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# Risk for Diabetes From Long Working Hours and Night Work in the United States: Prospective Associations and Machine Learning Techniques

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ABSTRACT

*Background:* Diabetes contributes significantly to death in the U.S., with many working-age individuals affected. This research determined the independent and joint associations of long working hours and night work with diabetes risk in U.S. workers, and their contribution to risk prediction.
*Methods:* This prospective study included 1,454 workers from the Midlife in the United States (MIDUS) study with 9-year follow-up. Long working hours included those working 55 or more hours per week. Night work involved those working 16 or more nights per year. Diabetes was determined by self-reported diagnosis or treatment. Multivariable Poisson regression analysis was applied to examine the prospective association of these work-related factors at baseline with incident diabetes. A gradient boosting machine learning model was used to investigate the contributions of both factors in predicting incident diabetes.
*Results:* Long working hours (RR and 95% CI = 1.60 [1.04, 2.46], $p < 0.05$) and night work (RR and 95% CI = 1.66 [1.05, 2.62], $p < 0.05$) were independently associated with the risk for diabetes, while controlling for baseline covariates. Gradient boosting analysis suggested long working hours and night work facilitated diabetes incidence. Exposure to both long working hours and night work increased the risk for diabetes (RR and 95% CI = 3.02 [1.64, 5.58], $p < 0.001$), suggesting additive interaction.
*Conclusion:* Organizations may consider reducing hours on duty and improving shift systems for primary prevention of diabetes.


## 1. Introduction

Nearly one in ten Americans (38.4 million individuals) have diabetes in the United States (U.S.) [1]. As the eighth leading cause of death in the U.S. in 2021, diabetes can lead to serious health implications, including blindness, chronic kidney disease, foot ulcers, and cardiovascular complications [1,2]. The social and economic costs of diabetes are estimated at 413 billion U.S. dollars, for direct (i.e., medical costs) and indirect costs (i.e., increased mortality) [1]. Unhealthy lifestyle, poor metabolic conditions, and aging are common risk factors for diabetes [2]. While lifestyle interventions may help to reduce the personal risk for diabetes, there are additional risk factors from the environment that need to be better understood.

The contribution of the workplace in developing diabetes has received more attention for those with certain job characteristics

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[3], including long working hours and shift work. Long working hours can be understood as working 55 or more hours per week [4]. Globally, it is estimated that 8.9%, or 488 million people, work 55 or more hours per week [4]. Around 7.2% of U.S. workers are estimated to work over 60 hours per week [5]. Long working hours have been associated with significant adverse effects on health, including outcomes of depression, anxiety, impaired sleep, and heart disease [6].

Long working hours may be considered with shift work, which includes working nights (6 pm- 4 am), rotating (changing schedules), or evening shifts (2 pm- 6 pm) [7]. Approximately 28.7% of U.S. employees reported working alternative shifts [5]. Shift work has been found to negatively impact family relationships, quality of life, and physical health due to different social hours and conflicting biological rhythms [8]. Shift work may lead to poor eating habits, increased risk for cancer, increased cardiovascular morbidity and mortality, gastrointestinal dysfunction, impaired immune system, and impaired sleep [8].

Long working hours and night work have been considered in association with diabetes previously. In one retrospective cohort study from Taiwan, long working hours and night shift work increased the risk for diabetes separately [9]. Another prospective cohort study conducted in Japanese male workers found that shift work was associated with increased risk of diabetes when working over 45 hours per week [10]. Among U.S. female nurses, long working hours and years of working night shift were positively associated with diabetes risk, but joint effects were not examined [11].

Various machine learning models have been developed to predict diabetes for early detection and identify important risk factors [12]. Leveraging the ability to learn nonlinear relationships from complex data, interpretable machine learning models can facilitate understanding the roles of different factors in diabetes prediction [13]. The roles of long working hours and night work in diabetes prediction remain under explored using machine learning approaches. Additionally, there is no research evidence in the U.S. exploring this joint effect on diabetes. The purpose of this research was to determine the independent and joint effects of long working hours and night work on the risk for diabetes and explore their contribution for diabetes prediction using both statistical analysis and machine learning.

## 2. Materials and methods

### 2.1. Study population

We analyzed data from the Midlife in the United States (MIDUS) study [14]. This ongoing national longitudinal study has collected data at three time points: 1995 (MIDUS I), 2004-2005 (MIDUS II), and 2013-2014 (MIDUS III). Participants were included for analyses if they completed the self-administered MIDUS wave II (baseline) and III (follow-up) surveys, were currently working, provided full data on sociodemographic factors and working conditions, and were free from diabetes at baseline (Supplementary Figure 1). In total, 1,454 workers were included for the analysis.

Our project was reviewed and approved for exemption by the University of California, Los Angeles Institutional Review Board (IRB#22-000604), and followed the Declaration of Helsinki guidelines and the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) guidelines.

### 2.2. Measures

Working hours and night work were assessed at baseline. Weekly working hours were total working hours for main job and other job(s), in line with a previous MIDUS report [15]. We dichotomized this variable into two groups: those who worked less than 54 hours per week (not long working hours) and those who worked 55 or more hours per week (long working hours) [16]. Night work was measured by asking numbers of overnight work in the past 12 months [17]. We dichotomized those who worked more than 15 nights per year (night work) and those who worked 0-15 nights per year (not night work), based on a previous large study [18].

Diabetes was self-reported and determined with a “yes” answer to the following questions asked at baseline and follow-up: “in the past 12 months, have you experienced or been treated for diabetes or high blood sugar?” and “during the past 30 days, have you taken prescription medicine for diabetes?” This approach has been applied in a previous publication using the MIDUS data [19].

Sociodemographic characteristics were collected at baseline, including age, sex, race, marital status, education, household income, smoking, alcohol consumption, physical exercise, body mass index, and major depressive episode.

### 2.3. Data analysis

Baseline characteristics were compared between groups of long working hours and night work by two-sample t-tests for continuous variables or Chi-squared tests for categorical variables. Prospective associations were estimated by Poisson regression models with robust error variance [20], and results were expressed as risk ratios (RRs) and 95% confidence intervals (CIs). Analyses were adjusted in 4 steps: Model I adjusted for age and sex; Model II additionally adjusted for race, marital status, education, and household income; health-related behaviors (including smoking, alcohol consumption, physical exercise, and body mass index) and major depression at baseline were further adjusted for in the Model III and Model IV, respectively. We estimated the independent associations of long working hours and night work with incident diabetes with mutual adjustment for these two exposure variables.

We completed feature importance analysis through developing a gradient boosting machine learning model. Input features to the models involved all covariates. Gradient boosting has been used for identifying important risk factors for diabetes prediction and has achieved promising results [21,22]. A gradient boosting model is an ensemble method that adds weak learners (e.g., trees) in a sequential manner, with each tree being added one by one to minimize the prediction loss. To overcome challenges in an imbalanced dataset, data augmentation with synthetic minority oversampling technique (SMOTE) was used [23]. Shapley Additive Explanations (SHAP) were used to interpret the developed gradient boosting model, calculated as the average marginal contribution to the overall model score [24]. SHAP values were used to investigate the effects of individual exposure variable factors for diabetes prediction. We conducted 5-fold cross validation and fine-tuned our gradient boosting model, including the number of estimators and maximum depth of the individual estimators. Our model performance is measured by the area under the receiver operating characteristic curve (AUROC) score.

For the joint effects, a composite variable with different combinations of long working hours and night work was created: exposure to neither ($RR_{00}$ reference), exposure to long working hours ($RR_{10}$), exposure to night work ($RR_{01}$), exposure to both ($RR_{11}$). A synergy index, $(RR_{11} - 1)/([RR_{01} - 1] + [RR_{10} - 1])$, and 95% CI were calculated. A synergy index greater than 1 indicates positive interaction, equal to 1 indicates additive interaction, and less than 1 indicates negative interaction [25]. Furthermore, we tested the multiplicative interaction term of long working hours and night work with incident diabetes. A p-value <0.05 was considered statistically significant.

To test the robustness of the associations, we conducted sensitivity analyses: (i) without adjusting for household income because long working hours and night work might lead to higher income; (ii) additional adjustment for hypertension and cardiovascular diseases; (iii) interaction between exposures and sex/body mass index on incident diabetes. The SAS 9.4 statistical software (SAS Institute, Cary, North Carolina) was used for traditional data analyses. Python 3.9.13 with scikit-learn 1.0.2 was used for machine learning model development and analysis.

## 3. Results

Participants' mean age was 51 years, with fairly equal sex distribution between males and females (Table 1). The majority were White, married, and nearly half had university or more education. Most were nonsmokers, with low or light alcohol consumption, engaged in high levels of physical exercise. More than 60% of participants were overweight or obese, and 8.8% had major depressive episode. A total of 216 participants (14.8%) worked long working hours and 176 (12.1%) worked nights. Those who worked long hours or nights were primarily younger, male, married, with relatively higher household income, and higher alcohol consumption.

After nine years, 103 new cases of diabetes were identified, with cumulative incidence rate of 7.08%. The analysis revealed significant associations between long working hours and night work with incident diabetes independently. The fully adjusted risk for diabetes for those in the long working hour group was elevated by 60% (RR and 95% CI: 1.60 [1.04, 2.46], $p < 0.05$) compared to those not working long hours. The fully adjusted risk for diabetes for those in the night work group was increased by 66% (RR and 95% CI: 1.66 [1.05, 2.62], $p < 0.05$) compared to those not working nights (Table 2).

Fig. 1 shows the contribution of long working hours and night work for diabetes prediction, using our gradient boosting model ($AUROC_{night\ work} = 0.76$ and $AUROC_{long\ working\ hours} = 0.76$) based on SHAP values. Red dots represent participants with long working hours and night work. Blue dots represent participants without long working hours or night work. Positive SHAP values reflect positive effects, while negative values reflect negative effects. The results suggest that both factors could facilitate diabetes incidence.

Table 3 presents the joint effect findings. The cumulative incidence of diabetes was 6.23% in the group exposed to neither factor and 14.75% in the group exposed to both. The fully adjusted diabetes risk was 3 times higher in the group exposed to both compared to those exposed to neither ($p < 0.001$). Regarding the interaction analysis, the synergy index was not significantly different from 1 (in the fully adjusted model, point estimate = 2.30, with 95% CI = 0.53 to 9.98), indicating an additive interaction between exposure variables; the multiplicative interaction term of exposure variables with incident diabetes was also not significant (fully adjusted $p = 0.43$).

Several sensitivity analyses were further performed. Without adjustment for household income or with additional adjustment for hypertension and cardiovascular diseases, the results did not substantially change, and the pattern of associations remained unchanged (Supplementary Table 1). No significant interaction between exposures and sex/body mass index was observed ($p > 0.10$).

## 4. Discussion

Another U.S. cohort study, the Coronary Artery Risk Development in Young Adults (CARDIA) with a baseline age of 45 years, reported a 10-year diabetes incidence of 8.1%, which is comparable to our 7.08% cumulative incidence [26]. Our findings revealed that long hours and night work could independently increase the risk of diabetes by 60% and 66%, respectively; and the risk was greatly elevated threefold among workers with joint exposure to these working conditions. Previous evidence has analyzed these factors

**Table 1**
Baseline characteristics of participants (*N*, %)

| Characteristics | | Overall ($n = 1454$) | Long working hours | | *p* | Night work | | *p* |
|---|---|---|---|---|---|---|---|---|
| | | | No ($n = 1238$) | Yes ($n = 216$) | | No ($n = 1278$) | Yes ($n = 176$) | |
| Age (years) | Mean ± (SD) | 51.22 ± 9.12 | 51.44 ± 9.22 | 49.98 ± 8.42 | 0.0305 | 51.45 ± 9.08 | 49.57 ± 9.29 | 0.0106 |
| Sex | Male | 698 (48.01) | 541 (43.70) | 157 (72.69) | <0.001 | 558 (43.66) | 140 (79.55) | <0.001 |
| | Female | 756 (51.99) | 687 (56.30) | 59 (27.31) | — | 720 (56.34) | 36 (20.45) | — |
| Race | White | 1357 (93.33) | 1153 (93.14) | 204 (94.45) | 0.7524 | 1190 (93.12) | 167 (94.89) | 0.6337 |
| | Black | 37 (2.54) | 32 (2.58) | 5 (2.31) | — | 33 (2.58) | 4 (2.27) | — |
| | Others | 60 (4.13) | 53 (4.28) | 7 (3.24) | — | 55 (4.30) | 5 (2.84) | — |
| Marital status | Married | 1070 (73.59) | 894 (72.21) | 176 (81.48) | 0.0156 | 932 (72.93) | 138 (78.41) | 0.1703 |
| | Never married | 129 (8.87) | 117 (9.45) | 12 (5.56) | — | 113 (8.84) | 16 (9.09) | — |
| | Others | 255 (17.54) | 227 (18.34) | 28 (12.96) | — | 233 (18.23) | 22 (12.50) | — |
| Education | High school or less | 344 (23.66) | 297 (23.99) | 47 (21.76) | 0.3176 | 313 (24.49) | 31 (17.61) | 0.0834 |
| | Some college | 398 (27.37) | 345 (27.87) | 53 (24.54) | — | 351 (27.46) | 47 (26.70) | — |
| | University or more | 712 (48.97) | 596 (48.14) | 116 (52.70) | — | 614 (48.05) | 98 (55.69) | — |
| Annual household income (US$) | <60,000 | 538 (37.00) | 485 (39.18) | 53 (24.53) | <0.001 | 504 (39.44) | 34 (19.32) | <0.001 |
| | 60,000–99,999 | 467 (32.12) | 394 (31.82) | 73 (33.80) | — | 408 (31.92) | 59 (33.52) | — |
| | ≥100,000 | 449 (30.88) | 359 (29.00) | 90 (41.67) | — | 366 (28.64) | 83 (47.16) | — |
| Current smoking | No | 1262 (86.80) | 1067 (86.19) | 195 (90.28) | 0.1013 | 1103 (86.31) | 159 (90.34) | 0.1383 |
| | Yes | 192 (13.20) | 171 (13.81) | 21 (9.72) | — | 175 (13.69) | 17 (9.66) | — |
| Alcohol consumption | Low or light | 850 (58.46) | 740 (59.77) | 110 (50.93) | 0.0149 | 764 (59.78) | 86 (48.86) | 0.0059 |
| | Moderate or heavy | 604 (41.54) | 498 (40.23) | 106 (49.07) | — | 514 (40.22) | 90 (51.14) | — |
| Physical exercise | Low | 684 (47.04) | 591 (47.74) | 93 (43.06) | 0.2033 | 600 (46.95) | 84 (47.73) | 0.8461 |
| | High | 770 (52.96) | 647 (53.26) | 123 (56.94) | — | 678 (53.05) | 92 (52.27) | — |
| Body mass index | Normal | 513 (35.28) | 445 (35.95) | 68 (31.48) | 0.2904 | 464 (36.31) | 49 (27.84) | 0.0501 |
| | Overweight | 572 (39.34) | 487 (39.34) | 85 (39.35) | — | 500 (39.12) | 72 (40.91) | — |
| | Obese | 369 (35.38) | 306 (24.71) | 63 (29.17) | — | 314 (24.57) | 55 (31.25) | — |
| Major depressive episode | No | 1326 (91.20) | 1122 (90.63) | 204 (94.44) | 0.0679 | 1162 (90.92) | 164 (93.18) | 0.3215 |
| | Yes | 128 (8.80) | 116 (9.37) | 12 (5.56) | — | 116 (9.08) | 12 (6.82) | — |

**Table 2**
Independent associations of long working hours and night work at baseline with incident diabetes

| Exposures | New cases of diabetes at follow-up (*n*, %) | Model I | Model II | Model III | Model IV |
|---|---|---|---|---|---|
| Long working hours | — | — | — | — | — |
| No | 6.54% (81/1238) | 1.00 | 1.00 | 1.00 | 1.00 |
| Yes | 10.19% (22/216) | 1.56 (0.99, 2.44) | 1.66 (1.06, 2.59)* | 1.60 (1.04, 2.46)* | 1.60 (1.04, 2.46)* |
| Night work | — | — | — | — | — |
| No | 6.49% (83/1278) | 1.00 | 1.00 | 1.00 | 1.00 |
| Yes | 11.36% (20/176) | 1.68 (1.05, 2.68)* | 1.83 (1.14, 2.92)* | 1.66 (1.05, 2.62)* | 1.66 (1.05, 2.62)* |

Poisson regression, *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.
Model I: adjusted for age and sex at baseline.
Model II: Model I + additionally adjusted for race, marital status, education, and household income at baseline.
Model III: Model II + additionally adjusted for smoking, alcohol consumption, physical exercise, and body mass index at baseline.
Model IV: Model III + additionally adjusted for major depressive episode at baseline.
(Long working hours and night work were mutually adjusted).

independently, including one meta-analysis with a sample size >200,000, which supported the association between long working hours (≥55 hours per week) and diabetes among those in lower socioeconomic groups (RR and 95% CI = 1,29 [1.06, 1.57]) [22]. Another large study in >200,000 workers found that those working night work were at higher diabetes risk by 37% (95% CI = 1,29 [1.13, 1.65]) compared to those never working nights [18]. These findings are consistent with our machine learning results, which showed that both long working hours and night work contribute positively to diabetes. Our study provides additional insight into the joint impact of these occupational risks on incident diabetes. While another prospective cohort study found a 2.4 times higher risk of diabetes associated with joint exposure to long working hours and shift schedules in Japanese men [10], our study expanded to both sexes in the U.S.

The relationship between working hours, shift schedules, and diabetes risk may stem from interrupted circadian rhythms and increased inflammation. A recently study of U.S. workers suggested that long work hours and shift work may increase inflammation [27], which is a major factor in developing diabetes [28]. Inflammation may also result from sleep loss [29], placing individuals working night and rotating shifts at risk. Previous reviews suggest that circadian misalignment and sleep disturbances caused by night shift work can lead to metabolic and cardiovascular consequences due to the interruption in the fasting/feeding cycle and reduced energy expenditure [30].

Future research should explore those who are at risk for diabetes based on work characteristics such as working long hours and night work [31]. Such workers range from healthcare workers, emergency responders, and law enforcement, to energy production, manufacturing, hospitality, and transportation industries [8]. Researchers may also continue to utilize machine learning to explore these worker groups, employing novel algorithms for more accurate predictions to assist early detection and intervention of diabetes. For example, an AI diagnostic system was 94% accurate in using retinal images to detect diabetic retinopathy, a complication of diabetes. The system also had better sensitivity and specificity when compared to traditional diagnostic methods, highlighting the potential for predictive tools to optimize disease detection and management [32].

Diabetes prevention requires collaboration from organizations and occupational health professionals. Occupational health providers may continue screening for diabetes, educate on lifestyle modifications, and provide care management or referrals [33]. Industries where workers adhere to such schedules and hours may consider making organizational changes, including having occupational health professionals complete sleep health evaluations, improving shift system options, reducing work hours with work time reduction policies, and allowing for additional break times [34,35].

This study has strengths and potential limitations. This study was based on a national sample of workers in the U.S. with a prospective cohort design, increasing generalizability of results among U.S. workers, and supporting the examination of temporal relationships. This study is also the first to test joint effects of long working hours and night work on the risk of diabetes in the U.S., offering practical implications for industries to consider regarding the risks of work scheduling on diabetes. Additionally, we used interpretable machine learning models to confirm that night work and long working hours are important predictors

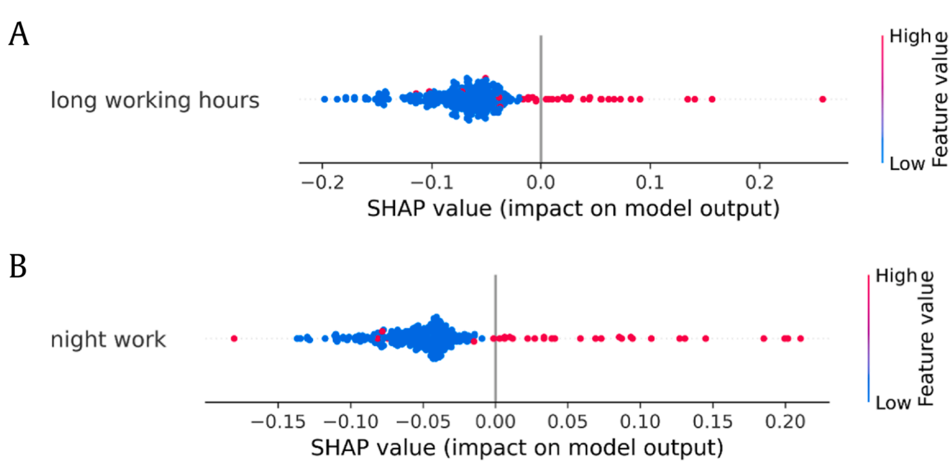


**Fig. 1.** Roles of long working hours (A) and night work (B) in diabetes predictions.

**Table 3**
Joint associations of long working hours and night work at baseline with incident diabetes

| Exposures | New cases of diabetes at follow-up (*n*, %) | Model I | Model II | Model III | Model IV |
|---|---|---|---|---|---|
| Long working hours + Night work | — | — | — | — | — |
| No + No | 6.23% (70/1123) | 1.00 | 1.00 | 1.00 | 1.00 |
| Yes + No | 8.39% (13/155) | 1.43 (0.82, 2.50) | 1.51 (0.87, 2.63) | 1.43 (0.83, 2.45) | 1.43 (0.83, 2.45) |
| No + Yes | 9.57% (11/115) | 1.52 (0.83, 2.77) | 1.64 (0.90, 2.98) | 1.45 (0.80, 2.63) | 1.45 (0.80, 2.63) |
| Yes + Yes | 14.75% (9/61) | 2.88 (1.52, 5.46)** | 3.36 (1.77, 6.38)*** | 3.02 (1.64, 5.57)*** | 3.02 (1.64, 5.58)*** |
| Synergy index | — | 1.98 (0.45, 8.73) | 2.05 (0.55, 7.61) | 2.29 (0.53, 9.98) | 2.30 (0.53, 9.98) |

Poisson regression, *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.
Model I: adjusted for age and sex at baseline.
Model II: Model I + additionally adjusted for race, marital status, education, and household income at baseline.
Model III: Model II + additionally adjusted for smoking, alcohol consumption, physical exercise, and body mass index at baseline.
Model IV: Model III + additionally adjusted for major depressive episode at baseline.

of diabetes, supporting our findings from classic statistical models.

Limitations include the self-report of working hours, schedules, and diabetes diagnosis/medication, which might result in misclassifications of both exposures and outcomes. Objective measures of working conditions and validated clinical diabetes may be used in future research to strengthen findings. Despite this, self-reporting of diabetes has been used in studies regarding the MIDUS dataset [19] and has been supported with high validity and reliability [36]. Working hours and night work were measured at baseline only. Thus, we lack information on the changes of these variables over time, and potential exposure misclassification bias could not be ruled out. Additionally, we were unable to account for job transitions during the 9-year follow-up, which may limit the precision of our diabetes risk estimates. Findings might further be impacted by selection bias. Though characteristics (including long working hours and night work) were generally similar between follow-up and attrition groups, those lost to follow-up were more likely to be unmarried, less educated, smokers, and with higher prevalence of diabetes at baseline (see Supplementary Table 2). Examining sex and gender differences is beyond the scope of this study but the researchers have considered the Sex and Gender Equity in Research (SAGER) guidelines [37].

## 5. Conclusion

Industries with long hours and night work can consider the increased diabetes risk when scheduling their workers. Organizations can improve shift system options, reduce hours on duty to ensure adherence to standard weekly hour policies, and allow for additional break times. Policy makers can advocate for primary prevention strategies to mitigate diabetes among workers, ensuring organizations take necessary actions to provide a safe environment.

## CRediT authorship contribution statement

**Elizabeth Keller:** Writing – review & editing, Writing – original draft, Investigation. **Liwei Chen:** Writing – review & editing, Writing – original draft, Methodology. **Feng Gao:** Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Formal analysis. **Jian Li:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

## Data availability statement

Publicly available data from the MIDUS study were used for this research (https://www.icpsr.umich.edu/web/NACDA/series/203). Program code and scripts for statistical packages are available from the corresponding author upon request.


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## Conflicts of interest

The authors declare that they have no conflicts of interest.


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## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.shaw.2025.05.005.

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