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Sleep profiles as a longitudinal predictor for depression magnitude and variability following the onset of COVID-19

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ABSTRACT

The coronavirus disease 2019 (COVID-19) has disrupted multiple domains of life including sleep. The present study used a longitudinal dataset ($N = 671$) and a person-centered analytic approach – latent profile analysis (LPA) – to elucidate the relationship between sleep and depression. We used LPA to identify profiles of sleep patterns assessed by Pittsburg Sleep Quality Index (PSQI) at the beginning of the study. The profiles were then used as a predictor of depression magnitude and variability over time. Three latent profiles were identified (medicated insomnia sleepers [MIS], inefficient sleepers [IS], and healthy sleepers [HS]). MIS exhibited the highest level of depression magnitude over time, followed by IS, followed by HS. A slightly different pattern emerged for the variability of depression: While MIS demonstrated significantly greater depression variability than both IS and HS, IS and HS did not differ in their variability of depression over time. Medicated insomnia sleepers exhibited both the greatest depression magnitude and variability than inefficient sleepers and healthy sleepers, while the latter two showed no difference in depression variability despite inefficient sleepers' greater depression magnitude than healthy sleepers. Clinical implications and limitations are discussed.

The global outbreak of the novel coronavirus disease 2019 (COVID-19) was one of the most threatening public health crises in modern history. Declared a pandemic by the [World Health Organization \(2020\)](#), the highly infectious disease has wreaked severe havoc worldwide. In addition to numerous deaths and great economic cost, the COVID-19 pandemic has given rise to a large number of psychosocial stressors both directly (e.g., infection) and indirectly (e.g., unemployment) and exerted highly adverse impacts on multiple domains of life ([Gruber et al., 2021](#)).

1. Sleep and depression in pre-pandemic times

Among the domains of life that have been adversely affected, of particular concern is COVID-19's severe disturbance to sleep quality. The bidirectional relationship between sleep quality and psychopathology even in pre-pandemic times has been widely documented (for a review, see [Fang et al., 2019](#)). Additionally, sleep disturbance is a criterion for common psychiatric disorders such as PTSD and major depressive disorder ([American Psychiatric Association, 2013](#)). Notably, findings on prevalence estimates of insomnia prior to the pandemic have

been mixed. For example, [Kay-Stacey and Attarian \(2016\)](#) estimated that 3.9–22.0% of the general population worldwide suffer from clinical insomnia. In the U.S., it is estimated that up to 40% of adults in the general population are suffering from insomnia ([Stoller, 1994](#)). In a recent study sampling Indian adults attending family outpatient departments ([Bhaskar et al., 2016](#)), the estimated prevalence of insomnia was 33%. As for the association between sleep and psychopathology, studies thus far can be roughly classified into three types (for a review, see [Scott et al., 2017](#)): (1) cross-sectional; (2) longitudinal; (3) randomized controlled trial (with sleep quality as the manipulated independent variable [IV] and mental health outcomes as the dependent variable [DV]). Cross-sectional studies could not infer causality, whereas the latter two types could better elucidate the causal effect of sleep quality. In addition to the consistently replicated association between sleep quality and psychopathology, a recent randomized controlled trial also yielded promising results, showing that improvement in sleep led to better mental health and further shedding light on the causal effect sleep quality has on mental health ([Freeman et al., 2017](#)). Another recent meta-analysis reviewing 21 longitudinal studies with insomnia as a baseline predictor found similar results, showing that

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those who experienced insomnia at baseline were at higher risk for depression later (Baglioni et al., 2011). In addition, unlike most studies considering only the total scores of sleep quality scales such as PSQI, a few studies have examined the relationship between PSQI sub-components and depression by including individual components or factors derived from principal component analysis on the PSQI's seven components. These findings showed that subcomponents of subjective quality and sleep latency (Maglione et al., 2014), and factors of sleep inefficiency, perceived sleep quality, and daily disturbances (Casement et al., 2012) were associated with depression.

2. Sleep and depression during COVID-19

Since the onset of the pandemic, timely studies on COVID-19's psychological impact have emerged, highlighting its potential psychological impact (for a review, see Brooks et al., 2020). With regards to sleep disturbance during the pandemic, many, if not most, studies had utilized the total scores of sleep quality measures and found a high prevalence of sleep problems among the general population and even a higher prevalence among those who contracted COVID-19 (Deng et al., 2020; Jahrami et al., 2021). Meanwhile, studies on clinically relevant insomnia symptoms typically found a higher prevalence during the pandemic than pre-pandemic estimated incidence rate, providing preliminary evidence that COVID-19 may have caused severe disruptions to sleep quality (for a review, see Cox and Olatunji, 2021). In addition, a study with more sophisticated design (i.e., longitudinal) also found that COVID-19 lockdown may precede poorer sleep quality operationalized by PSQI total scores (Martínez-de-Quel et al., 2021). In terms of the link between sleep problems and psychopathology during the pandemic, timely cross-sectional studies using sleep measure totals found results similar to those prior to the pandemic, demonstrating a negative association between sleep quality and psychopathology (e.g., Franceschini et al., 2020; Stanton et al., 2020; Werneck et al., 2020). A longitudinal study in China also provided further evidence for the causal effect of poor sleep on increased negative emotions, showing that sleep quality mediated the relationship between severity of COVID-19 (i.e., death counts in a region) and general negative emotions (Zhang et al., 2020). As mentioned above, a few studies prior to COVID-19 investigated the association between components of sleep and depression, (e.g. Casement et al., 2012; Maglione et al., 2014). Nonetheless, to the best of our knowledge, few cross-sectional COVID-19 studies, let alone longitudinal ones, have taken this approach.

3. A person-centered approach linking sleep patterns and depression

Although the short-term psychological impact of COVID-19 was documented by timely cross-sectional studies (e.g., Brooks et al., 2020), later-coming longitudinal studies have found more nuanced results, demonstrating the pandemic's small impact (on average) in the longer term (for a review, see Prati and Mancini, 2021). There may be great heterogeneity in psychological adjustment in the long term, thus highlighting the importance of taking a person-centered approach and of implementing longitudinal design. A particularly suitable data-driven analytic tool that can uncover nuanced and hidden subgroups is the latent profile analysis (LPA; Masyn, 2013). While many previous sleep studies both before and during the pandemic either treated total sleep quality scores as a continuous variable or divided participants into "bad sleepers" and "good sleepers" using established cutoffs to examine sleep quality's effect (e.g., Cho et al., 2008; Franceschini et al., 2020; Fu et al., 2020; Martínez-de-Quel et al., 2021), doing so may preclude more nuanced findings that may be more informative to targeted prevention and intervention efforts during the pandemic. As noted above, relating PSQI individual component scores to psychopathology is one approach that is rarely seen in COVID-19 studies and could produce more informative findings. Compared to this approach, person-centered

approaches like LPA may be even better positioned to reveal subtle but important nuances. This may be the case, given their capacity to assist researchers/clinicians in identifying more vulnerable subgroups that only score high on a few sleep items/components/symptoms, even if their mean total scores of sleep quality may not differ much from more adaptive subgroups. Specifically, although global sleep disturbance has been linked to depression, whether and how different sleep components work together to influence depression remain unknown. It is likely that certain sleep deficits tend to co-exist with others, a possibility rarely examined in previous sleep research. Moreover, few studies have considered whether certain combination of sleep deficits may be more detrimental for mental health. Latent profile analysis (LPA) is a statistical approach that allows researchers to address these questions. In specific, LPA identifies predominant subgroups of participants that exhibit different types of deficits across sleep components. Such an approach helps discover more nuanced findings that may be more informative for clinicians to identify risks and provide targeted prevention and intervention. While LPA and similar approaches remain underutilized in sleep research, studies have demonstrated their value in psychological science through successful attempts at classifying depressive symptoms, emotion regulation flexibility, and sleep patterns into latent subgroups (Chen and Bonanno, 2021; Saracino et al., 2018; Witcraft et al., 2021; Yu et al., 2017; Zhou et al., 2019). To the best of our knowledge, there were two recent studies that linked latent sleep patterns to depression before the COVID-19 pandemic. In a sample of 80 children with craniopharyngioma, Witcraft et al. (2021) identified three sleep profiles (variable sleepers, consistently poor sleepers, and night wakers) and linked them to concurrent depression and anxiety. Their results showed that variable sleepers exhibited the highest rates of depression and anxiety. Yu et al. (2017) used five components of the PSQI and identified four sleep patterns (i.e., inadequate sleep, disturbed sleep, trouble falling asleep, and multiple problems) among participants reporting at least one sleep problem. Their results indicated that those showing multiple problems exhibited significantly greater depression and anxiety cross-sectionally than the control group who did not report any sleep problem. Despite LPA's potential, to the best of our knowledge, few COVID-19 studies have used LPA to investigate sleep patterns in the context of the initial pandemic outbreak and relate them to distal outcomes, let alone depression, in a longitudinal design.

4. The current investigation

The current investigation has two aims. First, we aimed to apply LPA to an open access dataset (Cunningham et al., 2021) to identify distinct profiles of sleep components measured by PSQI. Compared to the common practices of summing up component scores to reflect a global sleep disturbance, LPA has several advantages. It allows researchers to identify subgroups of participant exhibiting different patterns of sleep deficits. Heterogeneity in sleep deficits is often neglected despite that there are likely distinct types of sleep problems in the real world. Moreover, identifying subgroups of participants with different sleep problems will enable clinical risk identification at a more individualized level. For example, maybe a certain combination of deficits in a few components carry the most risk for depression. This enables clinicians to better assess risk and provide interventions. Second, we aimed to conduct two ANOVAs with the identified profiles as the predictor for depression magnitude and variability to understand if group memberships identified by LPA would be predictive of the distal outcome of psychopathology.

Our research advances previous research in two important ways. First, it uses a person-centered approach that remains underutilized in sleep research. Taking this approach helps researchers avoid using cutoffs often criticized for being arbitrary and may reveal nuances of the roles of individual sleep components and identify latent subgroups of sleep patterns that may be at higher risk of psychopathology following an adverse event (i.e., the pandemic) and thus warrant more attention.

Second, unlike most psychopathological studies using LPA that are cross-sectional, our study took advantage of a complex dataset that took multiple clinically relevant assessments during the initial wave of COVID-19 and therefore was able to have incorporated the longitudinal information of depressive symptoms that spanned a near three-month period.

5. Methods

5.1. Participants and procedure

The present study used the Boston College Daily Sleep and Well-Being Survey Data, an open access dataset incorporating the results from multiple surveys including demographic surveys, and repeated daily assessments of participants' sleep and mental well-being starting from March 20, 2020 (Cunningham et al., 2021). Specifically, the participants completed a baseline demographic survey, multiple daily surveys that assessed sleep behavior (using self-designed items), depressive symptoms, alcohol consumption, quarantine status and other variables, with two different versions of daily survey implemented to reduce burden (only the longer version included depression-related questions using Physical Health Questionnaire-9 [PHQ-9]), and three one-time assessment with Round 1¹ one launched on May 19, 2020 assessing sleep patterns using PSQI and other variables (for a detailed description, see Cunningham et al., 2021). In total, 1518 participants participated in the original study, 839 participants completed Round 1 assessment, and 1365 participants completed the longer version of the daily survey at least once.

In order to generate sleep profiles, we decided to use the Round 1 assessment dataset instead of the daily surveys, because only the Round 1 assessment included the PSQI, a scale that has been successfully used to investigate latent classes of sleep (e.g., Zhou et al., 2019). After making this decision, we then manually created a fourteen-day assessment window for the PSQI assessment starting from the first day of Round 1 Assessment (May 19, 2020), resulting in a total of 739 participants left in the Round 1 assessment dataset. In order to link sleep profiles to longitudinal depression (collected by longer daily surveys) starting from May 19, 2020 to August 12, 2020 (the last day this survey was completed), we combined the Round 1 assessment dataset and longer daily surveys by the unique subject identifier, which resulted in a total of 671 participants in the final analysis. In the present study, the participants ranged in age from 18 to 90 ($M = 39.35$, $SD = 17.13$), and 84.2% were female. 82.9% of participants were from US, 4.2% from Canada, 2.8% from Australia, and 10.1% from other countries. The original study was approved by the Institutional Review Board of Boston College, and informed consent was provided by the participants prior to study participation.

5.2. Measures

Depression was assessed via the Patient Health Questionnaire 9 (PHQ-9; Spitzer et al., 1999), a 9-item scale that assesses an individual's depression-related thoughts and behaviors during the past two weeks on a 4-point scale from 0 (*not at all*) to 3 (*nearly every day*) with items such as "Little interest or pleasure in doing things" and "Feeling down, depressed, or hopeless". The totals of PHQ-9 range from 0 to 27, with higher totals indicating greater depression. The item assessing suicidality was omitted upon the request of the IRB of the original study, and the item assessing sleep quality was removed because of its overlap with PSQI. Internal consistency was good for all PHQ-9 assessments

¹ Though Cunningham et al. (2021) presented three rounds of one-time assessments, the PSQI used to generate sleep profiles was only assessed in Round 1, but not in Round 2 or 3. Therefore, the present study did not use assessments in Round 2 and 3.

completed in the original study ($\alpha = .87$).

Sleep patterns were measured by Pittsburgh Sleep Quality Index (PSQI; Buysse et al., 1989). The PSQI has 24 items, from which seven components are derived. The seven components include subjective sleep quality, sleep duration, habitual sleep efficiency, sleep latency, sleep disturbances, use of sleeping medication, and daytime dysfunction. The scores for each component range from 0 (*good sleep/no problems*) to 3 (*poor sleep/severe problems*), with higher total scores suggesting worse sleep quality and a usual cut-off of 5 suggesting sleep disturbance (Buysse et al., 1989). We did not include in our analysis the subjective sleep quality component because of its subjective nature relative to the other six components that intend to measure objective sleeping behaviors/patterns. The internal consistency of the six components was acceptable in the current study ($\alpha = .61$).

5.3. Analytic plan

Statistical analyses were performed in R Version 4.0.4 via the *mclust*, *tidyLPA*, *DMwR2* and *WRS* packages (Scrucca et al., 2016; R Core Team, 2021; Rosenberg et al., 2018; Torgo, 2016; Wilcox and Schönbrodt, 2014). 1.66% of data was missing and *K*-nearest neighbor (KNN) imputation with a *K* of 10 was used. First, we conducted LPA and identified the optimal number of profiles. To determine the most appropriate number of profiles, we considered fit indices including Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Bootstrap Likelihood Ratio Test (B-LRT). Specifically, lower AIC and BIC values are indicative of better model fits, while a significant test result ($p < .05$) of B-LRT for *n*-profile solution suggests that this solution may be a better fit than the *n*-1-profile solution. Moreover, results of simulation studies suggested that rare classes (percentage <5%) are hard to replicate (e.g., Morovati, 2014). Therefore, following the recommendation of Nylund-Gibson and Choi (2018), we would not choose a solution with a class accounting for less than 5% of the total participants, even if it yielded slightly better fit indices. In addition, interpretability of the class solution was also taken into account when making the final model selection.

After a profile solution is identified, the memberships of the solution would be used as the predictor of longitudinal depression in one-way analysis of variance (ANOVA). Two one-way ANOVAs would be conducted. First, we would use sleep profile memberships as a predictor to predict the magnitude of depression, or the mean score of the depression total scores belonging to the same participant resulting from frequent longer daily surveys. Second, we would use the same memberships as a predictor to predict the variability (i.e., standard deviation) of the depression total scores belonging to the same participant from the same period. In addition to reporting *p* values, we also reported effect sizes as appropriate using Hedge's *g* (Hedge's *g* of 0.80, 0.50, 0.20 are considered large, medium, and small, respectively; Hedges, 1981). Hedge's *g* is considered a less biased estimate of effect size than Cohen's *d* when the group sizes vary (Cohen, 1988).

6. Results

6.1. Latent profile analysis

First, to find the model that best fits the data, we compared and reported solutions with varying restrictions of variances and covariances across profiles (see Table 1). In the *TidyLPA* package, four model specifications on variance and covariance named Model 1, Model 2, Model 3, and Model 6 could be specified (for a detailed discussion, see Wardeenaar, 2021). Due to model non-convergence, no solutions were found using Model 2 and 6 specifications beyond one-profile solutions (see Table 1). Because in every solution with the same number of profiles, the results of Model 3 outcompeted those of Model 1 in terms of both AIC and BIC except in five-profile solution comparison and because of Model 1's five-profile solution's low entropy (.62), we focused on Model 3 in

Table 1
Model fit indices for latent profile analysis.

Latent Profile Analyses (N = 671)						
Model	No. of Classes	AIC	BIC	Entropy	B-LRT	Per. Small
1 Equal variances and covariances fixed to 0	1	8985.50	9039.61	1.00	–	–
1 Equal variances and covariances fixed to 0	2	8525.87	8611.53	.88	.01	16.40%
1 Equal variances and covariances fixed to 0	3	8416.18	8533.41	.79	.01	15.50%
1 Equal variances and covariances fixed to 0	4	8430.15	8578.94	.51	.94	15.50%
1 Equal variances and covariances fixed to 0	5	7974.65	8155.01	.62	.01	5.21%
2 Varying variances and covariances fixed to 0	1	8984.50	9039.61	1.00	–	–
2 Varying variances and covariances fixed to 0	2	–	–	–	–	–
2 Varying variances and covariances fixed to 0	3	–	–	–	–	–
2 Varying variances and covariances fixed to 0	4	–	–	–	–	–
2 Varying variances and covariances fixed to 0	5	–	–	–	–	–
3 Equal variances and equal covariances	1	8571.82	8693.55	1.00	–	–
3 Equal variances and equal covariances	2	8349.31	8502.61	.96	.01	15.50%
3 Equal variances and equal covariances	3	8027.87	8212.73	.89	.01	6.11%
3 Equal variances and equal covariances	4	7728.93	7945.35	.95	.01	2.53%
3 Equal variances and equal covariances	5	8220.70	8468.68	.79	.97	3.42%
6 Varying variances	1	8571.82	8693.55	1.00	–	–

Table 1 (continued)

Latent Profile Analyses (N = 671)						
Model	No. of Classes	AIC	BIC	Entropy	B-LRT	Per. Small
and varying covariances						
6 Varying variances and varying covariances	2	–	–	–	–	–
6 Varying variances and varying covariances	3	–	–	–	–	–
6 Varying variances and varying covariances	4	–	–	–	–	–
6 Varying variances and varying covariances	5	–	–	–	–	–

Note. No. = Number. AIC = Akaike Information Criterion. BIC = Bayesian Information Criterion. B-LRT = Bootstrapped likelihood ratio test. Per. Small = Percentage of participants in the smallest group. - indicates either model-nonconvergence because of too many parameters being estimated or not available. Bolded lines indicate the best profile solution based on AIC, BIC, B-LRT, Per. Small, and interpretability of that solution.

our final model selection. Of note, the B-LRTs' results were significant for the two-, three-, and four-profile solutions in Model 3 ($p.s., < .05$), but not for the five-profile solution ($p = .97$). This indicates that the four-profile solution had the highest fit assessed by B-LRT. This choice was also supported by its corresponding BIC and AIC, both of which were the lowest. However, the four-profile solution yielded a class that only accounted for 2.8% of the total participants. Because rare classes (percentages $< 5\%$) were often unstable and lacked replicability (Nylund-Gibson and Choi, 2018), we chose the three-profile solution which produced slightly higher BIC and AIC. With regards to interpretability, the three-profile solution provided a set of highly interpretable profiles: those who exhibited high sleep latency and high frequency of sleeping medication use (medicated insomnia sleepers [MIS]; 6.1%), those who exhibited low sleeping duration and habitual sleeping efficiency (inefficient sleepers [IS]; 21.3%), and those who exhibited the lowest estimated scores across six components (healthy sleepers [HS]; 72.6%). In addition, further analysis also revealed that 100% medicated insomnia sleepers and 86.5% inefficient sleepers would have been classified into the same group of bad sleepers according to PSQI's recommended cutoff of 5 (Buysse et al., 1989).

Because the entropy for the three-profile solution was high (.89), we proceeded and allocated the participants into the profiles based on classification probabilities, which were high across the profiles, ranging from 90.22% to 99.99%. Fig. 1 shows the estimated individual PSQI component means for the selected three-profile solution.

6.2. Sleep profiles and longitudinal depression magnitude

After the best profile solution was determined, we conducted one-way analysis of variance (ANOVA) to examine the association between profile membership and longitudinal depression magnitude. The data failed both the Levene's test ($p = .004$) and the Shapiro-Wilk tests (two $p.s. < .0001$), suggesting the violation of equal variance and normality and the need to conduct robust ANOVA based on bootstrapping (nboot = 2,000) and trimmed means (tr = .2) using the WRS package's t1waybt() function and robust *post-hoc* tests based on the same bootstrapping and trimmed means parameters using the mcppb20() function (Wilcox and Schönbrodt, 2014). The robust ANOVA of longitudinal depression magnitude revealed a statistically significant main effect, $F_t = 15.87, p <$

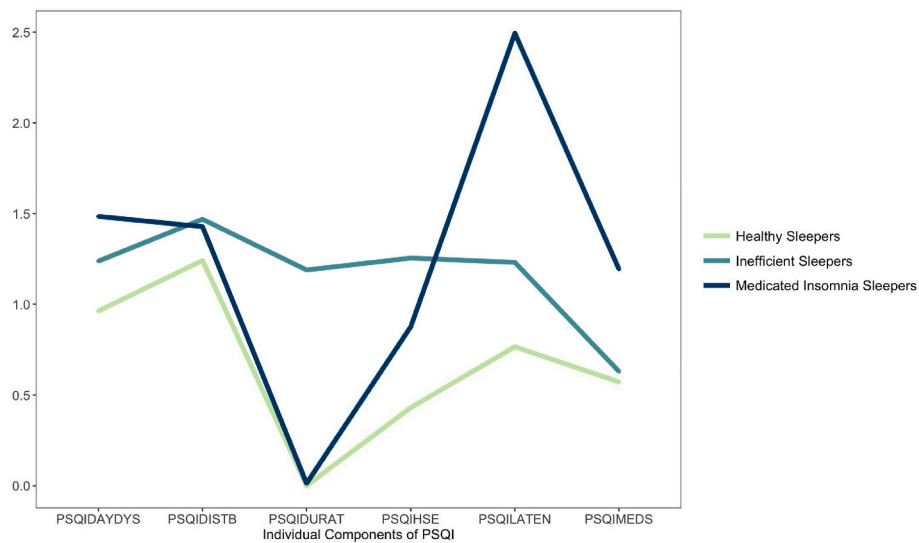


Fig. 1. Estimated sample item means for the three latent profiles of sleep Patterns.

Note. PSQI = pittsburgh sleep quality index, PSQIDAYDYS = PSQI daytime dysfunction, PSQIDISTB = PSQI disturbances, PSQIDURAT = PSQI duration, PSQIHSE = PSQI habitual sleeping efficiency, PSQILATEN = PSQI latency, PSQIMEDS = PSQI medications.

.0001, indicating that there existed statistically significant differences in depression magnitude among the latent subgroups (see Fig. 2).

The results of the robust *post-hoc* tests controlling for type 1 errors indicated that the medicated insomnia sleepers ($M = 7.73, SD = 4.60$) exhibited significantly greater depression magnitude than inefficient sleepers ($M = 5.70, SD = 4.22$) and healthy sleepers ($M = 4.21, SD = 3.49$), $p.s. < .01$ (see Fig. 2). The Hedge's *g.s.* for these two significant effects were 0.47 and 0.98, respectively. In addition, inefficient sleepers exhibited significantly greater depression magnitude than healthy sleepers, $p < .001$, Hedge's $g = 0.41$.

6.3. Sleep profiles and longitudinal depression variability

Another one-way analysis of variance (ANOVA) was conducted to examine the association between profile membership and longitudinal depression variability. The Levene's test yielded a non-significant result

($p = .16$), indicating no violation of equal variance assumption. However, the Shapiro-Wilk tests yielded significant results, all three $p.s. < .01$, suggesting violation of normality and the need to use a Kruskal-Wallis test, the non-parametric alternative to ANOVA. The Kruskal-Wallis test revealed a statistically significant difference in depression variability across the latent profiles, $H(2) = 8.73, p = .013$ (see Fig. 2).

The Bonferroni-adjusted *post-hoc* tests controlling for type 1 errors indicated that the medicated insomnia sleepers exhibited significantly greater longitudinal depression variability ($Mdn = 1.53$) than inefficient sleepers ($Mdn = 1.10$) as well as healthy sleepers ($Mdn = 1.14$), $p.s. < .05$, (see Fig. 2). No statistically significant result was found in depression variability between inefficient sleepers and healthy sleepers, $p = 1.00$.

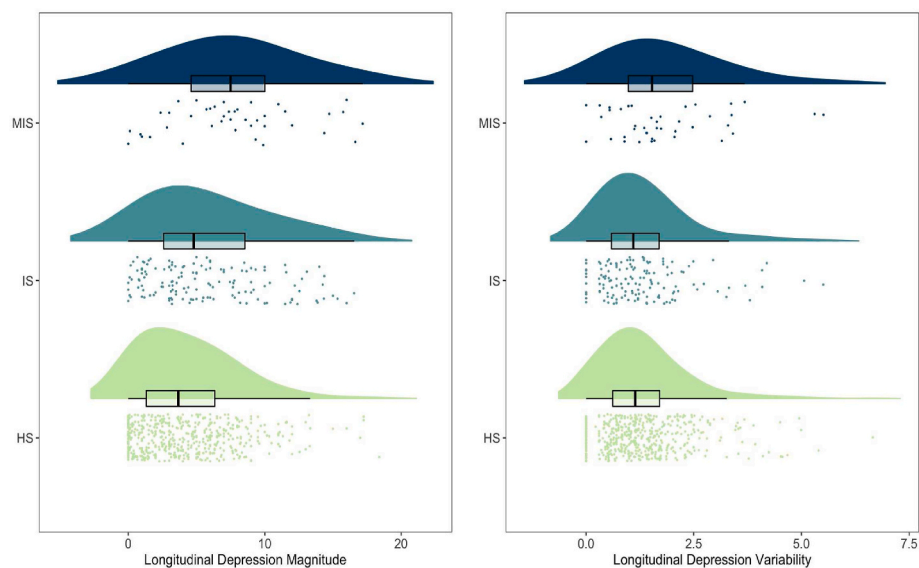


Fig. 2. Raincloud plots (Allen et al., 2021) of longitudinal depression magnitude (left) and longitudinal variability (right) among the three latent profiles of sleep patterns.

Note. HS = healthy sleepers, IS = inefficient sleepers, MIS = medicated insomnia sleepers.

7. Discussion

In this study, we identified three subgroups of sleepers. The majority (72.6%) were healthy sleepers, whose scores were consistently the lowest across the six PSQI components compared to other groups. The group of sleepers who account for the second highest proportion (21.3%) were the inefficient sleepers, who reported the lowest sleep duration and habitual sleeping efficiency. The remainder (6.1%) were medicated insomnia sleepers, who exhibited greater use of sleeping medication and greater sleep latency.

We found that medicated insomnia sleepers exhibited greater depression magnitude averaged across multiple assessments than both inefficient sleepers and healthy sleepers, and that between the latter two, inefficient sleepers were more depressed than healthy sleepers (see Fig. 2). Using a person-centered approach, we revealed the more nuanced finding (vs most studies considering PSQI total scores) that those who use more medication and suffer from higher sleep latency may be at significantly higher risk of depression than those who suffer from low sleeping efficiency and duration. These results were consistent with findings by Yu et al. (2017) that participants with multiple sleep problems exhibited greater depression and anxiety than healthy controls concurrently. We could have missed our finding if we had applied PSQI's recommended cutoff of 5, because the vast majority of medicated insomnia sleepers and inefficient sleepers in the current study would have been classified into the same bad sleeper group. In addition, our findings also highlight the potential negative effect of insufficient sleep (duration) as well as low habitual sleeping efficiency on depression, given that inefficient sleepers were more depressed than healthy sleepers over time. In sum, our findings suggest that, following COVID-19 and related restrictions starting from March, the majority of individuals completing PSQI between May 19, 2020 and June 1, 2020 were healthy sleepers and that a minority of them were suffering from sleep problems and greater depression magnitude longitudinally and could be further classified into two groups. Among these two groups, medicated insomnia sleepers exhibited even greater depression magnitude and may warrant more clinical attention compared to inefficient sleepers.

Regarding the findings about depression variability across time, we found that while there is no difference between inefficient sleepers and healthy sleepers, medicated insomnia sleepers exhibited greater depression variability than both healthy sleepers and inefficient sleepers (see Fig. 2). That healthy sleepers and inefficient sleepers' depression variability are not significantly different suggest that duration and efficiency may have no effect on depression variability over time. That medicated insomnia sleepers exhibited the greatest variability demonstrates that the use of medication and/or high sleep latency may contribute to greater variability in depression over time. The main implication of this finding is that it would be harder to accurately assess this group and determine the severity of depressive symptoms if a diagnosis is warranted. This suggests that psychiatrists and clinical psychologists assessing outpatients following a disaster-like event like the pandemic may need to take extra caution in making diagnoses when outpatients report frequent use of sleep medication and high sleep latency. Moreover, that there exists significant difference in variability among the profiles also highlights the possibility that factors other than the profiles may account for these differences.

Our findings should be viewed in light of several limitations. First, a concerning limitation of the present study was the selection bias, in part due to snowballing sampling. Additionally, there was a significant gender imbalance in the sample (84.2% females). This selection bias likely limits the generalizability of our findings. Future studies using representative samples are needed to assess if the same sleep profiles could be replicated. Second, although our study has taken advantage of the longitudinal information in the original dataset, suggesting the long-term mental health implications of different sleep profiles, we cannot apply more advanced statistical methods (e.g., latent transition analysis

[LTA] or multilevel modeling), because the original dataset only assessed sleep quality using PSQI once. Lastly, another important limitation of the present longitudinal study is its short observation time of depression (just over a month). In the final resultant sample we analyzed, the last assessment of depression took place on July 1st, 2020, which potentially limits our understanding of the longer-term relationship between the study variables. Future studies that span longer observation time (e.g., over six months) are critically needed to address this limitation.

In conclusion, this study identified three groups of sleepers using LPA. Of the three groups, two groups – inefficient sleepers and medicated insomnia sleepers – may warrant clinical attention. Between these two groups, medicated insomnia sleepers exhibited both highest longitudinal depression magnitude and variability and may require even greater clinical attention, both in clinical assessment/diagnosis and prevention/intervention.

Data availability statement

The longitudinal open access data analyzed in this paper is publicly available with download instructions provided at <https://doi.org/10.1038/s41597-021-00886-y> (Cunningham et al., 2021).

Contributors

SC and KB conceptualized the study. KB performed the analysis and wrote the initial manuscript. SC played the supervising role, reviewed the analysis and R codes, provided critical feedback on the manuscript, and revised the manuscript.

Declaration of competing interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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References

- Allen, M., Poggiali, D., Whitaker, K., Marshall, T.R., van Langen, J., Kievit, R.A., 2021. Raincloud Plots: a multi-platform tool for robust data visualization. *Wellcome Open Res.* 4, 63. <https://doi.org/10.12688/wellcomeopenres.15191.2>.
- American Psychiatric Association, 2013. *Diagnostic and Statistical Manual of Mental Disorders*, fifth ed. <https://doi.org/10.1176/appi.books.9780890425596>
- Baglioni, C., Battagliese, G., Feige, B., Spiegelhalter, K., Nissen, C., Voderholzer, U., Lombardo, C., Riemann, D., 2011. Insomnia as a predictor of depression: a meta-analytic evaluation of longitudinal epidemiological studies. *J. Affect. Disord.* 135 (1–3), 10–19. <https://doi.org/10.1016/j.jad.2011.01.011>.
- Bhaskar, S., Hemavathy, D., Prasad, S., 2016. Prevalence of chronic insomnia in adult patients and its correlation with medical comorbidities. *J. Fam. Med. Prim. Care* 5 (4), 780. <https://doi.org/10.4103/2249-4863.201153>.
- Brooks, S.K., Webster, R.K., Smith, L.E., Woodland, L., Wessely, S., Greenberg, N., Rubin, J., 2020. The psychological impact of quarantine and how to reduce it: rapid review of the evidence. *Lancet* 395, 912–920. [https://doi.org/10.1016/S0140-6736\(20\)30460-8](https://doi.org/10.1016/S0140-6736(20)30460-8).
- Buysse, D.J., Iii, C.F.R., Monk, T.H., Berman, S.R., Kupfer, D.J., 1989. The Pittsburgh Sleep Quality Index: a new instrument for psychiatric practice and research. *Psychiatr. Res.* 28 (2), 193–213.
- Casement, M.D., Harrington, K.M., Miller, M.W., Resick, P.A., 2012. Associations between pittsburgh sleep quality index factors and health outcomes in women with posttraumatic stress disorder. *Sleep Med.* 13 (6), 752–758. <https://doi.org/10.1016/j.sleep.2012.02.014>.
- Cho, H.J., Lavretsky, H., Olmstead, R., Levin, M.J., Oxman, M.N., Irwin, M.R., 2008. Sleep disturbance and depression recurrence in community-dwelling older adults: a prospective study. *Am. J. Psychiatr.* 165 (12), 1543–1550. <https://doi.org/10.1176/appi.ajp.2008.07121882>.

- Cohen, J., 1988. *Statistical Power Analysis for the Behavioral Sciences*, second ed. Lawrence Erlbaum, Mahwah, New Jersey.
- Cox, R.C., Olatunji, B.O., 2021. Sleep in a pandemic: implications of Covid-19 for sleep through the lens of the 3p model of insomnia. *Am. Psychol.* <https://doi.org/10.1037/amp0000850>.
- Cunningham, T.J., Fields, E.C., Kensinger, E.A., 2021. Boston College daily sleep and well-being survey data during early phase of the COVID-19 pandemic. *Sci. Data* 8 (1). <https://doi.org/10.1038/s41597-021-00886-y>.
- Chen, S., Bonanno, G.A., 2021. Components of emotion regulation flexibility: linking latent profiles to depressive and anxious symptoms. *Clinical Psychol. Sci.* 9 (2), 236–251. <https://doi.org/10.1177/2167702620956972>.
- Deng, J., Zhou, F., Hou, W., Silver, Z., Wong, C.Y., Chang, O., Huang, E., Zuo, Q.K., 2020. The prevalence of depression, anxiety, and sleep disturbances in COVID-19 patients: a meta-analysis. *Ann. N. Y. Acad. Sci.* 1486 (1), 90–111. <https://doi.org/10.1111/nyas.14506>.
- Fang, H., Tu, S., Sheng, J., Shao, A., 2019. Depression in sleep disturbance: a review on a bidirectional relationship, mechanisms and treatment. *J. Cell Mol. Med.* 23 (4), 2324–2332. <https://doi.org/10.1111/jcmm.14170>.
- Franceschini, C., Musetti, A., Zenesini, C., Palagini, L., Pelosi, A., Quattropiani, M.C., Lenzo, V., Freda, M.F., Lemmo, D., Vegni, E., Borghi, L., Saita, E., Cattivelli, R., De Gennaro, L., Plazzi, G., Riemann, D., Castelnovo, G., 2020. Poor Quality of Sleep and its Consequences on Mental Health during Covid-19 Lockdown in Italy. <https://doi.org/10.31234/osf.io/ah6j3>.
- Freeman, D., Sheaves, B., Goodwin, G.M., Yu, L.M., Nickless, A., Harrison, P.J., Emsley, R., Luijk, A.L., Foster, R.G., Wadekar, V., Hinds, C., Gumley, A., Jones, R., Lightman, S., Jones, S., Bentall, R., Kinderman, P., Rowse, G., Brugha, T., Blagrove, M., Espie, C.A., 2017. The effects of improving sleep on mental health (OASIS): a randomised controlled trial with mediation analysis. *Lancet Psychiatr.* 4 (10), 749–758. [https://doi.org/10.1016/S2215-0366\(17\)30328-0](https://doi.org/10.1016/S2215-0366(17)30328-0).
- Fu, W., Wang, C., Zou, L., Guo, Y., Lu, Z., Yan, S., Mao, J., 2020. Psychological health, sleep quality, and coping styles to Stress facing the COVID-19 in Wuhan, China. *Transl. Psychiatry* 10 (1). <https://doi.org/10.1038/s41398-020-00913-3>.
- Gruber, J., Prinstein, M.J., Clark, L.A., Rottenberg, J., Abramowitz, J.S., Albano, A.M., Weinstock, L.M., 2021. Mental health and clinical psychological science in the time of COVID-19: challenges, opportunities, and a call to action. *Am. Psychol.* 76 (3), 409–426. <https://doi.org/10.1037/amp0000707>.
- Hedges, L.V., 1981. Distribution theory for Glass's estimator of effect size and related estimators. *J. Educ. Stat.* 6 (2), 107–128. <https://www.jstor.org/stable/1164588>.
- Jahrami, H., BaHammam, A.S., Bragazzi, N.L., Saif, Z., Faris, M.A.I., Vitiello, M.V., 2021. Sleep problems during the COVID-19 pandemic by population: a systematic review and meta-analysis. *J. Clin. Sleep Med.* 17 (2), 299–313. <https://doi.org/10.5664/jcsm.8930>.
- Kay-Stacey, M., Attarian, H., 2016. Advances in the management of Chronic Insomnia. *BMJ* i2123. <https://doi.org/10.1136/bmj.i2123>.
- Maglione, J.E., Ancoli-Israel, S., Peters, K.W., Paudel, M.L., Yaffe, K., Ensrud, K.E., Stone, K.L., 2014. Subjective and objective sleep disturbance and longitudinal risk of depression in a cohort of older women. *Sleep* 37 (7), 1–9. <https://doi.org/10.5665/sleep.3834>.
- Martínez-de-Quel, Ó., Suárez-Iglesias, D., López-Flores, M., Pérez, C.A., 2021. Physical activity, dietary habits and sleep quality before and during COVID-19 lockdown: a longitudinal study. *Appetite* 158, 105019. <https://doi.org/10.1016/j.appet.2020.105019>.
- Masyn, K.E., 2013. Latent class analysis and finite mixture modeling. In: Little, T.D. (Ed.), *The Oxford Handbook of Quantitative Methods in Psychology*, 1. Ed., 2. Oxford University Press, New York, NY, pp. 551–611. <https://doi.org/10.1093/oxfordhb/9780199934898.013.0025>.
- Morovati, D., 2014. *The Intersection of Sample Size, Number of Indicators, and Class Enumeration in LCA: A Monte Carlo Study (Unpublished Doctoral Dissertation)*. University of California, Santa Barbara.
- Nylund-Gibson, K., Choi, A.Y., 2018. Ten frequently asked questions about latent class analysis. *Translat. Issues Psychol. Sci.* 4 (4), 440–461. <https://doi.org/10.1037/tps0000176>.
- Prati, G., Mancini, A.D., 2021. The psychological impact of COVID-19 pandemic lockdowns: a review and meta-analysis of longitudinal studies and natural experiments. *Psychol. Med.* 51, 201–211. <https://doi.org/10.1017/S0033291721000015>.
- R Core Team, 2021. R: A Language and Environment for Statistical Computing [Computer Software]. R Foundation for Statistical Computing, Vienna, Austria. <https://www.R-project.org/>.
- Rosenberg, J., Beymer, P., Anderson, D., van Lissa, C., Schmidt, J., 2018. tidyLPA: an R package to easily carry out Latent Profile Analysis (LPA) using open-source or commercial software. *J. Open Source Software* 3 (30), 978. <https://doi.org/10.21105/joss.00978>.
- Saracino, R.M., Cham, H., Rosenfeld, B., Nelson, C.J., 2018. Latent profile analyses of depressive symptoms in younger and older oncology patients. *Assessment* 27 (7), 1383–1398. <https://doi.org/10.1177/1073191118784653>.
- Scott, A.J., Webb, T.L., Rowse, G., 2017. Does improving sleep lead to better mental health? A protocol for a meta-analytic review of randomised controlled trials. *BMJ Open* 7 (9). <https://doi.org/10.1136/bmjopen-2017-016873>.
- Scrucca, L., Fop, M., Murphy, T.B., Raftery, A.E., 2016. Mclust 5: clustering, classification and density estimation using Gaussian Finite Mixture Models. *R J.* 8 (1), 289. <https://doi.org/10.32614/rj-2016-021>.
- Spitzer, R.L., Kroenke, K., Williams, J.B., 1999. Validation and utility of a self-report version of PRIME-MD: the PHQ primary care study. Primary care evaluation of mental disorders. Patient health Questionnaire. *JAMA* 282 (18), 1737–1744. <https://doi.org/10.1001/jama.282.18.1737>.
- Stanton, R., To, Q.G., Khalesi, S., Williams, S.L., Alley, S.J., Thwaite, T.L., Fenning, A.S., Vandelanotte, C., 2020. Depression, anxiety and stress during COVID-19: associations with changes in physical activity, sleep, tobacco and alcohol use in Australian adults. *Int. J. Environ. Res. Publ. Health* 17 (11), 4065. <https://doi.org/10.3390/ijerph17114065>.
- Stoller, M.K., 1994. Economic effects of insomnia. *Clin. Therapeut.: Int. Peer-Rev. J. Drug Ther.* 16 (5), 873–897.
- Wardenaar, K. J. (2021, April 9). Latent Profile Analysis in R: A Tutorial and Comparison to Mplus. <https://doi.org/10.31234/osf.io/wzfr>.
- Torgo, Luis, 2016. *Data mining with R: Learning with case studies, Second edition*. Chapman and Hall/CRC.
- Werneck, A.O., Silva, D.R., Malta, D.C., Lima, M.G., Souza-Júnior, P.R.B., Azevedo, L.O., Barros, M.B.A., Szwarcwald, C.L., 2020. The mediation role of sleep quality in the association between the incidence of unhealthy movement behaviors during the COVID-19 quarantine and mental health. *Sleep Med.* 76, 10–15. <https://doi.org/10.1016/j.sleep.2020.09.021>.
- Wilcox, R.R., Schönbrodt, F.D., 2014. *The WRS Package for Robust Statistics in R*. R Package. Version 0.24.
- Witcraft, S.M., Wickenhauser, M.E., Russell, K.M., Mandrell, B.N., Conklin, H.M., Merchant, T.E., Crabtree, V.M.L., 2021. A latent profile analysis of sleep, anxiety, and mood in youth with craniopharyngioma. *Behav. Sleep Med.* 1–12. <https://doi.org/10.1080/15402002.2021.1996363>.
- World Health Organization. (2020, March 11). Director-General's Opening Remarks at the Media Briefing on COVID-19. Retrieved from <https://www.who.int/director-general/speeches/detail/who-director-general-s-opening-remarks-at-the-media-briefing-on-covid-19--11-march-2020>.
- Yu, J., Mahendran, R., Abdullah, F.N., Kua, E.-H., Feng, L., 2017. Self-reported sleep problems among the elderly: a latent class analysis. *Psychiatr. Res.* 258, 415–420. <https://doi.org/10.1016/j.psychres.2017.08.078>.
- Zhang, Y., Zhang, H., Ma, X., Di, Q., 2020. Mental health problems during the COVID-19 pandemics and the Mitigation effects of exercise: a longitudinal study of college students in China. *Int. J. Environ. Res. Publ. Health* 17 (10), 3722. <https://doi.org/10.3390/ijerph17103722>.
- Zhou, J., Jin, L.-R., Tao, M.-J., Peng, H., Ding, S.-S., Yuan, H., 2019. The underlying characteristics of sleep behavior and its relationship to sleep-related cognitions: a latent class analysis of college students in Wuhu city, China. *Psychol. Health Med.* 25 (7), 887–897. <https://doi.org/10.1080/13548506.2019.1687915>.