

The Association Between Increased Workload and Mental Health Outcomes Among Higher Education Staff in Australia

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Abstract

Background: High workload is associated with adverse mental health outcomes, yet its impact on academic staff remains underexplored.

Aims: This study aimed to examine the relationship between workload and mental health among academics in Australian higher education (HE) institutions.

Methods: A cross-sectional study was conducted with 626 academics in an online survey. Excess workload and mental health outcomes were analyzed using regression and G-method analyses.

Results: Academics reported an average annual workload of 3,256 hours, significantly exceeding the standard 1,824 hours. Approximately 25% experienced moderate to severe anxiety or depression, substantially higher than the general population. Mental health service utilization was three times higher among academics, yet 30% did not seek help. Each additional hour worked beyond 1,824 hours was associated with increases in anxiety and depression scores ($\beta = 0.001$) and odds of moderate to severe mental health issues (0.01%–0.02%). G-method analyses supported these findings showing a 2-3 point and a 13%–15% increase in respective scores and likelihood among those working excessive hours.

Conclusions: The findings underscore the significant association between excessive workload and poor mental health among academics in Australian HE institutions. Addressing workload imbalances could play a critical role in improving mental health in this population.

INTRODUCTION

The health and wellbeing of Australian higher education (HE) staff have emerged as a pressing concern. A large survey conducted between 2020 and 2023 revealed that 43% of Australian university employees reported experiencing extreme tiredness, anxiety, or depression during this period (Neser et al., 2023). These issues have worsened annually, reaching the lowest levels in 2023 (Neser et al., 2023). While the COVID-19 pandemic and associated government restrictions have significantly influenced these trends at a macro level [2], workload and work pressure have been identified as critical micro-level determinants (Rahman et al., 2024). A survey by Neser et al. found that 66% of Australian university staff reported burnout, academic staff experienced the highest levels of work pressure, and nearly three in five respondents reported conflicts between work and family life (Neser et al., 2023).

Excessive workload is recognized as a critical risk factor for employee mental health, with several mechanisms linking workload to psychological distress. According to the World Health Organization (WHO), excessive workload is a major source of stress which contributes to poor mental health outcomes (WHO, 2024). Research by Hassanie et al. indicates that workload impacts mental health both directly and indirectly, with work adaptability mediating this relationship (Hassanie et al., 2022). Heavy workloads are also strongly associated with burnout and exhaustion, common precursors of workplace mental health problems (The Greater Good Science Center, 2024). Despite the importance of workload

as a determinant of mental health, research quantifying its impact among HE staff remains limited and even inconsistent (Hassanie et al., 2022; Nesar et al., 2023).

Addressing this research gap, the present study aims to quantify the relationship between workload and mental health among Australian HE staff. Given this context, we aim to address one of these research gaps by quantifying the relationship between workload and mental health among Australian HE staff. Using a regression framework, we sought to provide robust estimates of this association. Regression models are well-established tools for both prediction and explanation in epidemiological studies (Harrell, 2015; Shmueli, 2010). However, recognizing the limitations of our cross-sectional study design and the potential for residual confounding due to unmeasured covariates, we employed G-methods to enhance the validity of our findings. These methods, such as inverse probability weighting (IPW) and G-computation, are designed to balance confounder distributions through re-weighting exposure (Hernán & Robins, 2006) or to estimate potential outcomes (Hernán, 2004; Le Borgne et al., 2021). These approaches enable the estimation of causal effects, including the average treatment effect (ATE)

This study has two primary objectives: (1) to examine workload, mental health outcomes, and mental health service utilization among academic staff; and (2) to investigate the specific relationship between workload and mental health outcomes in this population. Our findings aim to provide critical insights into the intersection of workload and wellbeing in higher education. These insights are intended to inform both public health policy and institutional practices, ultimately promoting healthier work environments in Australian HE.

MATERIALS AND METHODS

Study design and setting

A cross-sectional study was conducted across Australian universities between February and August 2022 using a self-reported structured questionnaire survey.

Study sample and sampling

Participants who worked as academics – either research only, teaching only or combining teaching and research working in any HE institutions in Australia were eligible for inclusion. To estimate an adequate sample size, a power analysis was conducted using a two-tailed linear regression model with five variables: workload (exposure) and four covariates. Assuming a power of 0.80, a significance level of 0.05, and a small effect size (Cohen's $f^2 = 0.02$), the minimum required sample size was 395 participants. Accounting for potential participant withdrawal (30%) and incomplete responses (15%), the adjusted target sample size was 591 participants to ensure sufficient statistical power and data quality.

Data collection

Participant recruitment commenced following the approval of the study protocol. Invitations to participate were disseminated through multiple channels to maximize reach and enhance response rates. To be specific, an email was sent to all Australian universities through their public-facing contact points requesting that a prepared invitation to participate in the study be circulated to all academic staff. An invitation was also sent to a number of additional invitation-to-participate avenues through various academic networks that investigators had. While some academics may have received more than one invitation to participate, respondents with consent could only complete the survey once. A total of 626 academic staff responded to the survey.

Measures

A structured questionnaire was developed in three sections. The first sections include questions about demographic and academic profile (age, gender, countries of birth, highest academic level, type of employment, number of years working as an academic). The second section collected data on workload (measured in working hours, see the section below) and mental health (GAD-7 and PHQ-9, see the section below). The final section asked participants about mental health services utilisation.

Outcomes (GAD-7, PHQ-9)

Two main outcomes, GAD-7 and PHQ-9 score, were included for measuring mental health. The GAD-7 and PHQ-9 scores were composited from the GAD-7 and PHQ-9 scales, respectively. These are among the leading validated and most frequently used depression and anxiety measures and are available in more than 80 translations (Kroenke et al., 2016). GAD-7 (Löwe et al., 2008; Spitzer et al., 2006) and PHQ-9 (Kroenke et al., 2001; Kroenke et al., 2016) are reliable and valid 7-item and 9-item measures of generalised anxiety and depression, respectively widely used in clinical and research settings. Internal reliability using alpha for GAD-7 and PHQ-9 was excellent at 0.92 (equivalent to the standardising sample) and 0.88. GAD-7 score was categorised as Minimal: 0–4, Mild: 5–9, moderate: 10–14, severe: 15–21 with highest two deemed ‘case level’ and requiring treatment. PHQ-9 score was categorised as Minimal: 1–4, Mild: 5–9, Moderate: 10–14, Moderately severe: 15–19, Severe: 20–27 with the latter three case level. These categories were recoded to establish binary GAD-7 and binary PHQ-9 measures, with 1 reflecting moderate or severe anxiety and depression versus 0 minimal or mild. GAD-7 score and PHQ-9 score were used as continuous outcomes for linear regression analysis, while binary GAD-7 and PHQ-9 were for logistic regression analysis.

Exposure

Workload questions were developed using the prior research and guideline by Kenny and Fluck (Kenny & Fluck, 2019; Kenny & Fluck, 2017, 2018, 2022, 2023; Kenny & Fluck, 2014) on the different tasks academics undertook in their work. The scoring tools within Qualtrics were then used to calculate annual working hours based on studies by Kenny and Fluck (Kenny & Fluck, 2019; Kenny & Fluck, 2017, 2018,

2022, 2023; Kenny & Fluck, 2014). Academic (teaching and research) hours were summed to form total working hours per year. To reduce bias, some extreme or outlier data were excluded, for example when respondents reported zero or more than 80 hours a week. As G-methods require the exposure variable to follow a binomial distribution, total annual working hours were categorized into binary values: 1 for working more than 1,824 hours per year, and 0 otherwise. This threshold was based on Australia's standard full-time working hours, typically 38 hours per week, adjusted for annual leave, public holidays, sick leave, and other absences, resulting in an approximate total of 1,824 hours annually (Fair Work Ombudsman, 2024).

Statistical methods

Categorical and continuous data were estimated in numeric and percentage forms and mean and SDs where appropriate, respectively, to characterise the study sample. To assess the association between workload and mental health, the authors first initially employed a regression framework to test the unadjusted association between them as well as identify any possible confounders for inclusion in adjusted analyses. As shown in **Appendix**, only academic level and age group were significantly associated with GAD-7 scores (**Table A1**) and binomial PHQ-9 (**Table A2**), thereby being included in the following models.

Adjusted regression analyses were then conducted to further explore the relationship between workload and mental health. Once a significant association has been detected, we applied G-methods, specifically inverse-probability weighting (IPW) and G-computation, to estimate the potential causal effect of workload on mental health outcomes (both continuous and binary measures). The IPW method can be described as follows:

$E[I(A = a)Y/P(A = a|L)] = E[Y(a)]$ from which we can estimate the following effect:

$$E[Y(1)] - E[Y(0)] = E[I(A = 1)Y/P(A = 1|L)] - E[I(A = 0)Y/P(A = 0|L)]$$

By re-weighting each subject's outcome with the inverse probability of receiving the exposure that they experienced, it is possible to create a pseudo-population in which the confounder distribution is balanced across the entire sample. This allows for the estimation of the average causal effect (ACE) or average treatment effect (ATE) (Hernán & Robins, 2006). For this estimate to be valid, several assumptions must hold: the consistency assumption, the correct specification of the propensity score model, and the positivity assumption (i.e., $P(A = a|L) > 0$ for all a).

To illustrate the G-computation approach, let $Y(1)$ and $Y(0)$ represent the two potential outcomes under the exposure and the non-exposure, respectively. Let (Z, X) denote the variables related to the exposure status, where $Z = 1$ for exposed individuals, and 0 otherwise, and X represents the k covariates ($X = X_1, \dots, X_k$) measured before exposure. The average causal effect (ACE) is defined as $ACE = E[Y(1) - Y(0)]$, representing the mean difference between the outcomes of individuals if every subject, regardless of

their observed exposure or non-exposure, had been either exposed or unexposed (Hernán, 2004; Le Borgne et al., 2021). By standardising in this manner, statistical modelling can be applied to recover the outcome means for the exposed and unexposed groups, similar to a target trial. This is achieved by weighting back to the total-sample confounder distribution, allowing an estimate of the mean outcome if the entire population had been exposed, and the mean outcome of the entire population had been unexposed, thereby enabling estimation of the average treatment effect (ATE).

A sensitivity analysis was conducted to assess whether the effect of workload on mental health remained consistent. This was done by applying both G-methods, as described above, to both types of outcomes (continuous and binary). Both approaches yielded consistent results.

Initially, a *p*-value of < 0.05 was considered indicative of statistical significance. However, given the multiple statistical tests conducted in the main regression analyses, the Benjamini-Hochberg-based FDR (false discovery rate) (Benjamini & Hochberg, 1995) was applied to adjust for multiple testing, meaning that an FDR of < 0.05 was defined as statistical significance. All analyses were performed using Stata version 18.5 (Stata, 2023).

Ethical approval

The research ethics was granted by the Federation University Human Research Ethics Committee (HREC No A21-179). Participants provided informed consent to participate in the survey and agreed for data usage in the research.

RESULTS

The key characteristics of the sample are outlined in **Table 1**. The majority of participants were middle-aged (35-59 years old, 77.2%) and female (64.7%), with nearly all (99.5%) born in Australia. Most were employed full-time (80.8%), and academics at levels B through D made up 76.7% of the sample. In terms of tenure, a larger proportion of academics had either 1-9 years or 15 or more years of experience, compared to those with 10-14 years.

Table 1. Characteristics of the study sample

Variables (N = 626)	n (%)
Demographic and academic characteristics	
Age group	
<25-34	67 (10.7%)
35-59	482 (77.2%)
60-65+	75 (12.0%)
Gender	
Male	196 (31.4%)
Female	404 (64.7%)
Non-binary / third gender	9 (1.4%)
Prefer not to say	15 (2.4%)
Countries of birth	
Australia	622 (99.5%)
Others	3 (0.6%)
Academic Level	
Sessional/Casual/Adjunct Academic	50 (8.0%)
Lecturer/Level A (Assistant Professor in US system)	52 (8.3%)
Lecturer/Level B (Assistant Professor in US system)	200 (32.1%)
Senior Lecturer/Level C (Associate Professor in US system)	179 (28.7%)
Associate Professor/Level D (Full Professor in US system)	99 (15.9%)
Professor/Level E (Endowed Chair in US system)	44 (7.1%)
Type of employment	
Full Time	504 (80.8%)
Part Time	69 (11.1%)
Sessional/Casual/Adjunct Academic	51 (8.2%)
Number of years working as an academic	
1-9 years	247 (39.6%)
10-14 years	150 (24.0%)
15 years or more	227 (36.4%)

Table 2 characterises workload, mental health, and mental health service use among the study sample. Participants worked an average of 3,256 hours (SD = 2,113.84) adjusted for time fraction, significantly higher than the standard 1,824 hours typical of academic institutions. Of the total hours, teaching (mean = 1,370.11, SD = 1,106.77) and research (mean = 1,354.5, SD = 1,095.55) took up more time than service-related activities (mean = 503.40, SD = 393.83). On average, participants reported anxiety and depression scores close to 6, with approximately one in four experiencing moderate or severe anxiety (25.1%) and depression (24.8%). In total, 40.6% of the sample used at least one mental health service in the past year. Among those experiencing moderate or severe anxiety or depression, around 70% sought mental health services, leaving 30% without service use. Among service users with moderate or severe symptoms, most consulted a GP (36.8%), followed by psychologists (22.5%) and Employee Assistance Programs (EAP, 14.7%).

Table 2. Descriptives of workload, mental health and mental health service use among the study sample

Variables (N = 626)	n (%) or mean (SD)
Workload	
Total teaching & HDR hours, mean (SD)	1370.11 (1106.77)
Total research hours, mean (SD)	1354.53 (1095.55)
Total service hours, mean (SD)	503.40 (393.83)
Adjusted total hours (adjusted for time fractions), mean (SD)	3256.07 (2113.84)
Mental health	
GAD-7, mean (SD)	5.78 (5.86)
PHQ-9, mean (SD)	5.73 (5.97)
GAD-7 (moderate or severe)	157 (25.1%)
PHQ-9 (moderate or severe)	155 (24.8%)
Use of at least one service or more among the entire sample (N=626)	254 (40.6%)
Use of at least one service or more among those with moderate or severe anxiety/depression (N=196)	138 (70.4%)
Telephone counselling service	11 (5.9%)
EAP	29 (14.7%)
GP	72 (36.8%)
Psychiatrist	16 (8.1%)
Mental health nurse	3 (1.6%)
Psychologist	44 (22.5%)
Other counsellor	16 (8.5%)
Hospital emergency department	2 (1.3%)
Hospital mental health ward	1 (0.7%)

Table 3 displays the results of standard regression analyses for different mental health outcomes, including GAD-7 and PHQ-9, both as continuous and binary variables. Each additional hour beyond 1,824 annual working hours was associated with a 0.001-point increase in both the GAD-7 (anxiety) and PHQ-9 (depression) scores. The odds of experiencing moderate or higher levels of anxiety and depression (as

measured by binary GAD-7 and PHQ-9) increased by approximately 0.01% to 0.02% for each additional hour of work beyond 1,824 hours. All associations were statistically significant (p 's: <0.0001, <0.0001, 0.0110, and 0.0050, respectively). **Figure A1 (Appendix)** further illustrates the positive association between increased workload and higher levels of each of these mental health measures, indicating their consistent trends.

Table 3. Adjusted association between workload and mental health as per standard regression approach

Main independent variable	Outcome			Outcome		
	Point estimate	p	FDR	Point estimate	p	FDR
	[95%CI]			[95%CI]		
	GAD-7 score ^A			PHQ-9 score ^B		
	Beta [95%CI]			Beta [95%CI]		
Adjusted total hours per year ^E	0.001 [0.0004, 0.0010]	<0.0001	<0.0002	0.001 [0.0002, 0.0008]	<0.0001	<0.0002
	GAD-7 (binomial) ^C			PHQ-9 (binomial) ^D		
	OR [95%CI]			OR [95%CI]		
Adjusted total hours per year ^E	1.0001 [1.00003, 1.0002]	0.0110	0.0110	1.0002 [1.00005, 1.00025]	0.0050	0.0067

A & B: linear regression model; A: adjusted for academic level; C & D: logistic regression model; D: adjusted for age group; E Adjusted total hours per year was centred at 1,824 hours.

Figure 1 demonstrates the results of two robust analytical methods, inverse-probability weighting (IPW) and G-computation, to estimate the effect of workload on two continuous outcomes: GAD-7 (anxiety) and PHQ-9 (depression) scores. Using the IPW method, for those having a total annual working hour > 1,824, the GAD-7 score increased by an estimated 2.91 points (FDR < 0.0002). With the G-computation method, if everyone worked > 1,824 hours annually, the anxiety score increased by 2.79 points compared to if everyone's annual working hour was below 1,824 (FDR < 0.0002). For the PHQ-9 score, the IPW method estimated a 1.84-point increase for respondents with an annual total working hour > 1,824 (FDR

< 0.0002). The G-computation method estimated a 2.75-point increase in PHQ-9 score if every participant worked > 1,824 annually against everyone working below this number (FDR < 0.0002). Both IPW and G-computation methods provided statistically significant estimates for the effect of the workload on GAD-7 and PHQ-9 scores. This consistent pattern across two different methods (IPW and G-computation) strengthens the validity of the observed associations between the workload and mental health measures (GAD-7 and PHQ-9 scores).

Figure 2 indicates the estimated effect of workload on two binomial outcomes, binomial GAD-7 and binomial PHQ-9. In the IPW analysis, the probability of experiencing moderate or severe anxiety increased by 11.5% for respondents with annual working hours > 1,824 (FDR = 0.0290). The G-computation analysis showed that the probability of experiencing moderate or severe anxiety increased by 12.7% if everyone worked > 1,824 hours annually compared to if everyone's annual total working hour was below 1,824 (FDR = 0.0217). For the PHQ-9, the IPW analysis estimated a 12.6% increase in the probability of moderate or severe depression among respondents with an annual total working hour > 1,824 (FDR = 0.0187). The G-computation method estimated a 14.8% increase in the probability of moderate or severe depression if every participant worked > 1,824 annually against everyone with working below this number (FDR = 0.0096). Both IPW and G-computation approaches provided statistically significant estimates for the effect of the workload on GAD-7 and PHQ-9, enhancing the validity of the observed associations between the workload and probability of mental health measures (anxiety and depression).

DISCUSSION

This study is among the first to examine working hours as a measure of workload and its association with mental health outcomes among academic staff in Australian HE institutions. The findings reveal a significant workload burden and its strong association with anxiety and depression among academics, highlighting the urgent need to address the mental health challenges faced by this group and the contributing factors, particularly excessive workload.

Academics in our study reported an adjusted annual workload averaging 3,256 hours, far exceeding the standard 1,824 hours typical in Australian HE institutions (Fair Work Ombudsman, 2024). This elevated workload maybe partly attributable to the cascading impacts of the COVID-19 pandemic and the subsequent policy responses by HE institutions. As noted by Rahman et al. (Rahman et al., 2024) and Owens et al. (Owens et al., 2022), the pandemic-induced decline in international student enrolments prompted cost-cutting strategies in HE institutions across developed countries, including Australia and the UK. These measures—such as organizational restructuring, staff redundancies, early retirements, and reductions in non-salary expenditures—have disproportionately increased the workload for remaining staff, adding complexity to their roles and adversely affecting their health and well-being (Rahman et al., 2024).

Approximately one in four academics experienced moderate to severe anxiety (25.1%) and depression (24.8%), substantially higher than rates observed in the general Australian population, where these conditions affect one in 13 to six individuals, respectively (Australian Bureau of Statistics, 2023). Despite this, the prevalence of mental health issues reported in our study was lower than that in other studies on HE staff, such as Rahman et al. (Rahman et al., 2024) (73.1%) and Naser et al. (Naser et al., 2023) (around 40%). These differences are likely due to variations in measurement tools and thresholds. While the aforementioned studies used the K-10 scale with varying cut-offs, our research employed the GAD-7 and PHQ-9 scales with thresholds set at moderate to severe. Despite methodological differences, all studies consistently highlight concerning high rates of mental health issues among HE staff, warranting attention from researchers, practitioners, and policymakers.

We also observed that the rate of mental health service utilization among academics was nearly three times higher than that of the general population—a finding consistent with the high prevalence of mental health issue in this group. However, a notable gap remains: 30% of academics with moderate to severe anxiety or depression did not seek mental health support. Future research should explore the barriers to accessing mental health services in this population, providing a basis for targeted interventions.

Using both standard regression and G-methods, we quantified the impact of excessive workload on mental health outcomes. Our findings were consistent across methods. In standard regression analyses, each additional hour worked beyond 1,824 annual hours was associated with a 0.001-point increase in GAD-7 and PHQ-9 scores, while the odds of experiencing moderate or severe anxiety or depression rose by 0.01%–0.02% per additional hour. G-method analyses showed that academics working more than 1,824 hours annually experienced increases of 2–3 points on the GAD-7 and PHQ-9 scales compared to those working fewer hours. Moreover, their probability of experiencing moderate to severe anxiety or depression was 13%–15% higher. These findings emphasize another need to address excessive workload as a critical factor in improving the mental health of HE staff.

This study has several limitations. While the use of G-methods reduces confounding, the cross-sectional design precludes establishing causality. Additionally, our reliance on an online survey may have introduced selection bias, limiting the generalizability of our findings. Another limitation is the focus on the direct association between workload and mental health, without exploring alternative pathways such as workload-induced stress (WHO, 2024), work adaptability (Hassanie et al., 2022), or burnout and exhaustion (The Greater Good Science Center, 2024). Investigating these pathways in future research could inform multifaceted interventions, as a single strategy is unlikely to adequately address the complex mental health challenges faced by HE staff.

CONCLUSIONS

This study provides valuable insights into the patterns of workload, mental health, and their associations among academics in Australian HE institutions. The findings underscore the urgent need to prioritize the health and well-being of this group. By addressing excessive workload, institutions have the potential to

significantly improve mental health outcomes for their staff. Future research should adopt longitudinal designs to establish temporal relationships and explore indirect pathways linking workload to mental health. Such efforts are essential for the development of holistic strategies to enhance the well-being of HE staff.

Declarations

AUTHOR CONTRIBUTIONS

E.Z: Conceptualization; Investigation; Methodology; Project administration; Resources; Supervision; Validation; Writing - review & editing.

H.N: Data curation; Formal analysis; Methodology; Software; Visualization; Writing original draft; and Writing - review & editing.

M.W: Investigation; Writing - review & editing.

S.E: Investigation; Writing - review & editing.

A.L: Investigation; Writing - review & editing.

F.C: Conceptualization; Investigation; Writing - review & editing.

DECLARATION OF INTEREST STATEMENT

The authors declared no competing interests on the authorship and publication of this article.

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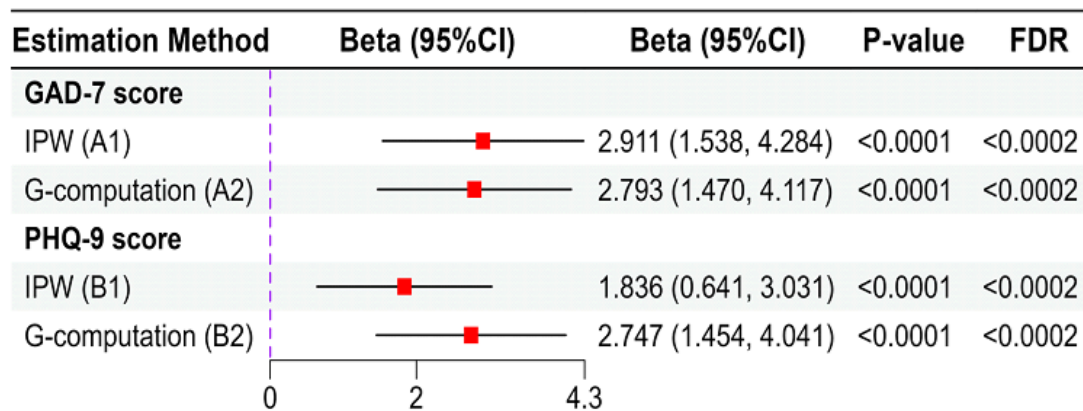
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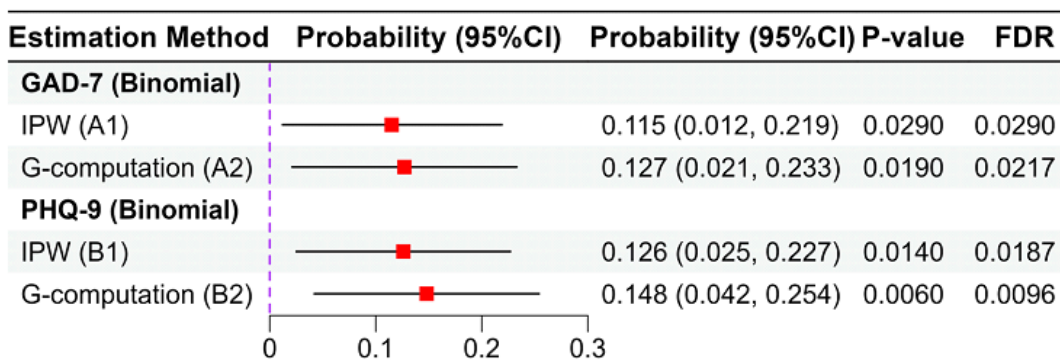
Figures



A1 & B1: estimated as per inverse-probability weighted (IPW) model; A2 & B2: estimated as per G-computation model; A1 & A2: adjusted for academic level; Exposure in these models was workload measured in adjusted total working hours = 1,824 versus < 1,824.

Figure 1

Effect of workload on mental health outcomes (continuous) as per G-methods



A1 & B1: estimated as per inverse-probability weighted (IPW) model; A2 & B2: estimated as per G-computation model; B1 & B2: adjusted for age group; Exposure in these models was workload measured in adjusted total working hours = 1,824 versus < 1,824.

Figure 2

Effect of workload on mental health outcomes (binomial) as per G-methods

Supplementary Files

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