the mental health of working professionals. By applying a person-centred approach to inquiry and data analysis, the present study gives credence to the notion that employees experience pandemic-related stressors in unique ways. By identifying classes or segments of employees with distinct configurations of stressors, as well as differential risk factors and levels of self-reported mental health, the present study makes novel and important contributions to the organizational health literature. Furthermore, it also offers a starting point for informing work-related interventions with the goal of helping vulnerable employees effectively cope with these stressors.

Conflicts of interest

The authors declare that there are no known conflicts of interest.

Authors' contributions and statement

ARB conceived this work, conducted the analyses and drafted the methods and results sections as well as parts of the introduction and discussion.

EMBH supported ARB in conceptualizing this project and drafting the manuscript, including parts of the introduction and discussion.

ML provided ideas and thoughts for discussion and revised the manuscript for important intellectual content.

All authors read and approved the final manuscript.

The content and views expressed in this article are those of the authors and do not necessarily reflect those of the Government of Canada.

References

1. Brooks SK, Webster RK, Smith LE, et al. The psychological impact of quarantine and how to reduce it: rapid review of the evidence. *Lancet*. 2020; 395(10227):912-20. [https://doi.org/10.1016/S0140-6736\(20\)30460-8](https://doi.org/10.1016/S0140-6736(20)30460-8)
2. Xiao H, Zhang Y, Kong D, Li S, Yang N. The effects of social support on sleep quality of medical staff treating patients with coronavirus disease 2019 (COVID-19) in January and February 2020 in China. *Med Sci Monit*. 2020;26:e923549. <https://doi.org/10.12659/MSM.923549>
3. Gallacher G, Hossain I. Remote work and employment dynamics under COVID-19: evidence from Canada. *Can Public Policy*. 2020;46(Suppl 1): S44-54. <https://doi.org/10.3138/cpp.2020-026>
4. Dozois DJ. Anxiety and depression in Canada during the COVID-19 pandemic: a national survey. *Can Psychol*. 2021;62(1):136-42. <https://doi.org/10.1037/cap0000251>
5. Coulombe S, Pacheco T, Cox E, et al. Risk and resilience factors during the COVID-19 pandemic: a snapshot of the experiences of Canadian workers early on in the crisis. *Front Psychol*. 2020;11:580702. <https://doi.org/10.3389/fpsyg.2020.580702>
6. Giorgi G, Lecca LI, Alessio F, et al. COVID-19-related mental health effects in the workplace: a narrative review. *Int J Environ Res Public Health*. 2020; 17(21):7857. <https://doi.org/10.3390/ijerph17217857>
7. Hamouche S. COVID-19 and employees' mental health: stressors, moderators and agenda for organizational actions. *Emerald Open Research*. 2020;2:15. <https://doi.org/10.35241/emeraldopenres.13550.1>
8. Zheng J, Morstead T, Sin N, et al. Psychological distress in North America during COVID-19: the role of pandemic-related stressors. *Soc Sci Med*. 2021;270:113687. <https://doi.org/10.1016/j.socscimed.2021.113687>
9. Kossek EE. Implementing organizational work-life interventions: toward a triple bottom line. *Community Work Fam*. 2016;19(2):242-56. <https://doi.org/10.1080/13668803.2016.1135540>
10. Martin A, Karanika-Murray M, Biron C, Sanderson K. The psychosocial work environment, employee mental health and organizational interventions: improving research and practice by taking a multilevel approach. *Stress Health*. 2016;32(3):201-15. <https://doi.org/10.1002/smi.2593>
11. Gibson B, Schneider J, Talamonti D, Forshaw M. The impact of inequality on mental health outcomes during the COVID-19 pandemic: a systematic review. *Can Psychol*. 2021;62(1):101-26. <https://doi.org/10.1037/cap0000272>
12. Fernández RS, Crivelli L, Guimet NM, Allegri RF, Pedreira ME. Psychological distress associated with COVID-19 quarantine: latent profile analysis, outcome prediction and mediation analysis. *J Affect Disord*. 2020;277:75-84. <https://doi.org/10.1016/j.jad.2020.07.133>
13. Gadermann AC, Thomson KC, Richardson CG, et al. Examining the impacts of the COVID-19 pandemic on family mental health in Canada: findings from a national cross-sectional study. *BMJ Open*. 2021;11(1): e042871. <https://doi.org/10.1136/bmjopen-2020-042871>
14. Bui CN, Peng C, Mutchler JE, Burr JA. Race and ethnic group disparities in emotional distress among older adults during the COVID-19 pandemic. *Gerontologist*. 2021;61(2):262-72. <https://doi.org/10.1093/geront/gnaa217>
15. Jenkins EK, McAuliffe C, Hirani S, et al. A portrait of the early and differential mental health impacts of the COVID-19 pandemic in Canada: findings from the first wave of a nationally representative cross-sectional survey. *Prev Med*. 2021;145:106333. <https://doi.org/10.1016/j.yjpm.2020.106333>
16. Lake JK, Patrick J, Tiziana V, et al. The wellbeing and mental health care experiences of adults with intellectual and developmental disabilities during COVID-19. *J Ment Health Res Intellect Disabil*. 2021;14(3):285-300. <https://doi.org/10.1080/19315864.2021.1892890>
17. Lebrasseur A, Fortin-Bédard N, Lettre J, et al. Impact of COVID-19 on people with physical disabilities: a rapid review. *Disabil Health J*. 2021; 14(1):101014. <https://doi.org/10.1016/j.dhjo.2020.101014>
18. Pettinicchio D, Maroto M, Chai L, Lukk M. Findings from an online survey on the mental health effects of COVID-19 on Canadians with disabilities and chronic health conditions. *Disabil Health J*. 2021;14(3):101085. <https://doi.org/10.1016/j.dhjo.2021.101085>
19. Lee JH, Nam SK, Kim A-R, Kim B, Lee MY, Lee SM. Resilience: a meta-analytic approach. *J Couns Dev*. 2013; 91(3):269-79. <https://doi.org/10.1002/j.1556-6676.2013.00095.x>
20. Eisenberger R, Huntington R, Hutchison S, Sowa D. Perceived organizational support. *J Appl Psychol*. 1986;71(3): 500-7. <https://doi.org/10.1037/0021-9010.71.3.500>
21. Kurtessis JN, Eisenberger R, Ford MT, Buffardi LC, Stewart KA, Adis CS. Perceived organizational support: a meta-analytic evaluation of organizational support theory. *J Manage*. 2017;43(6):1854-84. <https://doi.org/10.1177/0149206315575554>
22. Ahnquist J, Wamala SP, Lindström M. What has trust in the health-care system got to do with psychological distress? analyses from the national Swedish survey of public health. *Int J Qual Health Care*. 2010;22(4):250-8. <https://doi.org/10.1093/intqhc/mzq024>
23. Chen S, Bonanno GA. Psychological adjustment during the global outbreak of COVID-19: a resilience perspective. *Psychol Trauma*. 2020;12(S1): S51-4. <https://doi.org/10.1037/tra0000685>

24. Ding N, Berry HL, O'Brien LV. One-year reciprocal relationship between community participation and mental wellbeing in Australia: a panel analysis. *Soc Sci Med*. 2015;128:246-54. <https://doi.org/10.1016/j.socscimed.2015.01.022>
25. Heath C, Sommerfield A, von Ungern-Sternberg BS. Resilience strategies to manage psychological distress among healthcare workers during the COVID-19 pandemic: a narrative review. *Anaesthesia*. 2020;75(10):1364-71. <https://doi.org/10.1111/anae.15180>
26. Killgore WD, Taylor EC, Cloonan SA, Dailey NS. Psychological resilience during the COVID-19 lockdown. *Psychiatry Res*. 2020;291:113216. <https://doi.org/10.1016/j.psychres.2020.113216>
27. Neves P, Eisenberger R. Management communication and employee performance: the contribution of perceived organizational support. *Hum Perform*. 2012;25(5):452-64. <https://doi.org/10.1080/08959285.2012.721834>
28. Petzold MB, Bendau A, Plag J, et al. Risk, resilience, psychological distress, and anxiety at the beginning of the COVID-19 pandemic in Germany. *Brain Behav*. 2020;10(9):e01745. <https://doi.org/10.1002/brb3.1745>
29. Tam CW, Pang EP, Lam LC, Chiu HF. Severe acute respiratory syndrome (SARS) in Hong Kong in 2003: stress and psychological impact among front-line healthcare workers. *Psychol Med*. 2004;34(7):1197-204. <https://doi.org/10.1017/s0033291704002247>
30. Kniffin KM, Narayanan J, Anseel F, et al. COVID-19 and the workplace: implications, issues, and insights for future research and action. *Am Psychol*. 2021;76(1):63-77. <https://doi.org/10.1037/amp0000716>
31. Hayton JC, Carnabuci G, Eisenberger R. With a little help from my colleagues: a social embeddedness approach to perceived organizational support. *J Organ Behav*. 2012;33(2):235-49. <https://doi.org/10.1002/job.755>
32. Rhoades L, Eisenberger R. Perceived organizational support: a review of the literature. *J Appl Psychol*. 2002;87(4):698-714. <https://doi.org/10.1037/0021-9010.87.4.698>
33. Oberski D. Mixture models: latent profile and latent class analysis. In: Robertson J, Kaptein M, editors. *Modern statistical methods for HCI*. Human-Computer Interaction Series. Cham (CH): Springer; 2016. pp. 275-87. https://doi.org/10.1007/978-3-319-26633-6_12
34. Nylund KL, Asparouhov T, Muthén BO. Deciding on the number of classes in latent class analysis and growth mixture modeling: a Monte Carlo simulation study. *Struct Equ Modeling*. 2007;14(4):535-69. <https://doi.org/10.1080/10705510701575396>
35. Howard MC, Hoffman ME. Variable-centered, person-centered, and person-specific approaches: where theory meets the method. *Organ Res Methods*. 2018;21(4):846-76. <https://doi.org/10.1177/1094428117744021>
36. Cicchetti D, Rogosch FA. Equifinality and multifinality in developmental psychopathology. *Dev Psychopathol*. 1996;8(4):597-600. <https://doi.org/10.1017/S0954579400007318>
37. Sauro JM, Meenan C, Moorman J. Applying science to personas: merging small sample qualitative insights with large sample quantitative analysis [Internet]. Bloomington (IL): UXPA International; 2017 Jun 28 [cited 2021 Sep 16]. Available from: <https://www.slideshare.net/UXPA/applying-science-to-personas-merging-small-sample-qualitative-insights-with-large-sample-quantitative-analysis>
38. Morin AJ, Boudrias JS, Marsh HW, Madore I, Desrumaux P. Further reflections on disentangling shape and level effects in person-centered analyses: an illustration exploring the dimensionality of psychological health. *Struct Equ Modeling*. 2016;23(3):438-54. <https://doi.org/10.1080/10705511.2015.1116077>
39. Lanza ST, Rhoades BL. Latent class analysis: an alternative perspective on subgroup analysis in prevention and treatment. *Prev Sci*. 2013;14(2):157-68. <https://doi.org/10.1007/s1121-011-0201-1>
40. Palmer JC, Strickland J; The Science Student Council. A beginner's guide to crowdsourcing: strengths, limitations and best practices for psychological research. *Psychological Science Agenda*; 2016 Jun [cited 2021 Sep 16]. Available from: <https://www.apa.org/science/about/psa/2016/06/changing-minds>
41. Muthén LK, Muthén BO. *Mplus user's guide*. 8th ed [Internet]. Los Angeles (CA): Muthén & Muthén; 2017 [cited 2021 Sep 16]. Available from: https://www.statmodel.com/download/usersguide/MplusUserGuideVer_8.pdf
42. Asparouhov T. Sampling weights in latent variable modeling. *Struct Equ Modeling*. 2005;12(3):411-34. https://doi.org/10.1207/s15328007sem1203_4
43. Enders CK. *Applied missing data analysis*. New York; Guilford Press; 2010.
44. Hipp JR, Bauer DJ. Local solutions in the estimation of growth mixture models. *Psychol Methods*. 2006;11(1):36-53. <https://doi.org/10.1037/1082-989X.11.1.36>
45. Schwarz G. Estimating the dimension of a model. *Ann Stat*. 1978;6(2):461-4. <https://doi.org/10.1214/aos/1176344136>
46. Sclove SL. Application of model-selection criteria to some problems in multivariate analysis. *Psychometrika*. 1987;52(3):333-43. <https://doi.org/10.1007/BF02294360>
47. Bozdogan H. Model selection and Akaike's information criterion (AIC): the general theory and its analytical extensions. *Psychometrika*. 1987;52(3):345-70. <https://doi.org/10.1007/BF02294361>
48. Akaike H. A new look at the statistical model identification. In: Parzen E, Tanabe K, Kitagawa G, editors. *Selected papers of Hirotugu Akaike*. New York: Springer; 1974:215-22. https://doi.org/10.1007/978-1-4612-1694-0_16
49. Lo Y, Mendell NR, Rubin DB. Testing the number of components in a normal mixture. *Biometrika*. 2001;88(3):767-78. <https://doi.org/10.1093/biomet/88.3.767>

50. Celeux G, Soromenho G. An entropy criterion for assessing the number of clusters in a mixture model. *J Classif.* 1996;13(2):195-212. <https://doi.org/10.1007/BF01246098>
51. Morin AJ, Marsh HW. Disentangling shape from level effects in person-centered analyses: an illustration based on university teachers' multidimensional profiles of effectiveness. *Struct Equ Modeling.* 2015;22(1):39-59. <https://doi.org/10.1080/10705511.2014.919825>
52. Howard J, Gagné M, Morin AJ, van den Broeck A. Motivation profiles at work: a self-determination theory approach. *J Vocat Behav.* 2016;95-6:74-89. <https://doi.org/10.1016/j.jvb.2016.07.004>
53. Nylund-Gibson K, Choi AY. Ten frequently asked questions about latent class analysis. *Transl Issues Psychol Sci.* 2018;4(4):440-61. <https://doi.org/10.1037/tps0000176>
54. Asparouhov T, Muthén B. Auxiliary variables in mixture modeling: three-step approaches using Mplus. *Struct Equ Modeling.* 2014;21(3):329-41. <https://doi.org/10.1080/10705511.2014.915181>
55. Zimmerman MA, Stoddard SA, Eisman AB, Caldwell CH, Aiyer SM, Miller A. Adolescent resilience: promotive factors that inform prevention. *Child Dev Perspect.* 2013;7(4):10.1111/cdep.12042. <https://doi.org/10.1111/cdep.12042>
56. Kaniasty K, de Terte I, Guilaran J, Bennett S. A scoping review of post-disaster social support investigations conducted after disasters that struck the Australia and Oceania continent. *Disasters.* 2020;44(2):336-66. <https://doi.org/10.1111/disa.12390>
57. Badawy PJ, Schieman S. With greater power comes greater stress? Authority, supervisor support, and work-family strains. *J Marriage Fam.* 2021; 83(1):40-56. <https://doi.org/10.1111/jomf.12714>
58. Rudolph CW, Allan B, Clark M, et al. Pandemics: implications for research and practice in industrial and organizational psychology. *Ind Organ Psychol.* 2021;14(1-2):1-35. <https://doi.org/10.1017/iop.2020.48>
59. Herzberg PY, Roth M. Beyond resilients, undercontrollers, and overcontrollers? an extension of personality prototype research. *Eur J Pers.* 2006; 20(1):5-28. <https://doi.org/10.1002/per.557>
60. Greenglass E, Fiksenbaum L, Burke RJ. Components of social support, buffering effects and burnout: implications for psychological functioning. *Anxiety Stress Coping.* 1996;9(3):185-97. <https://doi.org/10.1080/10615809608249401>
61. House JS. Work stress and social support. Reading (MA): Addison-Wesley; 1981.
62. Cutrona CE, Russell DW. Type of social support and specific stress: toward a theory of optimal matching. In: Sarason BR, Sarason IG, Pierce GR, editors. *Social support: An interactional view.* Hoboken (NJ): John Wiley & Sons; 1990.
63. Barling J, Cloutier A. Leaders' mental health at work: empirical, methodological, and policy directions. *J Occup Health Psychol.* 2017;22(3):394-406. <https://doi.org/10.1037/ocp0000055>
64. Hamouche S. Santé mentale des cadres: travail, identité et pratiques de gestion des ressources humaines [online thesis dissertation]. [Montréal]: Université de Montréal; 2019. 313 p. <http://hdl.handle.net/1866/22690>
65. Ali S, Asaria M, Stranges S. COVID-19 and inequality: are we all in this together? *Can J Public Health.* 2020; 111(3):415-6. <https://doi.org/10.17269/s41997-020-00351-0>
66. Lin W, Shao Y, Li G, Guo Y, Zhan X. The psychological implications of COVID-19 on employee job insecurity and its consequences: the mitigating role of organization adaptive practices. *J Appl Psychol.* 2021;106(3):317-29. <https://doi.org/10.1037/apl0000896>