ACADEMIA MENTAL HEALTH & WELL-BEING

Research Article
Published: 20 March 2026
https://doi.org/10.20935/MHealthWellB8158

Health behaviours and outcomes in UK university students: a Bayesian network study

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Academic Editor: Wenwang Rao

Abstract

Introduction: Historically, university students have harmful lifestyle habits that have negative consequences for current and future health outcomes. However, there is limited understanding of the system within which factors interact to influence health status. Aim: This study aimed to explore the relationships between health-related behaviours and outcomes in UK university students using Bayesian network analysis.
Materials and methods: A total of 4132 university students completed an online, self-report survey to assess dietary and lifestyle markers of health at the start of the academic year in either 2021, 2022, or 2023. Directed Acyclic Graph (DAG) analysis was conducted to explore the relationships between variables of interest.
Results: The DAG demonstrated that ethnicity had the most profound influence on the model (model fit indices: CFI = 0.99, RMSEA = 0.02, and SRMR = 0.02). Perceived stress also had a substantial impact on the model ahead of alcohol consumption, smoking status, and body mass index. When separated by gender, the model for men was largely similar to the overall model. However, in women, the influence of smoking status and BMI diminished.
Conclusions: These findings provide novel insight into the complex system within which psychological and behavioural aspects of health interact to influence university students' health status.

Keywords: *university students, health behaviours, Bayesian network approach, directed acyclic graph*

Citation: Savage MJ, Vagnetti R, James RM, Hennis PJ, Procter EL, Steel RP, et al. Health behaviours and outcomes in UK university students: a Bayesian network study. *Academia Mental Health and Well-Being* 2026;3. https://doi.org/10.20935/MHealthWellB8158

1. Introduction

In the UK, there is a growing number of university students, with 50% of UK school leavers transitioning to higher education [1, 2]. Consequently, students now represent a substantial proportion of UK young adults, with 2.86 million students enrolled on undergraduate courses in higher education institutions across the UK [3]. This increase in uptake demonstrates a positive increase in accessibility to higher education, providing the opportunity for diverse populations to complete a degree programme and advance in their chosen career. However, whilst these institutes have a primary purpose of enhancing knowledge and understanding of a given topic, it should also be noted that universities are a unique setting within which students live, work, and play, creating an environment that can substantially impact the health status [4, 5] and health behaviours [6] of their students. However, the health and related behaviours of students are poor [7], demonstrating that a significant proportion of university students adopt unhealthy dietary habits, engage in inadequate physical activity, display elevated levels of sedentary behaviour, are in high or increased risk groups for alcohol consumption, and experience terrible or poor sleep quality [7]. Moreover, more than half (52%) of first-year university students in England reported experiencing significant weight gain (>0.5 kg) [8]. Additionally, one in five university students has a current mental health diagnosis, 30% of UK university students suffer from low mental wellbeing, and 35% report experiencing study-related stress [9, 10]. Although there are inconsistencies in defining and measuring university student well-being [11], these data are concerning, given that health status whilst young has a significant predictive influence on health outcomes during adulthood and as such, it is vital that research develops an in-depth understanding of factors influencing health outcomes and related behaviours in a student population.

To this point, the literature has investigated the influence of sociodemographic, psychological, and behavioural factors on outcomes of health and behaviours in students [7, 12–15]. Whilst these studies provide further understanding surrounding the determinants of individual elements of health behaviours (e.g., physical activity or eating behaviours), research has yet to capture the holistic system within which these variables interact. To facilitate this, sophisticated statistical tools are required to understand the

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complex, multi-directional relationships between these outcomes. Network analysis is a data-driven approach that uncovers connections among numerous variables that are otherwise autonomous of one another [16]. In the context of network theory, constructs of health are portrayed and visualised as networks arising from interactions between distinct variables, indicating that the variables and their active interactions contribute to the development and sustenance of a holistic system. Typically, the network comprises nodes representing variables and edges symbolising relations between them. The insights gained provide a clear analysis of how individual variables relate to each other and reveal important connections between concepts using edge weights. In contemporary research, the application of Bayesian approaches has provided a sophisticated means to investigate pivotal pathways of activation among variables [17]. As such, utilising network analysis with cross-sectional data may facilitate the identification of non-modifiable and modifiable factors that can be prioritised in the development of future targeted intervention strategies to improve outcomes of health and behaviours in university students. The current study aimed to explore, using Bayesian network analysis, the relationships between health-related behaviours and outcomes in UK university students.

2. Materials and methods

During the first few weeks of three academic years (2021/22; 2022/23; 2023/24), all students at a UK university were contacted via email and were asked to complete a self-administered online questionnaire. Details of the sampling and response rates are provided in Table S1. The responses of the 4132 individual undergraduate students who gave their informed consent and completed the questionnaire in full are included in this investigation (See **Table 1**). All data were pseudo-anonymised and maintained in strict confidence throughout the study period. Ethical approval was obtained from the Non-invasive Ethics Committee of the School of Science and Technology at a UK university (protocol code: 19/20-76).

The questionnaire included socio-demographic questions (4 items; **Table 1**). Two scales, validated in youth populations, were included: Cohen's Perceived Stress Scale [18] and the Short Warwick–Edinburgh Mental Wellbeing Scale [19]. The Perceived Stress Scale uses a 5-point Likert scale (0 = 'Never' to 4 = 'Very often') with total scores of 0 to 40, where lower scores denote lower levels of perceived stress. The Short Warwick–Edinburgh Mental Wellbeing Scale utilises a similar 5-point Likert scale (1 = 'None of the time' to 5 = 'All of the time') with total scores of 7 to 35, with higher scores indicating better mental wellbeing.

Table 1 • Participant characteristics. Data are presented as N (%) or mean ± SD.

		***N* (%)**
Age	18	769 (18.6)
	19	912 (22.1)
	20	937 (22.7)
	21	676 (16.4)
	22–25	551 (13.3)
	26–35	169 (4.1)
	35+	118 (2.9)
Gender	Female	2714 (65.7)
	Male	1304 (31.6)
	Neither/other/prefer not to say	114 (2.8)
Ethnicity	White	2996 (72.5)
	Minoritised ethnicity	1112 (26.9)
	Prefer not to say	24 (0.6)
University year group	1	1567 (37.9)
	2	1149 (27.8)
	3	1146 (27.7)
	4	270 (6.5)
		Mean ± SD
Self-reported anthropometry	Height (m)	1.69 ± 0.11
	Weight (kg)	67.8 ± 16.1
	BMI (kg/m^2)	23.7 ± 5.3

BMI: body mass index; SD: standard deviation.

The International Physical Activity Questionnaire—Short Form was also included. This allows assessment of a range of physical activity intensities (moderate: MPA; vigorous: VPA; walking: WPA) along with time spent sitting during the previous seven days (IPAQ-SF) [20]. The responses were interpreted following the IPAQ protocol [20] to determine the amount of moderate-to-vigorous physical activity (MVPA) undertaken per week, a measure previously validated in university students [21].

Furthermore, the questionnaire incorporated the validated [22] United States Alcohol Use Disorders Identification Test—Consumption. This is a scale designed to identify risky drinking behaviour, with questions scored on a 6-point Likert scale (0 = 'Never' or '1 drink' to 5 = 'Daily' or '10 or more drinks'), and total scores derived from the summation of individual items. Scores can range from 0 to 18, with a score of ≥ 7 indicating a positive risk indicator in women and a score of ≥ 8 in men.

A validated [23] single-item sleep quality scale, which evaluates subjective perceptions of night-time sleep quality over the preceding seven days, utilising a 10-point Likert scale ranging from 0 ('terrible') to 10 ('excellent'), was also included. Finally, a validated [24] short-form food frequency questionnaire, which comprises 27 items, was also included, allowing a single diet quality score to be computed according to the short-form food frequency questionnaire protocol [24].

Statistical analysis: To assess relationships between variables, a Directed Acyclic Graph (DAG) approach derived from network analysis was employed. DAGs represent Bayesian networks in which nodes are linked by arrows, known as directed edges. Arrows denote meaningful predictive connections, with their thickness reflecting their increased significance within the network structure. DAGs display a visual representation of ranked order, illustrating upstream and downstream variables. This enables the inference of causality [25], whereby variables at the top of the DAG have greater predictive capacity and are more pertinent than those beneath [26]. The structure of the Bayesian network represents the pattern of directed connections (arrows) among variables, indicating conditional dependencies learned from the data. In this study, the structure was identified in a data-driven manner, without imposing any prior constraints or theoretical assumptions. In the current study, the DAG was estimated using a score-based structure learning algorithm. Specifically, the Hill-Climbing greedy search algorithm [27] was used with 50 random restarts each involving 100 perturbations, and Bayesian Information Criterion (BIC) was employed as the model fit criterion. We assessed convergence of the structure learning algorithm by examining the BIC score across multiple restarts (10, 20, 50, and 100) and perturbations (10, 50, 100, and 200) combinations. The BIC values varied minimally across these settings (−165,600.4 to −165,598.9; ΔBIC < 2), suggesting that additional restarts or perturbations did not materially improve model fit. These results indicate that 50 restarts and 100 perturbations were sufficient to achieve convergence of the Hill-Climbing search (Table S2). Additionally, a set of 1000 networks was bootstrapped, whereby statistically significant edges were determined by an empirical threshold [28]. Subsequent paths obtained from the DAG were incorporated into a structural equation model (SEM) to estimate relationship parameters and understand the negative or positive strength of the associations. Fit adequacy was assessed with Comparative Fit Index (*CFI*) > 0.95, Root Mean Square Error of Approximation (*RMSEA*) < 0.06, and Standardised Root Mean Squared Residual (*SRMR*) < 0.08, minimising type I and II errors [29]. Multigroup analysis was also conducted to highlight potential gender differences in these relationships among the participants. Group differences in structural parameters were evaluated using critical ratios for differences. The Bayesian network analysis was conducted in R, version 4.3.3 [30], using the bnlearn package [28], which implements the Hill-Climbing structure learning algorithm. Body mass index, mental well-being, perceived stress, alcohol use, physical activity, walking, sedentary behaviour, diet quality, and sleep quality (coded as described above) were treated as continuous variables. The binary variables smoking status (non-smoker = reference; smoker = 1) and ethnicity (White = reference; minoritised group = 1) were treated as categorical variables. Accordingly, the algorithm automatically applied the conditional Gaussian Bayesian Information Criterion score, which is appropriate for mixed data types. No white lists or black lists were used in the fitting procedure; the network structure was learned in a fully data-driven manner. For gender and ethnicity, the participants who selected "Neither/Other/Prefer not to say" or "Prefer not to say," respectively, were included in descriptive summaries but excluded from inferential analyses due to the small and heterogeneous nature of these groups (n = 114; 2.8% and n = 24; 0.6%, respectively). Structural equation modelling was subsequently performed using IBM SPSS AMOS [31]. The R script for the DAG analysis is available as Supplementary materials, and all the data that support the findings of this study are openly available in Zenodo; see Data Availability Statement.

3. Results

Participant characteristics are displayed in **Table 1**. The majority of the participants were female, White, and in the first year of university.

3.1. Directed Acyclic Graph (DAG) analysis

The DAG indicates that ethnicity has the most impact on the behaviours included in the model, as indicated by its highest position within the network. Ethnicity had a cascading influence on alcohol behaviour and then smoking status. These factors, in turn, had a predictive influence on sedentary behaviour and sleep quality, and sleep quality had a direct impact on mental wellbeing. Perceived stress also emerged as a prominent factor, having a direct influence on smoking status, sleep quality, and mental wellbeing. Mental wellbeing was also directly associated with MVPA. MVPA directly influences both WPA and sedentary behaviour, while BMI directly influences sleep quality and MVPA (**Figure 1**).

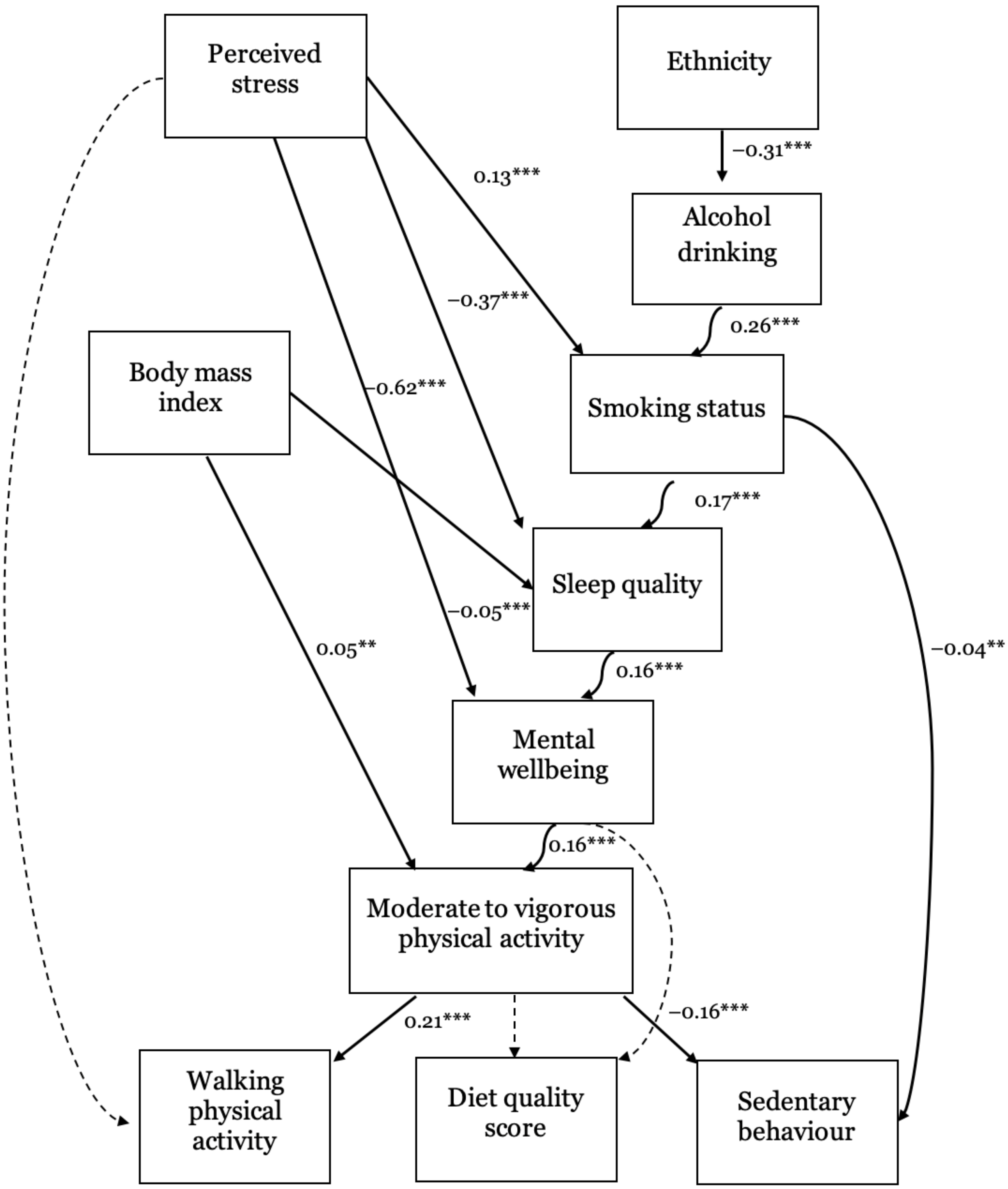

Figure 1 • Graphical model illustrating relationships among health behaviours and related outcomes in UK university students, combining a Bayesian network (DAG) based on an average of 1000 bootstrapped models with a structural equation model. Lines indicate significant relationships, and dashed lines indicate no significant relationship present. Arrowheads denote the direction of effects, and beta (β) coefficients represent the magnitude and direction of relationships, with positive values indicating positive associations and negative values indicating negative associations. *** $p < 0.001$; ** $p < 0.01$.

3.2. SEM confirmatory analysis

The SEM analysis indicated an excellent fit of the overall data, and when data were separated by gender (CFI = 0.99, RMSEA = 0.02, and SRMR = 0.02). Overall, ethnicity was negatively related to alcohol drinking behaviour ($p < 0.001$). Alcohol drinking behaviour and perceived stress were both positively related to smoking status ($p < 0.001$ and $p < 0.001$). Notably, perceived stress also had a profound negative influence on sleep quality and mental wellbeing ($p < 0.001$ and $p < 0.001$). Sleep quality was also negatively influenced by smoking status and BMI ($p < 0.001$ and $p < 0.001$) and, in turn, positively influenced mental wellbeing

($p < 0.001$). Mental wellbeing and BMI had a positive influence on MVPA ($p < 0.001$ and $p < 0.01$), while MVPA had a negative influence on sedentary behaviour and a positive influence on WPA ($p < 0.001$ and $p < 0.001$). Finally, smoking status was negatively related to sedentary behaviour ($p < 0.01$) (**Figure 1**).

Multiple-group analysis revealed differences between genders in the weights of the relationships ($\chi^2(13) = 22.91$, $p = 0.04$), suggesting variations between men and women. Indeed, a significant negative interaction was observed between smoking and sleep quality for men ($p < 0.001$) but not for women ($\beta = -0.03$, $p = 0.27$); the between-group difference was significant (Z = 2.18, $p = 0.03$). Similarly, significant relationships were present between BMI and sleep quality, and smoking behaviour and sedentary behaviour in men ($p < 0.001$ and $p = 0.02$ respectively) but not women ($p = 0.79$ and $p = 0.07$ respectively). The relationship between BMI and sleep quality differed significantly between men and women (Z = 2.51, $p = 0.01$), whereas the association between smoking behaviour and sedentary behaviour did not (Z = 0.10, $p = 0.92$). All other relationships were similar to the overall model, with the exception of the relation between BMI and MVPA, which were not significant for both genders ($p > 0.05$) (**Figure 2a,b**).

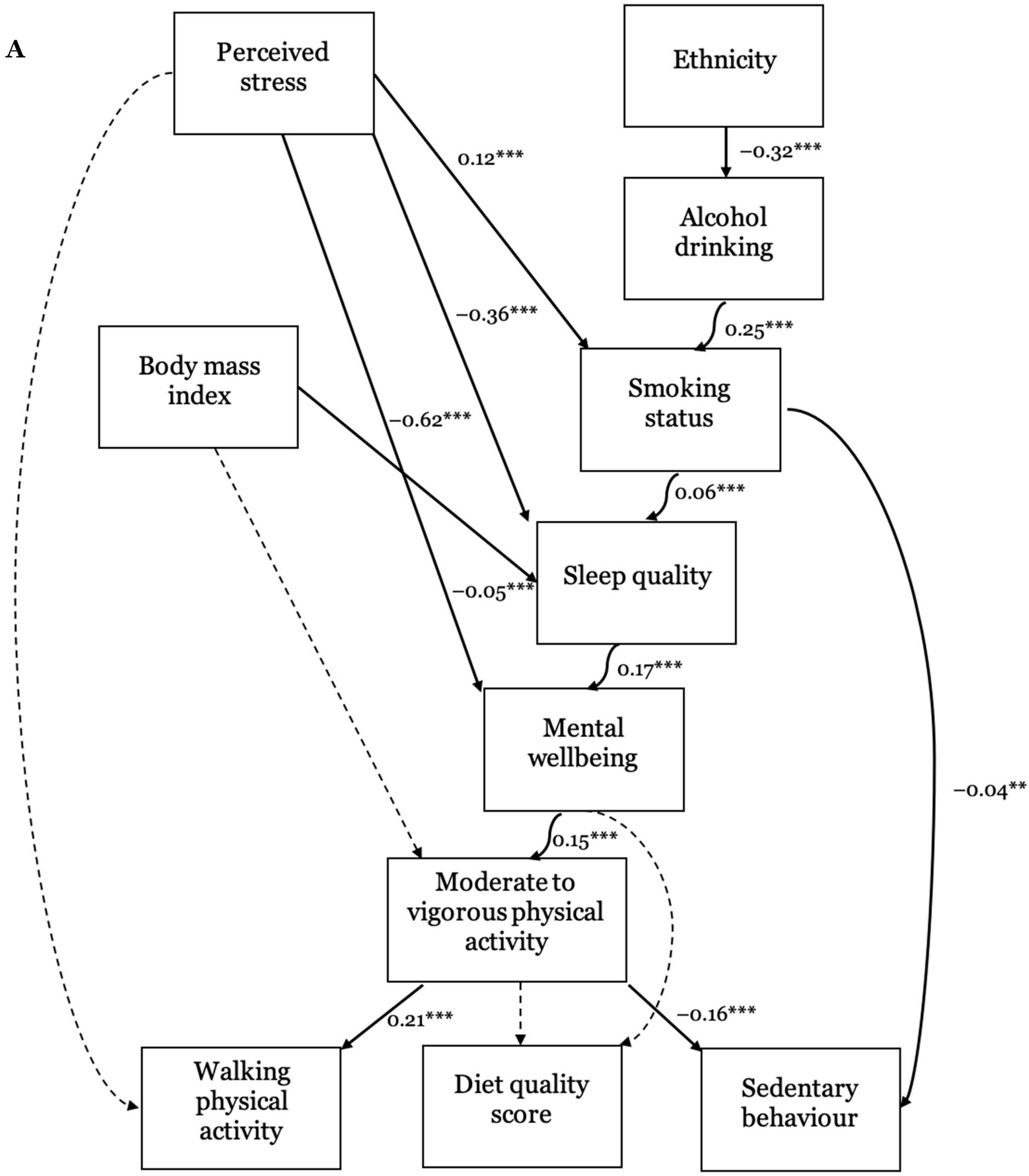

Figure 2 • *Cont.*

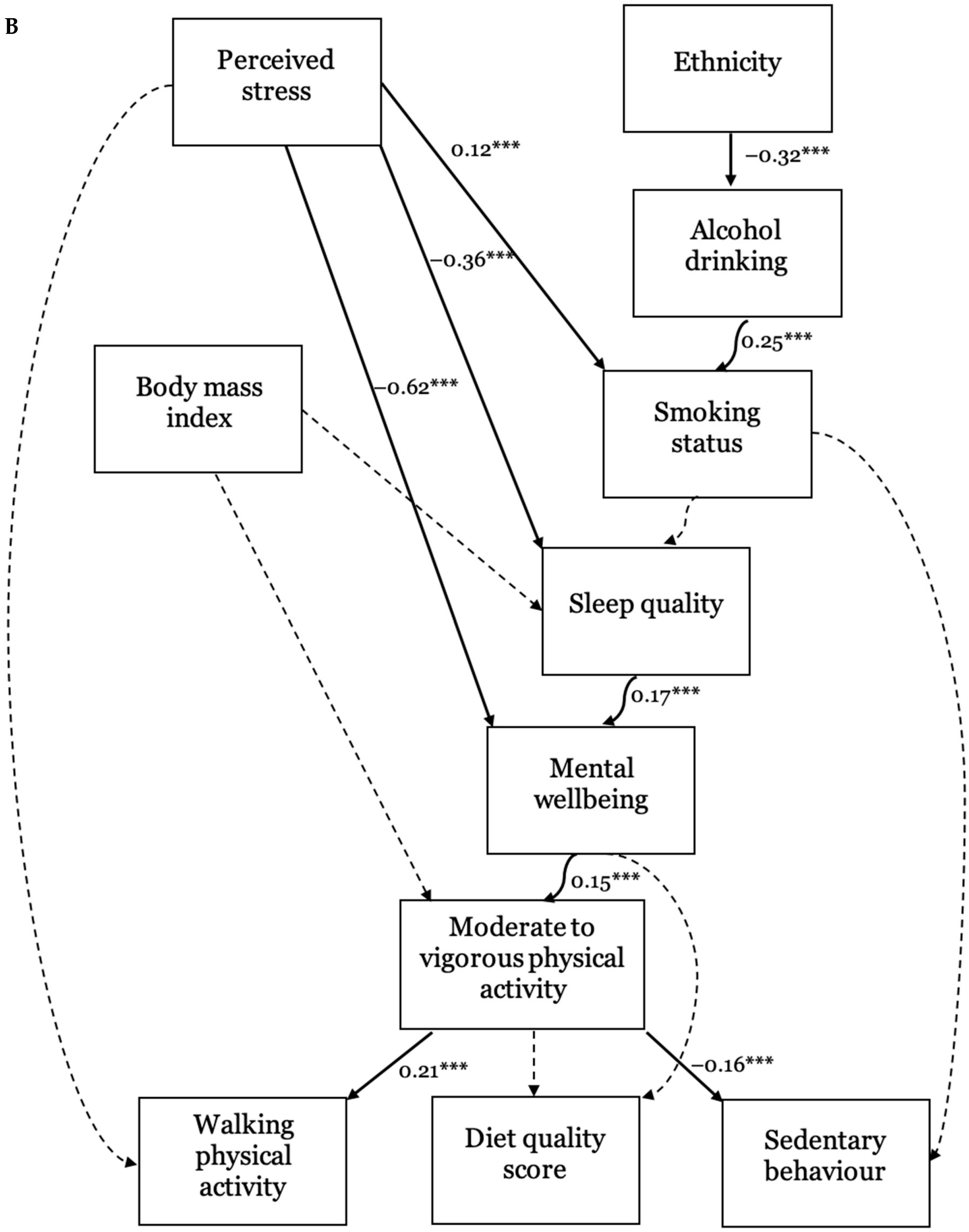

Figure 2 • The final structural equation model for male (**A**) and female (**B**) UK university students. *** $p < 0.01$; ** $p < 0.01$. Beta (β) values demonstrate the strength of the relationship, with positive values denoting a positive relationship and negative values denoting a negative relationship.

4. Discussion

The current study used Bayesian network analysis to explore factors influencing markers of health and health-related behaviours in UK university students.

The DAG and SEMs indicated that belonging to a minority ethnic group was associated with lower alcohol consumption, whereas higher alcohol use was positively associated with smoking. Smoking, in turn, was linked to sleep quality. Poorer sleep quality was related to lower mental well-being. Perceived stress emerged as a key psychological factor, showing positive associations with smoking and negative associations with both sleep quality and mental well-being, suggesting that stress may act as an upstream influence shaping several health-related behaviours within the cascade. Body mass index was negatively associated with sleep quality but positively associated with MVPA, indicating that higher BMI was linked to slightly poorer sleep but greater engagement in physical activity. Higher mental well-being was associated with greater engagement in MVPA, which in turn was positively related to walking activity and negatively related to sedentary behaviour.

The findings indicate that ethnicity has a prominent influence on the main cascade of the model, above alcohol consumption and smoking status. Perceived stress and BMI also play an important role in determining the overall model. However, the pertinence of smoking status and BMI diminishes in women when separated by gender. Notably, the students' perceived stress exhibits prominent cascade effects and high relative weights. These models demonstrate the importance of ethnicity as a non-modifiable factor that should be considered when designing health-based initiatives to optimise health in university students. However, given that this is a non-modifiable factor, the prominence of modifiable factors such as perceived stress and BMI could provide stakeholders with a greater opportunity to improve markers of health and health-related behaviours in students if targeted appropriately.

Previously, research has shown that during periods of increased stress, students are more likely to develop abnormal sleeping patterns to maximise study time and complete academic assignments [32], a behaviour likely to be different to age-matched non-students. Additionally, an increased perception of stress is often synonymous with poorer markers of mental health in students [33]. To cope with these periods of high perceived stress, students may seek social interactions and, in doing so, may begin or increase the frequency of smoking [34]. However, the current study indicates that engaging in smoking behaviours may initiate a cascade of poorer behavioural outcomes. Indeed, greater nicotine dependence has previously been associated with increased sleep disturbance [35]. In the current model, this reduced sleep quality was then associated with poorer mental wellbeing, a correlation that has been established in prior research [36] and indicates that disrupted sleep could negatively impact students' capacity to manage the social and academic stresses inherent in university life [37]. Furthermore, poorer mental wellbeing was then associated with impaired movement behaviours, findings that may be expected given the relationships between markers of mental health and movement behaviours in students [38, 39]. Additionally, the positive association observed between alcohol consumption and smoking status is perhaps expected given the social nature of these behaviours, particularly in the context of university life. Given these data, higher education institutions seeking to enhance student health should prioritise efforts to reduce perceived stress. These initiatives could potentially aid in mitigating against a cascade of poorer behaviours that include smoking, poor sleep quality, sub-optimal mental well-being, and impaired movement behaviours among university students.

The results obtained from the present study also indicate that a higher BMI was associated with poorer sleep quality [15]. Previously, it has been shown that reducing sleep duration has an inhibitory effect on ghrelin secretion, which could lead to elevated energy intake during the night [40]. In turn, this could increase the risk of developing adverse body composition outcomes. Additionally, these data demonstrate that higher BMI was associated with greater levels of MVPA. Whilst surprising, this may be indicative of the majority of students involved in the current study (71.6%) meeting UK physical activity guidelines ($\geq$150 min/week in MVPA); and as such, higher BMI in this context may be associated with greater muscle mass as a result of increased participation in MVPA [41].

Interestingly, these data also indicate that smoking status has a negative influence on sedentary behaviour. This suggests that students who smoke spend less time engaging in sedentary activities. Previously, similar findings have been reported in university students from Australia and may be explained by smokers exhibiting a more socially active lifestyle through observing higher amounts of physical activity and less sedentary behaviours, whilst tending to smoke and drink more [42]. Additionally, the previous literature has theorised that students who smoke may take more frequent breaks from studying to satisfy their underlying craving [43]. Considering these data, it is vital that those seeking to design effective interventions recognise the intricate connections between positive and negative health behaviours.

The prominence of ethnicity as a non-modifiable factor within the model should also be noted. The current study indicates that being from a White ethnic background leads to greater alcohol consumption, which has a cascading influence on the subsequent variables within the model. This is consistent with the results from the broader UK society [44] and may be reflective of the well-established drinking culture among White young adults, whereby this demographic congregates freely, expressing their personal autonomy by consuming alcohol [45]. In contrast, those from minority ethnic backgrounds are more likely to be lifetime abstainers [44], and the perception that drinking forms an integral part of student identity may be less pronounced among students of minoritised ethnicity [46]. Additionally, varying cultural, religious, and social factors derived from ethnicity have been shown to affect students' movement, diet, and sleep behaviours as well as outcomes of mental health [45]. It is therefore pertinent that stakeholders consider ethnicity when designing policy, practice, and interventions to improve students' health and behaviours. The current study is the first to demonstrate that the system within which health-related behavioural and psychological variables interact in university students differs between men and women. Specifically, relationships between smoking status and sleep quality, and between BMI and sleep quality, were evident among men but not in women. For smoking status and sedentary behaviour, although the association was significant only for men, the difference in this association between men and women was not statistically significant. The literature has suggested that the relationship between smoking status and sleep quality is not mediated by gender [35]. Additionally, the influence of gender was shown to be negligible when assessing the association between smoking status and sedentary behaviour in Swedish adults [47] and when investigating the relationship between BMI and sleep quality in Croatian university students [48]. The contrasting findings of the current study may be due to the novel statistical approach employed, being capable of capturing the intricate interplay between variables, in contrast to assessing associations in isolation.

Although some expected associations, such as between BMI and diet quality, were not represented as direct effects in the structural model, this pattern may suggest that these health behaviours share substantial common variance and operate as components of an interrelated lifestyle cluster rather than as independent predictors.

The use of DAG derived from network analysis is a major strength of this study. University stakeholders can therefore utilise these data to aid in the development, implementation, and tracking of future intervention strategies to improve aspects of students' health. Previous research has shown that various interventions (e.g., cognitive-behavioural therapy, coping skills, and social support) successfully reduce perceived stress in students [49]. Future research should examine the efficacy of these interventions in improving health-related behaviours as a byproduct of reduced stress. This may be of particular importance for universities, given that favourable behavioural outcomes have previously been related to better academic performance [50].

Self-reported surveys may lead to inaccuracies, such as overestimating PA levels and underestimating sedentary time and alcohol consumption [51, 52]. The use of validated survey questions minimises these inaccuracies, but there is still a risk of social desirability bias and self-selection bias based on gender and engagement with personal health [53]. The study also did not assess all social, cultural, economic, and environmental aspects of university life, meaning that whilst the model presented here is extensive, relationships may be altered by the inclusion of variables not measured. This study did not account for several potentially important confounders, including socioeconomic status, academic major, and social support, which may affect the observed network structure and the interpretation of the associations. Furthermore, we have not included a non-student, young adult population and therefore cannot comment as to the extent of any similarity or difference in models between these populations. Finally, the potential for reverse causation cannot be directly represented in DAG analysis due to the fundamental concept that a model is acyclical. Nonetheless, this study is the first to develop a model detailing how psychological and behavioural health markers interact in university students.

5. Conclusions

The current study uses a Bayesian network approach to demonstrate the complex system within which psychological and behavioural aspects of health interact to contribute to the health status of UK university students. Universities have a distinctive opportunity to prioritise students' health by creating and promoting a positive environment that fosters beneficial outcomes in relation to psychological and behavioural markers of health. The current data suggest that reducing perceived stress could be an effective approach to improve a plethora of other factors related to students' health. Additionally, these models demonstrate that ethnicity and gender have a prominent influence on outcomes of health and health-related behaviours in students. Future research should investigate the efficacy of improving other health markers as a consequence of reducing students' perceived stress. Equally, university stakeholders should consider the use of Patient and Public Involvement (PPI) type initiatives that represent the diverse university student population to address the specific needs of students effectively.

Acknowledgments

We gratefully acknowledge and thank all the students from Nottingham Trent University who generously gave their time to participate in this study. Their engagement and contribution were essential to the completion of this research and are sincerely appreciated.

Funding

This research received no external funding.

Author contributions

Conceptualization, M.J.S., R.M.J., P.J.H. and D.M.; methodology, M.J.S., R.M.J. and P.J.H.; software, D.M. and R.V.; formal analysis, D.M. and R.V.; investigation, M.J.S., R.M.J., P.J.H. and E.L.P.; writing—original draft preparation, M.J.S.; writing—review and editing, R.M.J., P.J.H., D.M., R.V., E.L.P. and R.P.S. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

The authors declare that they have no competing interests.

Data availability statement

The data supporting the findings of this publication has been made available within a publicly accessible repository at https://zenodo.org/records/12731838.

Institutional review board statement

The study was conducted according to the guidelines of the Declaration of Helsinki and approved by the Institutional Review Board of Nottingham Trent University (protocol code 19/20-76, approved on 6 May 2021).

Informed consent statement

Informed consent for participation was obtained from all subjects involved in the study.

Supplementary materials

The supplementary materials are available at https://doi.org/10.20935/MHealthWellB8158.

Additional information

Received: 16 September 2025

Accepted: 10 February 2026

Published: 20 March 2026

Academia Mental Health and Well-Being papers should be cited as *Academia Mental Health and Well-Being 2026*, ISSN 2997-9196, https://doi.org/10.20935/MHealthWellB8158. The journal's official abbreviation is *Acad. Ment. Health WellB.*

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