The impact of sleep quality on mental health in working Australians: A quasi-experimental approach

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Research Article

Keywords: work conditions, sleep quality, mental health, quasi-experimental approach, Australia.

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The impact of sleep quality on mental health in working Australians: A quasi-experimental approach

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ABSTRACT

Work conditions and major life events can impact individual sleep quality, and subsequently impact mental health. This study aims to investigate effect of sleep quality on mental health of working Australians. We pioneer to employ a novel method in public health studies, a quasi-experimental (Instrumental Variable) approach, which can address reciprocal relationships between sleep and mental health in order to estimate causal effect of sleep quality on mental health on a sample of 14,480 working Australians aged 25-64 from the Household, Income and Labour Dynamics in Australia (HILDA) survey waves 2013 and 2017. We find that work conditions such as high job demand, long workhours, long unpaid workhours, shift work, and major life events adversely affect sleep quality, and hence the changes in sleep quality strongly affect mental health of working Australians. The finding underscores the need for policies that should address current employment conditions by reducing long workhours, high work demand, irregular work shifts, and providing better support including emotional support programs, and creating worker-friendly settings to mitigate poor sleep quality in the Australian workforce. Doing so would help improve workers’ sleep quality, and ultimately mental health and overall health outcomes.

Keywords: employment conditions, sleep quality, mental health, quasi-experimental approach, Australia.
1. Introduction

Poor sleep quality and mental ill-health can negatively impact an individual’s overall health (Cappuccio et al., 2010; Productivity Commission, 2020). The direct cost of poor sleep on the Australian economy was AUD 160 million for the years 2016-2017, while the direct cost of poor mental health was AUD 43 to 70 billion for the years 2018-2019 (Hillman et al., 2018; Productivity Commission, 2020). However, not all Australians with existing poor sleep quality and mental ill-health seek and obtain treatment for their conditions (Australian Institute of Health and Welfare, 2022b; Lallukka et al., 2018; Parliament of Australia, 2019; Reynolds et al., 2019). The lack of treatment for both health conditions can increase the risk of certain poor sleep- and poor mental health-related diseases in non-treated individuals (Cappuccio et al., 2010; Walker et al., 2015).

A few studies found strong associations between mental health and sleep quality. For example, using data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey, Duncan et al. (2022) found that individuals aged 18 and above with insomnia had significantly higher odds of having poor mental health compared to individuals without insomnia. In another Singaporean study on 329 full-time workers, Dunleavy et al. (2019) also reported an association between subjective sleep quality and impaired mental health. Similarly, a meta-analysis of 63 studies found positive correlation between mental resilience and sleep quality among healthy individuals (Arora et al., 2022).

However, the direction of influence between sleep quality and mental health is not always clear and the existing evidence indicates that relationships between sleep quality and mental health are strong but complicated. On one hand, a meta-analysis of randomised controlled trials (RCTs) by Scott et al. (2021) found a dose response relationship, whereby better sleep quality led to improved mental health. On the other hand, there is evidence to suggest reciprocal
relationship; poor mental health also leads to poor sleep quality (Alvaro et al., 2013; Staner, 2003). The presence of this mutual relationship also implies that common regression methods such as Ordinary Least Squares (OLS) or standard Logistic models cannot effectively determine causal relationship between mental health and sleep quality, as sleep quality, a predictor used in these methods, is correlated with the estimation error term. In other words, sleep quality is endogenous, which leads to biased estimates of effect of sleep quality on mental health (Crosby et al., 2010). Hence, a more advanced method is required to address the reciprocal relationship between mental health and sleep quality in order to obtain causal effect of sleep on mental health.

The causal effect of sleep quality on mental health using secondary data remains well understudied. Most of the existing research studying causal relationships between mental health and sleep quality used costly (time and budget) methods, such as RCTs (Alvaro et al., 2013; Scott et al., 2021; Staner, 2003). Although RCTs are considered the gold standard in causal-inference research, conducting RCTs may not always be feasible due to various resource and ethical concerns (Newhouse & McClellan, 1998). Alternative approaches, in the form of econometric methods, used to examine causal relationships in observational secondary data, are more readily available (Mostazir et al., 2019). One of such methods is the instrumental variable (IV) estimator, a quasi-experimental approach, which is considered to be an effective but less expensive and more time-efficient approach than the RCTs as it uses existing secondary data (Doan et al., 2022; Lousdal, 2018; Mostazir et al., 2019; Stukel et al., 2007). Unlike traditional regression methods, which mostly identify simple associations between variables of interest, the IV estimator offers researchers more insight into the relationship between studied variables, as it provides an estimate for causality between studied variables (Crosby et al., 2010). Further, compared to certain causal inference methods (e.g., propensity score matching methods), the instrumental variables method accounts for bias from unmeasured confounders.
(Hernan et al., 2006; Martens et al., 2006; Matthay et al., 2020). We provide discussion on how the IV method works in Section 2.3 below.

Lack of studies using quasi-experimental approach in public health studies motivates us to conduct this study. To the best of our knowledge, this study is the first to estimate the causal effect of sleep quality on mental health in working individuals using the instrumental variable method.

2. Data and methods

2.1 Data and sample

This study uses data from the HILDA Survey. The HILDA Survey is a longitudinal study of a nationally representative sample Australians. Each study wave, since 2011, consists of more than 7000 households and 17,000 individuals. The survey offers various individual’s and household’s information such as employment, health, sleep, life events, and income. Further information on the survey’s design and sample collection methods are described in Watson (2021).

Data used in this study was restricted to working individuals aged 25 to 64 in HILDA waves 13 (year 2013) and 17 (year 2017), as sleep variables were only collected in these two waves between the years 2001 and 2020.

2.2 Variables

2.2.1 Mental health

Mental health data was constructed using five questions from Short-Form 36 (SF-36) (Ware et al., 2000) in the HILDA. The five questions enquired respondents about their feelings of anxiety, depression, happiness, and calmness (‘Have you been a nervous person?’, ‘Have you felt so down in the dumps that nothing could cheer you up?’, ‘Have you felt downhearted and blue?’, ‘Have you felt calm and peaceful?’, and ‘Have you been a happy person’). Each respondent
was required to respond using a 1-6 scale ([1] All of the time, [2] Most of the time, [3] A good bit of the time, [4] Some of the time, [5] A little of the time, and [6] None of the time). Mental health score was calculated by summing scores of these above 5 questions and then transforming to a 0–100 scale, with a higher score representing better mental health.

2.2.2 Sleep quality

The HILDA Survey had collected multiple sleep-related variables. The variable of *weekly sleep hours* was calculated and summed based on participants’ responses regarding their work schedule and the addition of data collected for the participants’ hours of sleep on workdays and non-workdays. Further, participants were asked to indicate either [1] Not during the past month, [2] Less than once a week, [3] Once or twice a week, [4] Three or four times a week, or [5] Five or more times a week in two questions: During the past month, how often have you… ‘had trouble sleeping because you cannot get to sleep within thirty minutes?’ and ‘taken medicine (prescribed or “over the counter”)’?’. Participants were also asked to rate their sleep (‘How would rate your sleep quality?’) using a 1-4 scale: [1] Very good; [2] Fairly good; [3] Fairly bad; and [4] Very bad. The principal component analysis (PCA) method was used to create one unique sleep quality variable, as previous research found sleep hours and sleep disturbance to contribute to sleep quality (O’Donnell et al., 2009). The method generated a variable with negative values (negative minimum value of -2.16); 2.16 was added to the variable to shift the sleep variable to all positive values, implying that the higher the variable’s score, the worse the sleep quality. However, in order to interpret more conveniently the relationship between mental health, which is the higher the score the better the mental health, and sleep quality, the sleep quality score, was multiplied by -1. The final sleep score means that the higher the variable’s score, the better the sleep quality.

2.2.3 Instrumental variables
Several studies found that certain factors such as particular work conditions (e.g., long workhours, high job demands, and shift work) and major life events can affect individual sleep quality (Afonso et al., 2017; Gao et al., 2019; Kim et al., 2016; Li et al., 2019; Torquati et al., 2019). We thus use these variables as instruments in our instrumental variables model.

The shift work variable was generated and recoded into yes/no responses using the question: ‘Which of the following best describes your current work schedule?’ The major life event variable was generated with yes/no responses based on six questions: ‘Partner or I gave birth to, or adopted, a new child’, ‘Death of a close friend’, ‘Death of other close relative/family member’, ‘Death of spouse or child’, ‘Serious personal injury or illness to self’, and ‘Pregnancy/pregnancy of partner’. For both long work hours (paid and unpaid) variables, yes/no responses were generated, where yes indicated individuals to have work hours within the top 75% workhour distribution; data for males and females were separately estimated, as long hours differ greatly between sexes (Workplace Gender Equality Agency, 2019). The PCA method was used to generate a job demand variable using participants’ responses to five statements: ‘My job is more stressful than I had ever imagine’, ‘My job is complex and difficult’, ‘My job often requires me to learn new skills’, ‘I fear the amount of stress in my job will make me physically ill’, and ‘I use many of my skills and abilities in my current job’. These five instruments were used to first predict sleep quality before estimating effects of sleep quality on mental health.

### 2.2.4 Controlling variables

Current evidence indicates that other variables may have a confounding effect on mental health. These variables included in this study were: age, sex, migration background, marital status, tertiary education, existing long-term health conditions, location (Australian states or territories, urban/rural), financial distress, having preschool children, alcohol drinking status, smoking status, and physical activity level. These are evidenced to have relationships with mental health
and/or sleep in Australia and elsewhere (e.g., Alegría et al., 2018; Doan et al., 2022; Lyons et al., 2022).

2.3 Empirical models

The Ordinary Least Squares (OLS) model was first used to provide a baseline estimate of the relationship between mental health (MH) and sleep quality (SQ). The model is as follow:

\[ MH_{it} = \alpha + \beta_1 SQ_{it} + \beta_2 X_{1it} + \beta_3 X_{2it} + \epsilon_{it} \]  

(1)

where \( MH_{it} \) represents the mental health score for individual \( i \) in year \( t \). \( SQ_{it} \) is sleep quality score. \( X_1 \) is the vector of individual and household characteristics (age, age squared, sex, marital status, migration background, tertiary education, long-term health conditions, financial distress index, having preschool children, alcohol drinking status, smoking status, physical activity level). \( X_2 \) is a vector for extra controlling variables including urban/rural, state and year dummy variables.

Due to potential mutual or reciprocal relationships between mental health (\( MH \)) and sleep quality (\( SQ \)), OLS estimates of \( \beta_1 \) from equation (1) are biased. The instrumental variable method is applied. The first stage predicted \( SQ \) using the five (\( Z \)) instruments above (equation 2). In the second stage, the predicted \( SQ \) (or \( \hat{SQ} \)) was used to estimate the causal effect of \( SQ \) on \( MH \) (equation 3). This two-equation system can be estimated in one single step procedure using the generalized method of moments (GMM) instrumental variable estimator, which is more efficient than the two-step procedure (Baum et al., 2003; Baum et al., 2007).

The system of two equations used for this study’s instrumental variables model is as below:

\[ SQ = f(Zs,Xs) \]  

(2)

\[ MH = f(\hat{SQ},Xs) \]  

(3)
Where \( Zs \) are five instrument variables (job demands, a dummy variable for long paid workhours, a dummy variable for long unpaid workhours, shift work, and major life events), \( Xs \) represents the exogenous controlling variables (age, age squared, migration background, sex, marital status, tertiary education, long-term health conditions, financial distress, having preschool children, alcohol drinking status, smoking status, physical activity level, urban, state and year dummy variables).

Similar to controlled experiment, in quasi-experiment (instrumental variable model) the population is divided into subgroups (treatment and control) who share the same values for unobserved attributes. Suppose the intervention (the instrument) affects only treatment group who are identical to those in comparison group, that is, both groups those have the same unobserved attributes would have the same sleep quality score and mental health outcome in the absence of the intervention (\( Zs \)). The instrument e.g., changes in working conditions e.g., starting irregular work shift, or shocks to life (life events) play a role like intervention that is why the instrumental variables method is named as a ‘quasi or natural experiment’ (Angrist & Krueger, 2001).

The validity of the instrumental variables estimator relies heavily on an assumption that the instruments (\( Zs \)) (intervention) are uncorrelated with unobserved attributes that affects mental health, i.e., \( \text{cov}(Zi, \epsilon_a) = 0 \). In the case of experiment of \( Zi \) (random assignment of the intervention), the difference in mean mental health between treatment/intervention and control/comparison group will not be exacerbated by the instrumental variables estimator, but this is not completely the case of quasi or natural experiments (Card, 1999). This is the limitation of instrumental variables estimator. The instrumental variables estimates in the presence of weak instruments (weakly correlated with sleep quality, but possibly correlated with the residual of the mental health equation), the estimates would be very imprecise and
seriously inconsistent (Belzil, 2007). Thus, the weak instrumental variables test is needed to ensure that instrumental variables estimation does not provide imprecise estimates of effect of physical health on mental health. We thus conduct series of instrumental variable tests including endogeneity, weak instrument, weak identification, and over-identification tests to determine if the instruments are valid or meet the assumptions (Baum et al., 2003; Baum et al., 2007; Finlay & Magnusson, 2009).

3. Results

3.1 Descriptive statistics

Table 1 provides the descriptive statistics for key variables used in the current analysis. The mean mental health score was 75.102, with a minimum of 0 and a maximum of 100. On average, working Australians sleep about 7 hours per day, mean of the sleep quality score is -2.216, ranging from -7.0 to 0.006. About 26% of the working individuals aged experienced bad sleep. More than one third of the sample reported at least once a week having difficulty falling asleep within 30 minutes, and about 12.5% of the working individuals aged 25-64 reported taking medicine to help sleep during the past month.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mental health (0-100)</td>
<td>75.102</td>
<td>15.837</td>
</tr>
<tr>
<td>Sleep quality score (-7.0 – 0.006)</td>
<td>-2.216</td>
<td>1.634</td>
</tr>
<tr>
<td>Sleep hours (weekly)</td>
<td>49.038</td>
<td>7.902</td>
</tr>
<tr>
<td>Overall sleep rating</td>
<td>100%</td>
<td></td>
</tr>
<tr>
<td>[1] Very good</td>
<td>16.8</td>
<td>37.3</td>
</tr>
<tr>
<td>[2] Fairly good</td>
<td>57.3</td>
<td>49.5</td>
</tr>
<tr>
<td>[3] Fairly bad</td>
<td>22.3</td>
<td>41.6</td>
</tr>
<tr>
<td>[4] Very bad</td>
<td>3.6</td>
<td>18.6</td>
</tr>
<tr>
<td>Had difficulty falling asleep within 30 minutes</td>
<td>100%</td>
<td></td>
</tr>
<tr>
<td>[1] Not during the past month</td>
<td>35.9</td>
<td>48.0</td>
</tr>
<tr>
<td>[2] Less than once a week</td>
<td>27.2</td>
<td>44.5</td>
</tr>
<tr>
<td>[3] Once or twice a week</td>
<td>20.0</td>
<td>4.0</td>
</tr>
<tr>
<td>[4] Three or four times a week</td>
<td>9.7</td>
<td>29.6</td>
</tr>
<tr>
<td>[5] Five or more times a week</td>
<td>7.2</td>
<td>25.8</td>
</tr>
<tr>
<td>Had taken medicine to help sleep</td>
<td>100%</td>
<td></td>
</tr>
<tr>
<td>Age (years)</td>
<td>Sex (male=1/female=0)</td>
<td>Marital status (0=never married, 1=married/de-facto)</td>
</tr>
<tr>
<td>------------</td>
<td>-----------------------</td>
<td>-----------------------------------------------------</td>
</tr>
<tr>
<td>42.7</td>
<td>0.52</td>
<td>0.76</td>
</tr>
</tbody>
</table>

Migration background (%)  

| [1] Non-Indigenous Australian | 76.2 | 42.6 |
| [2] Indigenous/Torres Strait Islander Australian | 2.0 | 13.9 |
| [3] Other English-speaking country | 9.4 | 29.3 |
| [4] Non-English-speaking country | 12.4 | 33  |

Drinking status (%)  

| [1] Never drink | 5.9 | 23.5 |
| [2] Very rarely/No longer drink | 27.0 | 44.4 |
| [3] Moderate drinker | 57.3 | 49.5 |
| [4] Heavy drinker | 9.8 | 29.8 |

Smoking status (%)  

| Never smoke | 53.9 | 49.9 |
| Past smoker | 28.4 | 45.1 |
| Current smoker | 17.7 | 38.2 |

Physical activity level (%)  

| Sedentary | 25.3 | 43.5 |
| Low | 40.5 | 49.1 |
| Moderate | 22.1 | 41.5 |
| High | 12.1 | 32.5 |

Note: estimates were adjusted for sample weights

3.2 Sleep quality and mental health: OLS estimates

Mental health was significantly associated (p<0.01) with sleep quality (Table 2, column 1), a 2.25 point increase in mental health score was associated with each unit increase in sleep quality
score (ranging from -7.001 to -0.006, see Table 1). Other confounding variables such as being married and male have better mental health, while financial distress and having long-term health conditions is negatively associated with mental health (Table 2, column 1).

3.3 Impact of sleep quality on mental health: instrumental variable estimates

In the first stage of the instrumental variables analysis (Table 2, column 2), all five instruments (shift work, job demand, experienced major life event(s), having long workhours, and having long unpaid hours) were found to be good predictors of sleep quality (all p<0.01). These factors are adversely associated with worker’s sleep. For example, working in shift (irregular work hours such as evening or weekend shift) leads to a decline of 0.30 points in sleep quality score (which ranges around -7 to 0). All of the instrument coefficients are highly significant at the 1% level.

Table 2: Effects of sleep quality on mental health, working individuals aged 25-64, 2013 and 2017 (OLS and IV estimates)

<table>
<thead>
<tr>
<th>Variables</th>
<th>OLS</th>
<th>IV</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>First stage (SQ)</td>
<td>Second stage (MH)</td>
</tr>
<tr>
<td>Sleep quality</td>
<td>2.2528** (0.1114)</td>
<td>11.3793** (0.9175)</td>
</tr>
<tr>
<td>Shift work (yes=1)</td>
<td>-0.3002** (0.0429)</td>
<td></td>
</tr>
<tr>
<td>Job demand (0-100)</td>
<td>-0.0118** (0.0010)</td>
<td></td>
</tr>
<tr>
<td>Experienced a major life event in the past year (yes=1)</td>
<td>-0.1878** (0.0396)</td>
<td></td>
</tr>
<tr>
<td>Long workhours (yes=1)</td>
<td>-0.1244** (0.0368)</td>
<td></td>
</tr>
<tr>
<td>Long unpaid hours (yes=1)</td>
<td>-0.1406** (0.0408)</td>
<td></td>
</tr>
<tr>
<td>Sex (0=female/1=male)</td>
<td>0.6192+ (0.3489)</td>
<td>0.0561 (0.0357)</td>
</tr>
<tr>
<td>Marital status (married or de facto=1)</td>
<td>2.3808** (0.4427)</td>
<td>0.2266** (0.0419)</td>
</tr>
<tr>
<td>Tertiary educated (yes=1)</td>
<td>-1.5376** (0.3413)</td>
<td>0.3413** (0.6148)</td>
</tr>
</tbody>
</table>
Table 2, column 2, the bottom panel, provides the instrumental variables test results (e.g., endogeneity test, weak instruments test, redundancy test, weak-identification test, and over-identification test). The significant GMM C statistics of 129.90 (P-value <0.0001) rejected the null hypothesis that sleep quality was exogenous and indicated that the sleep quality was endogenous and that the OLS estimate of β1 using equation (1) is biased. The Anderson-Rubin Wald test produced a significant F-statistic of 98.62 (P-value <0.0001) rejected the hypothesis of weak instruments. The significant LM test of 235.83 (P-value <0.0001) showed that the instrumental variables were not redundant. The Kleibergen-Paap rank Wald F-statistic was 51.72, which was greater than the Stock-Yogo weak identification test critical values at 5% maximal instrumental variables relative bias of 18.27. This meant that the model equation used in this analysis was not weakly identified. Finally, the Sargan Bassman test indicated that the
model used was over-identified, which meant that there were more valid instruments than number of equations.

After adjusting for endogeneity of sleep quality using the instrumental variables method, estimates showed that sleep quality strongly affected mental health. Each unit (in a -7.0 to 0.0 unit scaled variable of sleep quality score) increase in sleep quality score resulted in an increase of 11.38 points in a 0-100 scaled variable of mental health (Table 2, column 3). This is a very strong effect suggesting that improving sleep quality can lead to better mental health outcome for working people.

4 Finding summary and discussion

This study examines the causal effect of sleep quality on mental health using a novel method of quasi-experiment to existing data. The endogeneity of sleep quality or reciprocal relationship between sleep and mental health was adjusted for before estimating the effect of sleep on mental health. This study found that some adverse working conditions such as long workhours (paid and unpaid), high job demand, shift work, and experiences of major life events strongly and negatively affected sleep quality. Changes in sleep quality had a strong effect on mental health of working individuals. Each point increase (or decrease) in sleep quality score (-7.001 to -0.006) led to a rise (or decline) of 11.38 points of the mental health score (scaled 0-100). The effect of sleep quality on mental health obtained from the instrumental variables estimator (11.38, p<0.001) (Table 2, column 3) was much stronger than the estimate using the OLS estimator (2.25, p<0.01) (Table 2, column 1), suggesting that the OLS estimate was significantly downward-biased.

These findings are consistent with the currently limited literature that looked at the causal relationship between poor (or good) sleep quality and poor (or good) mental health. For example, Scott et al. (2021) found that the manipulation of sleep behaviour (for the better) and improved sleep quality led to significant medium-sized positive effects on composite mental
health. Alvaro et al. (2013) also reported causal relationships between sleep disturbance (or poor sleep quality) and anxiety and/or depression.

Compared to the RCTs reviewed by Scott et al. (2021) and Alvaro et al. (2013), this study relied on easily obtained secondary data (e.g., HILDA Survey) and applied the instrumental variables method, which is more effective in terms of time and financial costs while still provided robust and consistent estimates of the causal effect of sleep quality on mental health.

The instruments used in this study, such as long work hours, long unpaid work hours, high job demand, being assigned shift work, and having experienced major life events were found to strongly affect sleep quality. These findings are consistent with the existing literature that reviewed the relationship between certain work conditions or life events and sleep quality (Kim et al., 2016; Maume et al., 2010; Vahtera et al., 2007). As such, findings from this study identify key areas that policies can address to remedy mental health outcomes in the work force. For instance, reducing working hours, reducing job demands, and proper regulation of shift work hours will help improve employees’ sleep and ultimately improve employees’ mental health and well-being (Lyons et al., 2022; Linton et al., 2015; Strazdins et al., 2011). Additionally the availability of welfare and support for employees, such as sleep hygiene education, behavioural therapies, and emotional support programs in case workers facing adverse shocks to their life would help build resilience among workers from poor sleep and mental ill-health (Gilbert et al., 2021; Kaku et al., 2012; Gardner et al., 2018).

The current study adds to the currently limited literature on the casual effect of sleep quality on mental health using a large, population based Australian sample. Previous limited studies investigating the causal relationships were mostly conducted in non-Australian settings. Further, those studies were conducted using costly and time-consuming methods such as RCTs. Our instrumental variables method in this study offers a cheaper and quicker alternative to study causal relationships between mental health and sleep.
However, the current study has some limitations. The current study only focuses on working individuals aged 25-64. The findings are therefore not representative for the Australian population. The younger adults (aged 15-24) may face double burdens, schooling pressure and low income as they mainly work in lower paid jobs such as part time or casual jobs while studying. These factors would affect their sleep and hence mental health. Based on the Australian Institute of Health and Welfare (AIHW) (2022a), the young age group is most likely to report having experienced symptoms of mental ill-health compared to the other age groups. Our exclusion of individuals aged 65 and above was due to concerns over the potential impacts of old age as well as there is no market time and work condition variables, as older individuals were found to have poorer sleep quantity compared to younger individuals (Mander et al., 2017). These exclusions warrant further research to look at impact of sleep on mental health for these groups. One of the possible strategies is to look for suitable instruments for each group in order to apply the instrumental variables method appropriately. Additionally, all sleep data used in this paper were self-reported, which can be subject to recall bias; Fenwick et al. (2022) had proposed the usage of accelerometers to overcome such bias.

5. Conclusions

Good mental health is essential to individual health and wellbeing. Mental ill-health can have widespread negative impacts on workforces and their respective economies. This study has shown that working conditions and major life events can drive changes in individuals’ sleep quality, and ultimately mental health. Therefore, this study underscored the need for policies that address current employment conditions by reducing long workhours, high work demand, irregular work shifts, and providing better support including emotional support programs in case workers facing adverse shocks to their life, and creating worker-friendly settings to mitigate poor sleep quality in the general workforce. Doing so would lead to better mental health and overall health outcomes in the workforce.
Conflict of Interest
The authors declare no competing interests.

Ethical Approval
The research ethic protocol was approved by the Australian National University Human Research Ethics Committee.

Data Availability Statement
The dataset used in the current study is not publicly available, but it would be accessible from the Melbourne Institute if an access approval is granted by the institute.
References


