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Aging, Sleep Disturbance and Disease Status: Cross-Sectional Analysis of the Relationships Between Sleep and Multimorbidity Across the Lifespan in a Large-Scale United States Sample

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Abstract

Multimorbidity, or the presence of two or more co-occurring chronic medical conditions, is extremely prevalent within the United States (US), with disproportionately high incidence rates in individuals with minoritized identities. Sleep disturbances are an empirically supported risk factor contributing to disease status and maintenance throughout the lifespan. Given this, this study examines the relationship between disturbed sleep and multiple chronic conditions (MCCs) in adults using cross-sectional data from (n = 1013) participants enrolled in the *Survey of Midlife Development in the US Study* (MIDUS-2). Participants within this study were predominantly female (54.9%), white (93.2%), middle-aged (M_{AGE} = 58 years old), and experienced multimorbidity (56.6%) by having two or more (M_{CHRON} = 2.25) chronic health conditions in the past year. A negative binomial regression indicated that sleep disturbances significantly predict the number of chronic health conditions, with sleep-disturbed individuals reporting a 41% increase in reported health conditions (IRR = 1.407, $p < 0.001$). Findings suggest that disturbed sleep is significantly related to disease presence in aging populations and should be addressed through early intervention to mitigate negative health consequences.

Keywords: aging; chronic health; longevity; multimorbidity; sleep

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1. Introduction

1.1. Multimorbidity: Definition, Multi-Level Implications

Multimorbidity, a concept referring to the co-occurrence of two or more chronic medical conditions within an individual, has gained considerable attention in the field of health psychology [1]. The significant strain caused by multimorbidity has become increasingly recognized due to the profound impact on individuals and healthcare systems [2]. The coordination of care required to manage multiple complex medical conditions has resulted in universal increases in healthcare utilization, cost, and burden, leading to a search for solutions [3,4]. Despite the identification of multimorbidity as a public health issue, the prevalence rates of multimorbidity within the United States have reached new heights. Recent estimates indicated 58.4% of adults experience multimorbid medical conditions, with increased rates for individuals aged 70 to 74 years (94.1%) or classified as multiracial (66.9%) [5,6]. The trends reveal a 30% increase from 2018 for noninstitutionalized adults [7]. As increased rates of pain, disability, reduced quality of life, interpersonal relationships difficulties, adverse health outcomes, and mortality are experienced by individuals living

with multiple conditions, increased understanding is essential, particularly in areas where intervention could impact multimorbidity's trajectory across the lifespan [8,9].

In particular, multimorbidity has been associated with increased rates of psychopathology, disturbances in identity, social isolation, challenges with coping, and disturbances in sleep [10,11]. However, the relationship between multimorbidity and psychological distress is multifaceted [12,13]. For example, multimorbidity often requires strict adherence to complex pharmacological treatment protocols, placing individuals at increased risk of complications due to polypharmacy and treatment nonadherence [14]. Additionally, decreased quality of life, a known consequence of multimorbidity, has been found to impact treatment adherence and illness coherence across chronic conditions [15]. What is known is that the cumulative impact of impairments associated with having more than one condition complicates management efforts and exacerbates psychological distress and poor sleep [12,13].

1.2. Sleep Disturbances, Chronic Illness, Healthcare Utilization, and Quality of Life (QoL)

The relationship between sleep quality and health status has become a research priority, as the prevalence of sleep disruptions has increased along with the prevalence of multimorbidity [16]. Current estimates indicate 30% of the population has trouble sleeping, with 27% reporting daytime impairment as a function of poor nighttime sleep [17]. Given that individuals with untreated insomnia report increased healthcare utilization, 75% higher healthcare costs, significantly worse quality of life and subsequent disease burden, a deeper understanding is warranted [18–20]. Complicating the picture, poor sleep has been identified as a risk factor for the development and maintenance of chronic medical conditions [21,22], as well as a potential exacerbating factor of symptoms related to chronic health conditions [23]. And individuals with multimorbidity often suffer poorer sleep quality, shorter sleep duration, increased dissatisfaction with sleep, and higher rates of insomnia [24–26]. In short, there is substantial empirical support demonstrating the bidirectionality of the relationship between sleep disturbance and chronic illness across a variety of specific conditions (e.g., diabetes, cancer, pain conditions, cardiovascular disease) [22,23,27]. Further, individuals with sleep disturbances and specific chronic illnesses incur higher healthcare costs than peers with healthy sleep patterns, resulting in an additional $10,000 in annual healthcare costs [28–31]. However, the protective nature of good sleep within individuals with chronic illness conditions has also been found to increase quality of life and moderate depression [32,33]. Emphasizing the utility of conceptualization of sleep in individuals with chronic health conditions, as ripe for interventions that improve quality of life and disease state [18,33]. Given that initial research exploring the impact of sleep patterns on the prevalence of multimorbidity is still in its infancy, no randomized controlled trials (RCTs) have investigated the impact of targeted sleep interventions, such as CBT-I, on the incidence or progression of multimorbidity yet. The authors hope that the results of this study may contribute to the robust body of evidence linking poor sleep with multimorbidity across populations and inform future research regarding the utility of psychological sleep interventions on improving quality of life in individuals with MCCs.

1.3. The Impact of Age

It is well-established that the prevalence of disturbed sleep becomes more crucial to consider in later life, where community estimates reach up to 30% [34,35]. The relationship between sleep disturbance and adverse health consequences is amplified in aging populations, as impaired sleep has been proven to increase the risk of cardiac, respiratory, and neurological disease [36–40]. Given that the prevalence of having multiple, comorbid health conditions increases as we age [41], as well as the elevated incidences of sleep disturbances

in older adults [35], it becomes critical that research considers how the relationship between multimorbidity and disturbed sleep varies across the lifespan. Patterns of sleep disturbance and multimorbidity in older adult populations have been conceptualized in countries such as Brazil [42], Sweden [43,44], Germany [45], China [26], and the United Kingdom [46]. Across studies, authors have found sleep disturbance to be significantly associated with multimorbidity in adult populations over and above the impact of other variables, such as BMI, sex, age, and depression [44]. Despite the significance of repeated findings across the globe, the interrelationships have yet to be explored within the United States. Due to differences in healthcare policy and infrastructure, resource access, socioeconomic disparities, and cultural norms surrounding medicine, psychology, and sleep, it is imperative that this relationship be investigated within the US to explore how these differences may uniquely impact the relationship between sleep and MCCs.

Given the demonstrated associations between sleep disturbance and multimorbidity upon individual quality of life, as well as the corresponding global burden of multimorbidity on the US healthcare system, there is a need for further research to explore how sleep may serve as a modifiable risk factor for further health complications in individuals with multimorbidity within the United States. Thus, the current study aims to clarify the impact of demographic, lifestyle, and emotional factors on the relationship between sleep disturbances and multimorbidity in adults in the United States. This can be accomplished through examination of the association between disturbed sleep and multimorbidity severity at the time of assessment using available, cross-sectional data from *MIDUS 2.*

2. Materials and Methods

2.1. Participants

Participants within the current study were recruited originally through a national survey distributed to over 7000 Americans between the ages of 25–74 by the MacArthur Midlife Research Network in 1995–1996. Participants were eligible for survey completion if they met age requirements, spoke English, resided in the United States, and were non-institutionalized at the time of study recruitment [47]. Further details regarding *MIDUS* recruitment strategies, as well as inclusion/exclusion criteria, can be found within the *National Archive of Computerized Data on Aging* at the following DOI https://doi.org/10.3886/ICPSR04652.v8 [48]. In 2004, a follow-up study of the original *Midlife Development in the United States (MIDUS)* sample *(MIDUS-2)* was conducted to collect longitudinal information (Project 1) and expand data collection through the addition of protocols regarding neuroscience and biomarkers (Project 4). Alternate projects involving the collection of neuroscience and twin study data (Projects 2 and 3) are not relevant to the current analysis and, therefore, are not described in full here. Further information on all *MIDUS* projects is available via *MIDUS*'s public data repository [48]. In 2013, an additional follow-up of survey data was conducted, including repeated baseline measures and additional demographic/life experience questionnaires *(MIDUS-3)*. Data collection methodologies across waves consisted primarily of phone interviews and self-report questionnaires. Due to the absence of biomarker information collected in the *MIDUS-1* time point, this study solely utilizes participant responses from the *MIDUS-2* Projects 1 and 4 to determine cross-sectional relations between variables. The current study is a secondary analysis of data collected in 2004 by the *MIDUS* project and was downloaded retroactively in 2025 from the MIDUS Collectica Portal for this study.

2.2. Measures

Multimorbidity. Multimorbidity was quantified per study participant at the *MIDUS 2, Project 1 Daily Diary* timepoint through the subjective report of the number of chronic health

conditions experienced within the past 12 months. Participants were asked if they had experienced symptoms of 30 chronic conditions (ex., Tuberculosis, Thyroid Disease, HIV, etc.) within the past 12 months and provided a 'yes' or 'no' response. The total number of 'yes' responses was summed at each timepoint to calculate the variable 'number of chronic conditions' [47]. Higher values indicate increased severity of multimorbidity.

Sleep Disturbances. Sleep disturbances were operationalized at the *MIDUS 2, Project 4 Biomarker Sample* timepoint using the Sleep Disturbance subscale of the Pittsburgh Sleep Quality Index (PSQI). The PSQI is a 19-item measure that assesses subjective sleep quality and disturbance over a 4-week recall period [48]. The current study utilized component 5, Sleep Disturbances where individuals rated the frequency with which each listed activity has disturbed their sleep over the past month using a Likert-style response scale (0 = not during the past week, 1 = less than once per week, 2 = once or twice a week, 3 = three or more times per week). Responses to items on this component are summed to obtain a numerical index of sleep disturbance, with higher values indicating increased severity of sleep disturbances. The maximum value, or raw score, obtained by this component is 27. Component scores are then converted to categorical values based on the following ranges (0 = 0, 1 = 1–9, 2 = 10–18, 3 = 19–27). Scores of 3 represent increased dysfunction [48]. The PSQI has demonstrated strong internal consistency [49], convergent validity, divergent validity [50], sensitivity, and specificity across both clinical and nonclinical populations [48].

Depression. Depression was assessed at *MIDUS 2, Project 4 Biomarker Sample* timepoint through the Center for Epidemiologic Studies Depression Scale (CES-D). The CES-D is a 20-item measure that evaluates depression across multiple domains: somatic symptoms, negative affect, anhedonia, and interpersonal relations [51,52]. Participants provide item responses via a Likert-style scale assessing frequency of symptoms in the past week (Rarely or none of the time = 0, some or a little of the time = 1, occasionally or a moderate amount of time = 2, most or all the time = 3). Items for this measure are summed to provide a global score of depressive symptoms. Scores on this measure range from 0 to 60, with scores above 16 indicating the potential presence of clinically significant depression. The CES-D has strong psychometric properties in similar population-based cohorts [53].

Covariates. Information regarding participant education, racial origins, current marital status, total household income, and the subjective health rating was obtained from the *MIDUS 2, Project 1* daily diary dataset via a self-administered questionnaire *(SAQ)*. Subjective health rating was measured through asking participants for their rating of their health 'these days', using a 10-point Likert Scale (0 = worst possible health, 10 = best possible health). Information regarding participant sex, age at clinic visit, body mass index (BMI), and current exercise habits was obtained from the *MIDUS 2, Project 4* biomarker sample dataset. To assess BMI, participants were asked for their current height and weight at the time of the study visit. BMI was calculated by dividing the participant's self-reported weight (pounds, converted to kilograms) by self-reported height (inches, converted to square meters). Higher numbers represent increased body mass index. To assess current exercise habits, participants were asked if they engage in regular activity or exercise at least 3 times per week for 20 min or more. Regular exercise or activity was defined as light (requiring little physical effort), moderate (causing slight increases in heart rate or sweat), or vigorous (causing rapid increases in heart rate, breathing, and sweating), with examples provided for each category. Participants were instructed to respond yes or no to this question.

3. Results

3.1. Sample Characteristics

Analyses were conducted using IBM SPSS Version 29. A negative binomial regression was run with a total sample of (n = 1053) individuals. (n = 40) individuals were excluded from analysis, resulting in a final sample of (n = 1013) individuals included for analysis. As shown in Tables 1 and 2, the sample was predominantly female (54.9%), white (93.2%), married (72.1%), had an annual household income of >75 k (40.9%), college educated (52%), and engaged in regular physical activity (79.3%). On average, individuals were middle-aged (M_{AGE} = 58 years old), over the suggested weight as defined by the World Health Organization (WHO) standards (M_{BMI} = 29.17), and experienced multimorbidity by having two or more (M_{CHRON} = 2.25) chronic health conditions within the past year. Regarding the latter, 56.6% of individuals (n = 597) experienced multimorbidity. Additionally, individuals rated themselves as subjectively healthy (M_{HEALTH} = 7.6), at low risk of clinical depression (M_{CESD} = 7.98), and with mild sleep disturbances (M_{PSQISD} = 1.28).

Table 1. Categorical Sample Sociodemographic and Clinical Characteristics.

Characteristics	Category	Frequency	Percent
Sex	Female	454	51.9
	Male	420	48.1
Household Income	Low Income (<30,000)	172	19.7
	Middle Income (30,000–74,999)	335	38.3
	High Income (≥75,000)	367	42
Highest Education Level Obtained	High School or Less	198	22.7
	Some College/Bachelor's	459	52.5
	Graduate/Professional Certification	217	24.8
Race	White	811	92.8
	Non-White	63	7.2
Current Marital Status	Married	632	72.3
	Not Currently Married (Separated, Widowed, Divorced, Never Married)	242	27.7
Physical Activity	Engages in regular exercise/activity for 20+ minutes at least 3 times/week	696	79.6
	Does not engage in regular exercise/activity for 20+ minutes at least 3 times/week	178	20.4

Table 2. Continuous Sample Sociodemographic and Clinical Characteristics.

Variable	Mean	Minimum	Maximum	Std Dev
Number of Chronic Health Conditions (12 months)	2.07	0	12	1.99
Age at Clinic Visit	58.1	35	86	11.92
Current Health Rating	7.67	0	10	1.4
BMI	28.92	16	60	5.77
Depression (CES-D)	7.59	0	42	7.28
Sleep Disturbances (PSQI_Component 5)	3.04	0	16	2.59

3.2. Data Analyses

Prior to analysis, preliminary data quality checks were completed through assessing variable frequency distributions to investigate patterns of missing data, identify outliers, and flag any variables with substantial skewness/kurtosis values. Preliminary checks reveal no irregular patterns of missingness, outliers, or distributional abnormalities, and therefore, all variables were retained for statistical analysis. Regression analysis was selected to assess whether demographic, physiological, and psychological factors predict

the number of chronic health conditions experienced within the past year. The dependent variable (DV), the number of chronic health conditions experienced within the past year, is a count variable and thus, traditional approaches to linear regression were deemed inappropriate. Count distributions violate traditional regression model assumptions regarding normality of residuals and homoskedasticity [54]. Consequently, Poisson and Negative Binomial Regression (NBR) models were considered as they assume that the DV follows Poisson or negative binomial distributions, respectively [55]. A linear regression was initially run to evaluate for redundancy in the set of predictor variables (multicollinearity), and categorical variables were dummy-coded into a usable format for this regression. Multicollinearity was not present in the included set of predictor variables. Following assessment of multicollinearity, statistical analyses were run using Poisson and Negative Binomial regression models. Formal testing was conducted to determine which regression model significantly improved fit.

The following three strategies were employed to justify the use of a negative binomial regression accounting for overdispersion, as opposed to a more restrictive Poisson regression model. The first method included examination of the negative binomial parameter estimate of the NBR (B = 0.191, SE = 0.03). This suggests that the estimated variance within the model exceeds the mean by a value of 0.191 (CI: 0.136–0.255), indicating that the dispersion value is significantly above 0, and that the assumption of equidispersion fundamental to Poisson regression is not met. The second method involved examination of the Pearson Chi-Square to the degrees of freedom statistic associated with the NBR. The value for this statistic was 1.01 X^2 (998) = 1.01, which is close to the recommended value for this parameter of 1. This suggests that this model adequately fits the data when accounting for overdispersion. The third and final method included comparing each model's values for Akaike's Information Criterion (AIC) and Bayesian Information Criterion (BIC). AIC and BIC values speak to the complexity of model fit, with lower values suggesting a better model fit to the data. Differences in AIC and BIC values greater than or equal to 10 between models indicate strong evidence that the model with the lower value better fits the data [56]. Based upon this criterion, the NBR is a better fit for the dataset as AIC and BIC values for this model were lower (AIC_{NBR} = 3708.05; BIC_{NBR} = 3781.86) than those of the Poisson model (AIC_P = 3782.27; BIC_P = 3851.16). Further, the differences between AIC and BIC values for the Poisson versus negative binomial regression models were 74.22 (AIC_P–AIC_{NBR}) and 69.3 (BIC_P–BIC_{NBR}), respectively. Given that these values exceed the suggested threshold of 10, this presents strong evidence that the NBR model is a substantially better fit for the data than a Poisson regression. Additionally, the outcome variable did not demonstrate zero inflation, further supporting the use of a negative binomial regression model. The NBR model was interpreted through examining the incidence rate ratio (IRR), which reflects the exponentiated value of the original regression coefficient, reflected in the original scale of the DV. The IRR variable quantifies a predictive effect through reporting the expected multiplicative change in the dependent variable per each one-unit increase in each predictor variable, whilst holding other variables constant.

3.3. Negative Binomial Regression

The negative binomial regression (NBR) model was fit using Maximum Likelihood Estimation (MLE) and a log link function to model count data (see Table 3: Parameter Estimates). The model method was set to Fisher scoring with a one-step update and a fixed scale parameter of one. Parameter estimates utilized 95% confidence intervals derived from the profile likelihood method with a precision threshold of 0.0001. The omnibus test of model coefficients was significant, $X^2(13) = 313.93$, $p < 0.001$. Multiple variables included within the model significantly predicted the number of chronic health conditions

(CHC) experienced in the past 12 months when controlling for all other variables in the model. Significant predictors of CHC included: sex (X^2 (1) = 30.98, $p < 0.001$), education (X^2 (2) = 9.44, $p = 0.009$), age (X^2 (1) = 23.48, $p < 0.001$), subjective health rating (X^2 (1) = 65.47, $p < 0.001$), BMI (X^2 (1) = 6.36, $p = 0.012$), depression (X^2 (1) = 14.48, $p < 0.001$), and sleep disturbances (X^2 (1) = 48.9, $p < 0.001$). Notably, participants' income, race, current marital status, and physical activity level did not significantly predict variance in the number of chronic health conditions experienced over the past 12 months.

Table 3. Parameter Estimates (NBR).

Parameter	B	Std. Error	Hypothesis Test		95% CI for Exp (B)	
			Sig	Exp (B)	Lower	Upper
Intercept	0.136	0.298	0.649	1.15	0.637	2.06
Sex						
Female	0.305	0.055	<0.001	1.36	1.22	1.51
Male	0 [a]	.	.	1	.	.
Income						
Low (<30,000)	0.173	0.079	0.027	1.19	1.02	1.39
Middle (30,000–74,999)	0.107	0.061	0.082	1.11	0.986	1.26
High (≥75,000)	0 [a]	.	.	1	.	.
Education						
High School or Less	−0.166	0.079	0.035	0.847	0.725	0.988
Some College/Bachelor's	0.3	0.066	0.644	1.031	0.906	1.17
Graduate/Professional Certification	0 [a]	.	.	1	.	.
Race						
Non-White	0.045	0.103	0.66	1.046	0.854	1.28
White	0 [a]	.	.	1	.	.
Marital Status						
Not Currently Married	0.032	0.062	0.608	1.032	0.914	1.17
Currently Married	0 [a]	.	.	1	.	.
Physical Activity						
Currently engages (3×/week)	−0.015	0.064	0.808	0.985	0.869	1.12
Does not currently engage (3×/week)	0 [a]	.	.	1	.	.
Age	0.011	0.002	<0.001	1.01	1.01	1.02
Subjective Health Rating	−0.156	0.019	<0.001	0.855	0.824	0.888
BMI	0.011	0.004	0.012	1.01	1	1.02
CES-D	0.013	0.004	<0.001	1.01	1.01	1.02
PSQI_Sleep Disturbances	0.341	0.048	<0.001	1.41	1.28	1.55
(Negative Binomial)	0.191	0.03				

[a] Set to 0 because parameter is redundant.

Specifically, participants identifying as female reported a higher number of health complaints than those identifying as male, as demonstrated by the following: IRR= 1.36, 95% CI [1.22, 1.5], $p < 0.001$. This indicates a 36% increase in expected somatic complaints in female participants. Lower levels of total household income were associated with a significantly higher report of CHC within the past 12 months (IRR= 1.19, 95% CI [1.02, 1.39], $p = 0.027$). This suggests that for every one-unit increase in household income for individuals within the Low-Income category, CHC increased by approximately 19%. Lower levels of education were also associated with a significantly higher CHC (IRR= 0.85, 95% CI [0.725, 0.988], $p = 0.035$), suggesting that for every one-unit increase in education for individuals within the High School Education or Less category, CHC decreased by approximately 15%. Participant age at clinic visit was also associated with a significantly higher number of chronic conditions (IRR = 1.01, 95% CI [1.007, 1.02], $p < 0.001$),

suggesting that for every ten-year increase in age, CHC increased by approximately 12%. Subjective health rating was also associated with a significantly higher CHC (IRR= 0.86, 95% CI [0.824, 0.888], $p < 0.001$), suggesting that for every one-unit increase in subjective health status, CHC decreased by approximately 14%. BMI was significantly associated with a higher number of reported somatic symptoms (IRR = 1.011, 95% CI [1.002, 1.02], $p = 0.012$), indicating that for every one-unit increase in BMI, CHC increased by approximately 1.1%. Depression was also associated with a significantly higher number of reported somatic symptoms (IRR = 1.013, 95% CI [1.007, 1.02], $p < 0.001$), suggesting that for every one-unit increase in depression, CHC increased by approximately 1.3%. Finally, sleep disturbance was associated with a significantly higher number of reported somatic symptoms (IRR = 1.407, 95% CI [1.280, 1.546], $p < 0.001$), suggesting that for every one-unit increase in sleep disturbances, CHC increased by approximately 40.7%. Participants' race, current marital status, and physical activity did not significantly predict CHC within this model above and beyond the impact of other variables. Additionally, education and income did not significantly predict changes in CHC for participants within the middle (Some college/Bachelor's, Middle: 30,000–74,999) and upper level (Graduate/Professional Certification, High: >75,000) categories.

4. Discussion

4.1. General Discussion

The incidence rate of individuals in the US with multiple chronic health conditions has been steadily increasing, and the strain of managing these conditions places a significant burden on both affected individuals and the national healthcare system. The current study aimed to explore how everyday health behaviors may negatively impact overall health status and contribute to disease onset and progression and highlight intervention targets to promote healthy aging. Findings from this study contribute to previous literature demonstrating that chronic health conditions are multifactorial and are associated with various demographic, physiological, and psychological variables.

Results revealed that, in line with current estimates, 57% of the current sample experienced multimorbidity, with an average of 2+ conditions per individual. Notably, sleep disturbance emerged as the most robust predictor of chronic health conditions, beyond the set of other included variables previously demonstrated to impact multimorbidity (ex., BMI, depression, physical activity). Despite prior research having identified sleep and sleep disturbance as related to multimorbidity in other countries [44,45,57], this is the first study, to our knowledge, to relate subjective sleep disturbance to the number of chronic health conditions within a large-scale, United States sample. The thorough examination of sleep in comparison to various demographic, physiological, and psychological variables further supports the importance of sleep across the multifactorial nature of disease burden. In addition to solidifying what was previously known about the relationship between sleep disturbance and multimorbidity, findings from this study demonstrate its relative importance, as sleep disturbance increased an individual's expected multimorbidity by 41%, over double that of any other variable.

In addition to the impact of sleep on the number of chronic health conditions, the study demonstrated relationships between psychophysiological indicators (BMI, depression) and increased reports of chronic disease. These findings are consistent with prior research demonstrating relationships between physiological (BMI) and psychological (depression) variables to the development and persistence of multiple chronic conditions (MCC) [58–61]. Results of the current study also highlighted the relative importance of an individual's perception of their health status, as individuals with higher subjective health ratings reported decreased levels of chronic disease. The finding highlights the utility of assessing

subjective health in routine medical examinations, in addition to the traditional assessments of objective health status, such as disease count, to gain a comprehensive understanding of health-related risk in patient populations. Cumulatively, the results demonstrate the relative importance of psychophysiological variables and integrated approaches to care in regard to the development and treatment of MCCs. Future interventions aimed at improving individual quality of life or promoting successful aging within the United States should include components of both psychology and sleep medicine to address maladaptive health behaviors and ultimately reduce the risk of developing multimorbid health conditions. At the current moment, no such interventions exist that target multimorbidity risk through sleep; however, this study contributes valuable foundational evidence that can be used to guide eventual intervention development.

Notably, results of the current study did not align with previous empirical research in chronic illness, in that subjective physical activity levels and current marital status were not reported to be significant predictors for multimorbidity within this analysis. While the precise cause of this is unknown, potential factors influencing this result may have been the homogeneity of the sample, or limitations inherent to the structure and style of included assessments (ex., yes/no questions, self-report style). Future research should not discredit the importance of these variables upon the development of multiple chronic health conditions until their relative contributions are assessed without these measurement constraints.

The current study expanded upon knowledge regarding the disparate rates of MCCs in individuals identifying as older, female, or sociodemographically disadvantaged. Regarding age, findings demonstrated that individuals' expected count of chronic health conditions increased by 12% for every ten-year increase in age, suggesting that the likelihood of developing multimorbidity significantly increases each decade we age. The age-related finding could be driven by multiple factors, as increased disease count in aging adults has been previously correlated with increased biological frailty [62], subjective age [63], and disability [64], as well as decreased health literacy and reduced satisfaction with healthcare [65–67]. Further investigation of which factors, if any, were responsible for this study's results would be important to identify and address to reduce vulnerability to multimorbidity in older adult populations.

Individuals identifying as female also reported higher levels of chronic conditions within this study, placing them at an increased risk for developing multimorbidity. It is unclear whether females are at a higher risk for increased disease burden due to inherent sex differences or whether this result is an artifact of the increased likelihood for females to engage in health-seeking behaviors [68], routine medical care [69], or participate in healthcare-related research [70,71]. Further, within this study, individuals within the low education and low-income categories were predicted to have higher rates of multimorbidity. Such findings reflect the larger pattern observed within the United States regarding social determinants of health (SDOH), in which sociodemographic disparities may put disadvantaged Americans at higher risk for increased disease burden and poorer health-related QOL [72,73]. The pattern is often observed within individuals with minoritized identities, older age, reduced educational attainment, lower income, unstable or unsafe housing conditions, or residents of rural areas [74]. Importantly, SDOHs present structural barriers to attaining healthcare and should be addressed through targeted interventions designed for underserved, at-risk populations to ameliorate the increased risk of multimorbidity. Interestingly, despite differences in international healthcare infrastructure, resource access, and cultural norms surrounding medicine, findings from this preliminary US sample reflected similar patterns between disturbed sleep and multimorbidity as global studies based in Brazil, China, and Sweden [26,42–44]. Implications of this research within the US

may suggest the integration of assessment of relevant variables that predict multimorbidity (sleep disturbances, subjective health rating, depression level, and risk for SDOH) within the primary care setting. This may be an additional strategy to help attenuate risk for MCCs by facilitating earlier identification of vulnerable individuals and facilitating intervention to prevent disease progression.

4.2. Limitations

Multiple limitations impact this study's findings and should be addressed in future research. The first limitation concerned the operationalization of the study's outcome variable, multimorbidity. There are numerous ways in which one could operationalize the term 'multimorbidity', and research in this field faces challenges with generalizing findings across all combinations of conditions that could be classified as multimorbid [75]. One study, emanating in Australia, supports an operationalization of multimorbidity as a count variable, representing the number of chronic conditions when two or more disease states are present [76]. While the quantification of multimorbidity in this study was similar to our own (counting the number of chronic conditions), the current study relied solely on subjective assessment of chronic disease symptoms. Thus, the current study was limited due to a lack of objective CHC data, as no confirmatory information regarding diagnosed medical conditions was provided. Other research presented mixed findings regarding the equivalence of multimorbidity assessment [77,78], indicating the possibility that the current study results may have varied depending on which quantification of multimorbidity was used. Thus, these findings are limited in that results may only be generalized to healthcare settings in which multimorbidity is conceptualized similarly.

Moreover, the subjective nature of health behavior assessment utilized within this study (phone interviews, questionnaires) may be an additional factor limiting the strength of the study results. Multiple studies have previously detailed biases, such as social desirability, that influence the accuracy of a participant's subjective reporting and reduce the validity of study findings [79,80]. While this bias is generalizable across subjective symptom reporting in psychology, there are additional interpretational biases, specific to subjective sleep assessment, that may further limit the reliability of study findings across populations. Subjective sleep measures, such as the PSQI, are often viewed as less reliable than their objective counterparts (ex., polysomnography, actigraphy) due to observed discrepancies between subjective vs. objective reports of sleep parameters (sleep quality, total sleep time, sleep latency, WASO) [81,82]. Some factors that may drive this discrepancy are sleep state misperceptions, recall biases, depression, and the influence of sleep expectations [83,84]. Additionally, subjective assessments of sleep often require individuals to rate the severity or frequency of their sleep-related disturbances on a forced-response, Likert-style scale, thereby forcing participants to select responses based upon discrete intervals. Consequently, this coarsens participants' responses and potentially obscures meaningful differences in nighttime sleep patterns. Furthermore, the measures used in the study range from one to twelve months. Specifically, participants reported chronic conditions within the past 12 months and sleep disturbances within the past month. It remains unclear if current sleep disturbances were present twelve months ago. To address the predictive nature of sleep disturbances on disease acquisition in future studies, an assessment of these variables over time is warranted.

Further, this study's sample was predominantly socially and economically privileged (white, college-educated, high-income, low depressive symptoms), limiting the generalizability of the study findings across diverse populations. It is unclear if this is simply a reflection of the demographic composition of the local population in which the study was conducted, or if it is indicative of recruitment bias from the original *MIDUS* study's

sampling procedures. Regardless, due to the underrepresentation of individuals with vulnerability identities, study findings should be interpreted with caution for individuals with intersectional or minoritized identities. This could be addressed through the inclusion of targeted recruitment strategies that aim to intentionally engage with underrepresented communities to promote sufficient representation across population subgroups.

4.3. Future Directions

Future directions of research concerning the intersection of medicine and psychology should aim to integrate the strengths of each discipline by including both subjective and objective assessments of core variables. Specific to this study, future analyses exploring sleep disturbance in multimorbid samples should include both objective (ex., polysomnography, actigraphy) and subjective (ex., Consensus Sleep Diary, PSQI, ISI) assessments of sleep to address the above limitations. The gold standard for assessing sleep objectively across populations is polysomnography, which provides comprehensive reports on nighttime sleep without the risk of the reporting biases often observed in subjective sleep assessment [84–86]. Including subjective and objective sleep measurements in future projects would allow for increased precision in assessing sleep disturbances, while providing space for participants to report on additional experiential facets of sleep difficulty. Additionally, future research should explore the role of global sleep, as opposed to solely sleep disturbances, in the development and persistence of multimorbidity. This would allow clinicians to assess whether good sleep may protect against the onset of multiple chronic health conditions and provide further evidence for early sleep intervention. While this study primarily explored main effects, future research may also consider the investigation of interactions amongst predictor variables to tailor interventions for individuals at higher risk for multimorbidity. Additionally, future studies would also benefit from repeated measurements of sleep and multimorbidity across time, to yield insight into the length of time individuals may exhibit maladaptive health behaviors (such as a poor sleep routine) before their likelihood of developing multimorbidity increases. Finally, future research should prioritize diverse recruitment strategies with the goal of obtaining a representative sample so that future researchers may stratify analyses to better investigate the role of health disparities on multimorbidity.

5. Conclusions

The current study demonstrates the significance of sleep disturbances in predicting multimorbidity within the United States. Given the significant burden multimorbidity places upon healthcare spending and resource utilization, it may be important to explore how early sleep intervention may mitigate negative health consequences and promote longevity. Whilst findings were exploratory, study results emphasize the potential utility of screening for sleep disturbances in patients with MCCs to identify sleep as a modifiable risk factor for disease. Targeted intervention aimed at reducing the incidence of sleep disturbances within the US could aid in reducing the psychological, physiological, and somatic vulnerabilities that individuals with multimorbid conditions face.

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Abbreviations

The following abbreviations are used in this manuscript:

MIDUS	Survey of Midlife Development in the United States
CHC	Chronic Health Conditions
PSQI	Pittsburgh Sleep Quality Index
CESD	Center for Epidemiologic Studies Depression Scale
SAQ	Self-Administered Questionnaire
BMI	Body Mass Index
WHO	World Health Organization
SDOH	Social Determinants of Health
MCC	Multiple Chronic Conditions

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