Preventive Medicine 179 (2024) 107830

Contents lists available at ScienceDirect

Preventive Medicine

journal homepage: www.elsevier.com/locate/ypmed

Individual and dual trajectories of insomnia symptoms and body mass index before and after retirement and their associations with changes in subjective cognitive functioning

Antti Etholén [a,*], Anne Kouvonen [b,c], Mirja Hänninen [a,d], Jenni Kulmala [e,f,g], Ossi Rahkonen [a], Minna Mänty [a], Tea Lallukka [a]

[a] Department of Public Health, PO BOX 20 (Tukholmankatu 8 B), 00014 University of Helsinki, Finland
[b] Faculty of Social Sciences, University of Helsinki, POB 54, 00014 University of Helsinki, Finland
[c] Centre for Public Health, Queen's University Belfast, Royal Victoria Hospital, Belfast BT12 6BA, UK
[d] Western Uusimaa Wellbeing Services County, Social and Health Care Services, P.O. BOX 33, 02033 Espoo, Finland
[e] Faculty of Social Sciences (Health Sciences) and Gerontology Research Center (GEREC), Tampere University, Arvo Ylpön katu 34, 33520 Tampere, Finland
[f] Population Health Unit, Finnish Institute for Health and Welfare, POB 30, 00271 Helsinki, Finland
[g] Division of Clinical Geriatrics, Center for Alzheimer Research, Department of Neurobiology, Care Sciences and Society, Karolinska Institutet, Solnavägen 1, 171 77 Solna, Sweden

ARTICLE INFO

Keywords:
Subjective cognitive functioning
Insomnia symptoms
Body mass index
Retirement
Trajectory modelling
Dual trajectories
Ageing

ABSTRACT

Background: We examined individual and dual trajectories of insomnia symptoms and body mass index (BMI) before and after retirement, and their associations with changes in subjective cognitive functioning after retirement.

Methods: We used the Helsinki Health Study's ($n = 2360$, 79% women, aged 40–60 at baseline, Finland) repeated surveys to identify the developmental patterns of insomnia symptoms and BMI (2000–2017) and changes in subjective cognitive functioning (2017–2022). We analysed the data using latent group-based dual trajectory modelling and logistic regression analysis.

Results: Three latent groups were identified for insomnia symptoms (stable low, decreasing and increasing symptoms) and BMI (stable healthy weight, stable overweight and stable obesity). Insomnia symptoms were associated with declining subjective cognitive functioning and largely explained the effects in the dual models.

Conclusion:
The association between dual trajectories of insomnia symptoms and BMI with subjective cognitive decline is dominated by insomnia symptoms.

1. Introduction

The rapid ageing of the population continues to challenge the capacity of health and social care services (Mitchell and Walker, 2020). Cognitive decline and dementia become more common with advancing age, leading to an increased need for health and social care services (Nandi et al., 2022; Knapp et al., 2013). Both insomnia symptoms and high body mass index (BMI) have been associated with subjective cognitive decline (SCD) (Wen et al., 2021; Hao et al., 2019). Epidemiological, longitudinal and biomarker studies have found increasing evidence that SCD might be a potential first symptom of dementia (Mitchell et al., 2014; Verlinden et al., 2016; Eliassen et al., 2017; Jessen et al., 2020). The progression of Alzheimer's disease is slow and the first symptoms may appear decades before mild cognitive impairment (MCI) (Jack et al., 2013; Jack et al., 2018). As no curative treatments for memory disorders exist (Cummings et al., 2019), the prevention, and postponement of cognitive decline are essential (Kulmala et al., 2018).

In our previous study using a person-oriented approach persistent insomnia symptoms were associated with declined subjective cognitive functioning after retirement (Etholén et al., 2022). Another study combining two cohorts of older adults showed that early SCD with sleep problems increased the risk of severe cognitive decline (Tsapanou et al.,

* Corresponding author at: Department of Public Health, PB 20, FI-00014 University of Helsinki, Finland.
E-mail addresses: antti.etholen@helsinki.fi (A. Etholén), anne.kouvonen@helsinki.fi (A. Kouvonen), mirja.hanninen@helsinki.fi (M. Hänninen), jenni.kulmala@tuni.fi (J. Kulmala), ossi.rahkonen@helsinki.fi (O. Rahkonen), minna.manty@vantaa.fi (M. Mänty), tea.lallukka@helsinki.fi (T. Lallukka).

https://doi.org/10.1016/j.ypmed.2023.107830
Received 11 November 2023; Received in revised form 13 December 2023; Accepted 19 December 2023
Available online 23 December 2023

2019). A cross-sectional cohort study in the Netherlands found an association between subjective sleep problems and self-reported cognitive decline (Exalto et al., 2022). Several longitudinal studies using objectively measured cognitive functioning have found that sleep disturbances may be associated with cognition in older adults (Nebes et al., 2009; Blackwell et al., 2014). A British follow-up study of over 50 year-olds found that short sleep in midlife was associated with cognitive decline in later life (Sabia et al., 2021), whereas a US follow-up study among over 42 year-olds found no association (Zitser et al., 2020).

High BMI and obesity comorbidities in midlife have also been associated with cognitive decline in later life (Whitmer et al., 2005a; Morys et al., 2021; Whitmer et al., 2005b). However, the evidence is inconsistent (Albanese et al., 2015; Albanese et al., 2012). Moreover, two follow-up studies using data from the Korean Longitudinal Study of Ageing have suggested that high BMI in later life might even protect against cognitive decline (Kim et al., 2016; Kim et al., 2020a). Reverse causality is also a possibility, as weight loss has been linked to dementia and may precede the onset of cognitive symptoms (Johnson et al., 2006). In a British study, obesity in midlife was associated with a risk of dementia later life (Singh-Manoux et al., 2018). A large study comprising 39 cohorts with individual-level data on 1.3 million participants, found that high BMI was a risk factor for dementia in the longer run but that it could be a protective factor in the short term (Kivimäki et al., 2018).

Some studies have shown poor sleep quality to be associated with the risk of obesity (Rao et al., 2009; Rahe et al., 2015). There is also evidence of a bidirectional relationship between BMI and sleep (Koolhaas et al., 2019).

In sum, insomnia symptoms and high BMI are separately associated with poorer cognitive functioning. However, little is known about their dual associations with changes in subjective cognitive functioning. Additionally, previous research has mainly been variable-oriented ignoring the developmental patterns where latent new risk groups could be identified. The aim of our study was, using a person-oriented approach, to examine the dual development of insomnia symptoms and BMI and then to investigate the associations between the identified latent groups and changes in subjective cognitive functioning, adjusting for social and health-related covariates.

2. Method

2.1. Data

We used survey data from the Helsinki Health Study (Fig. 1) (Lahelma et al., 2013), Finland. The phase 1 survey was conducted among 40- to 60-year-old employees of the City of Helsinki in 2000–2002 (response rate 67%, $n = 8960$) and the follow-up surveys were collected in 2007 (Phase 2), 2012 (Phase 3), 2017 (Phase 4) and 2022 (Phase 5). The response rates of the follow-ups were 83%, 79%, 82%, and 75%, respectively. In Phase 4, 54% of the respondents had retired. We excluded disability retirees (7%), and those who had left employment for other reasons (6%). Insomnia symptoms and BMI were included from Phases 1–4. The inclusion criteria were participation in at least phases 1, 4 and 5. Therefore, our final analytic sample included 2360 statutory retirees, who were aged 62 to 82 years in Phase 5 (79% women).

The Helsinki Health Study has received ethical approval from the City of Helsinki authorities, and the ethics committee of the Department of Public Health, University of Helsinki.

2.2. Measurement

2.2.1. Outcome: subjective cognitive functioning

Three variables measuring subjective cognitive functioning were introduced in Phase 4 and were repeated using identical questions in Phase 5 (Etholén et al., 2022; Kouvonen et al., 2022). Almost 99% of the participants responded to these questions in both phases. We asked the participants to assess the following aspects: ‘How well my memory works’, ‘How well embracing and learning new things goes for me’, ‘Normally I can concentrate on something’. These items were used to define three different aspects of cognitive functioning: self-rated

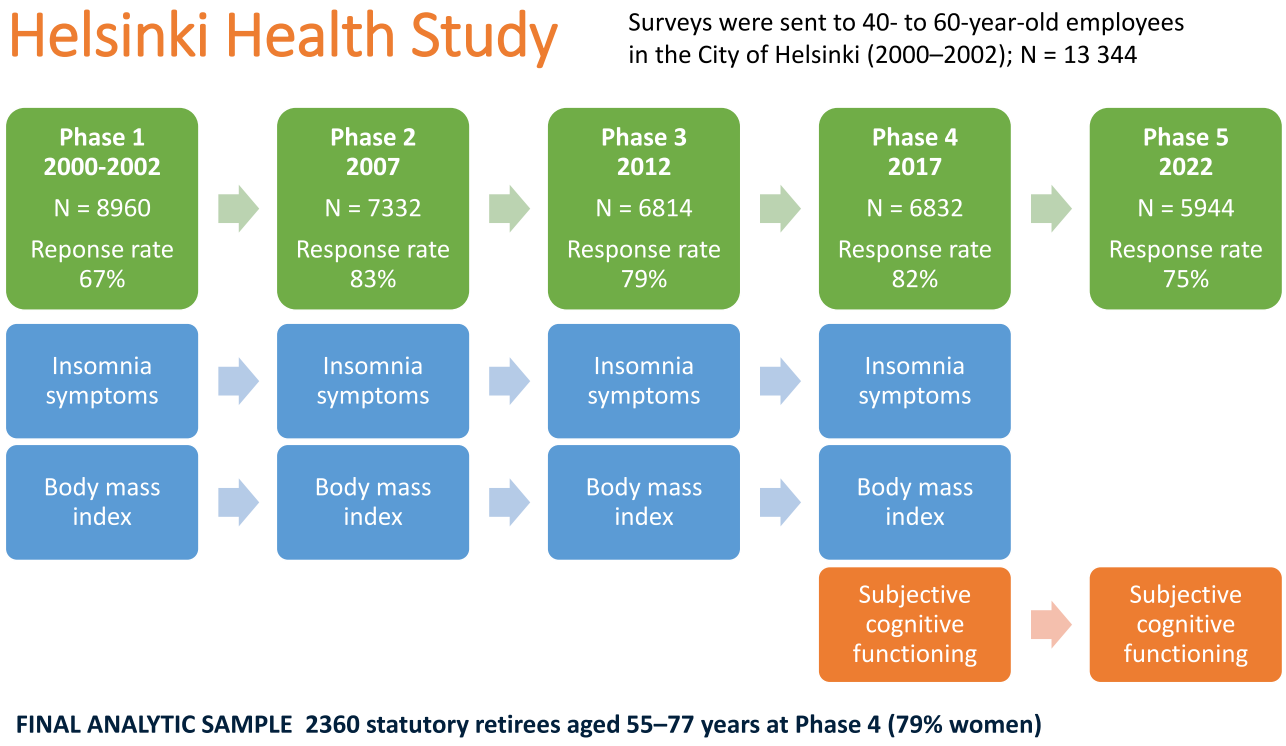

Fig. 1. Phases of the Helsinki Health Study cohort and outcome (subjective cognitive functioning) and exposure (insomnia symptoms and body mass index) variables used in different phases of the study.

memory, self-rated learning, and self-rated concentration, respectively. The participants rated themselves on a five-point scale ('very poorly', 'poorly', 'satisfactorily', 'well', 'very well'). The scales were re-categorised as good (including 'well' and 'very well') and poor (including 'satisfactorily', 'very poorly' and 'poorly'). From these, we formed the following variable that described the changes between Phases 4 and 5: stable good (good → good), declining (good → poor), improving (poor → good) and stable poor (poor → poor).

2.2.2. Explanatory variables: insomnia symptoms and body mass index

Insomnia symptoms were measured in Phases 1–4 asking how often in the past month the participants did 1) 'have trouble falling asleep?', 2) 'wake up several times per night?', 3) 'have trouble staying asleep (including waking far too early)?', '4) wake up after their usual amount of sleep feeling tired and worn out?'. Scores ranged from 0 to 5, corresponding responses 'not at all', '1–3 days', '4–7 days', '8–14 days', '15–21 days', '22–28 days') which were summed up to a total score (range 0–20). Cronbach's alpha was 0.84 indicating good internal consistency.

Body weight and height were also derived from Phases 1–4. BMI was calculated from self-reported weight in kilograms (kg) divided by self-reported height in square meters (m^2) (World Health Organization Regional Office for Europe, 2021). Self-reported BMI highly correlates with directly measured BMI (Elgar and Stewart, 2008), and thus can be used to categorise individuals at the higher end of the BMI scale, such as those with obesity (Chernenko et al., 2019). BMI was used as a continuous variable in the trajectory modelling. Additionally, we used a categorical variable: healthy weight (BMI range 18.5–24.9 kg/m^2), overweight (25–29.9 kg/m^2), and obesity (30+ kg/m^2). Underweight was defined as BMI below 18.5 kg/m^2.

2.2.3. Covariates

Covariates were mostly derived from Phase 4. Of sociodemographic factors we included gender, age and retirement age (as continuous variables), marital status, education, and occupational class. Of health-related factors we included smoking, alcohol consumption, consumption of fruit and vegetables, leisure-time and commuting physical activity. In addition, current pain status and the following physician-diagnosed chronic diseases were included as health-related covariates: cardiovascular risk diseases, pulmonary diseases, sleep apnoea, and psychiatric diseases. Covariates were selected based on their known associations with sleep, BMI, and cognitive functioning (Carroll and Turkheimer, 2018; Wen et al., 2021; Smagula et al., 2016). For a more detailed description of the covariates, see Appendix A.

2.3. Statistical analyses

We used χ^2 tests to analyse the differences between the health and other covariates among men and women (Table 1).

As missing covariate data were rare, the missing values were included in the reference groups in line with previous procedures (Etholén et al., 2022). Moreover, we did not identify any bias in the descriptive tables of the missing data (data not shown).

Data analyses were conducted using the R program, version 4.2.1 (R Core Team, 2021). The number of men was relatively low ($n = 486$), and the sizes of the subgroups were insufficient to conduct gender-stratified analyses. Thus, the analysis was run in gender-pooled data.

We used latent group-based dual trajectory modelling to investigate the multidimensional and dynamic associations between insomnia symptoms and BMI using the R program approximation of the SAS/Stata procedure traj (Nagin et al., 2018; Jones and Nagin, 2013). Firstly, the univariate trajectories of both insomnia symptoms and BMI were formed separately. We used the total score of insomnia symptoms and BMI as an outcome of the function over time periods. We used and tested the third-degree polynomial model in different numbers of groups from 1 to 4 to explore the best-fitting model (Supplementary Figs. S1 and S2). We applied censored normal distribution, and used time as a random effect. On the time axis the retirement age was defined as the zero-time point. The time axis also showed the years before and after retirement, which highlight the behaviour of the curves during ageing. We chose the best model on the basis of visual inspection, interpretation of the results according to the best understanding of the phenomenon, the highest value of the Bayesian information criteria (BIC), the Akaike Information Criteria (AIC), average posterior probability of assignment criteria (APPA) of >0.7, the odds of correct classification criteria (OCC), and the size of the classes being at least 5% (Supplementary Table S1) (Nagin and Odgers, 2010). The participants were assigned into a trajectory class on the basis of the highest probability of these latent classes. The model indicated good fit and high average group membership probability, and we concluded that the trajectory analysis assigned the distinct groups very well. Secondly, we used the number of groups in the best models of insomnia symptoms and BMI as the initial parameters in the dual trajectory modelling (Nagin and Tremblay, 2001). Thirdly, the interrelationships of these variables were presented as the joint probabilities of trajectory group membership for both insomnia symptoms and BMI.

The associations between the distinct dual trajectory groups, univariate trajectories, and the change in subjective cognitive functioning were analysed using cross-tabulations and χ^2. Next, we examined the associations between the dual trajectory groups and changes in subjective cognitive functioning using logistic regression models. We fitted three different models: Model 1 = adjusted for age and gender, Model 2 = adjusted for Model 1 + other socio-demographic covariates, and Model 3 = full model adjusted for Model 2 + health-related covariates. The results were presented as odds ratios (OR) and their 95% confidence intervals (CI).

3. Results

Of the participants, 25% were classified as having a stable poor memory, 43% stable poor learning, and 21% stable poor concentration (Table 1). Forty-six per cent of the participants reported that they had insomnia symptoms <4 nights/month, 28% 4–14 nights/month, and 26% >14 nights/month. Forty-one per cent of the participants had a healthy weight, 39% were with overweight and 18% were with obesity.

We selected a dual trajectory model with three latent trajectory groups (based on statistical and other criteria, Supplementary Table S1) of insomnia symptoms and BMI over the follow-up period (Fig. 2). The insomnia symptom groups were defined as having stable low (62%), decreasing (20%), and increasing (19%) symptoms. The BMI groups were defined as having stable healthy weight (43%), stable overweight (40%), and stable obesity (17%). Supplementary Table S2 shows the associations between the insomnia symptoms and BMI latent groups. Fig. 3 shows the 100% scaled percentages of the BMI trajectory groups within each insomnia symptom trajectory group. In the increasing insomnia symptoms group, 20% had obesity, whereas the corresponding figures were 18% and 15% in the decreasing insomnia symptoms group and the stable low insomnia symptoms group, respectively. Stable healthy weight was more common in the stable low insomnia symptoms group.

Supplementary Table S3 shows the associations between the dual trajectories of insomnia symptoms and BMI. Supplementary Table S4 presents the odds ratios of the three different models to compare the associations between the individual (Fig. 4) and dual (Fig. 5) latent trajectory groups and subjective cognitive functioning. In the age- and gender-adjusted models, those with increasing insomnia symptoms were more likely to report poor memory (OR 2.3, 95% CI 1.8–3.0), poor learning (OR 2.9, 95% CI 2.2–3.7), and poor concentration (OR 3.2, 95% CI 2.4–4.1) than those with stable low insomnia symptoms. Those with decreasing insomnia symptoms were more likely to report poor memory (OR 2.1, 95% CI 1.6–2.7), poor learning (OR 2.2, 95% CI 1.7–2.8), and poor concentration (OR 2.7, 95% CI 2.0–3.5) than those with stable low

Table 1
Background characteristics of the study population based on survey data from the Helsinki Health Study follow-up 2000–2022. The baseline study population consisted of 40- to 60-year-old employees of the City of Helsinki, Finland.

Statutory retirees	Gender (phase I)			Changes in memory (phases IV → V)					Changes in learning (phases IV → V)					Changes in concentration (phases IV → V)				
	Male	Female		Stable good	Improving	Declining	Stable poor		Stable good	Improving	Declining	Stable poor		Stable good	Improving	Declining	Stable poor	
(*N* = 2360)	(*N* = 486)	(*N* = 1874)		(*N* = 1349)	(*N* = 180)	(*N* = 246)	(*N* = 585)		(*N* = 873)	(*N* = 211)	(*N* = 268)	(*N* = 1008)		(*N* = 1399)	(*N* = 198)	(*N* = 277)	(*N* = 486)	
Explanatory variables																		
Body mass index (phase IV)			0.0013					0.7446					0.0022					0.1856
Underweight −18.5	-	26 (1.4%)		17 (1.3%)	-	-	-		-	-	-	-		13 (0.9%)	-	-	-	
Recommended healthy weight 18.5–24.9	191 (39.3%)	788 (42%)		563 (41.7%)	75 (41.7%)	97 (39.4%)	244 (41.7%)		375 (43%)	91 (43.1%)	100 (37.3%)	413 (41%)		580 (41.5%)	70 (35.4%)	123 (44.4%)	206 (42.4%)	
Overweight 25–29.9	223 (45.9%)	702 (37.5%)		521 (38.6%)	70 (38.9%)	92 (37.4%)	242 (41.4%)		320 (36.7%)	86 (40.8%)	96 (35.8%)	423 (42%)		553 (39.5%)	73 (36.9%)	104 (37.5%)	195 (40.1%)	
Obesity 30+	71 (14.6%)	351 (18.7%)		245 (18.2%)	33 (18.3%)	53 (21.5%)	91 (15.6%)		164 (18.8%)	29 (13.7%)	65 (24.3%)	164 (16.3%)		249 (17.8%)	49 (24.7%)	45 (16.2%)	79 (16.3%)	
No answer	0 (0%)	-		-	0 (0%)	-	-		-	0 (0%)	0 (0%)	-		-	-	0 (0%)	-	
Insomnia symptoms (phase IV)			0.1603					<0.001					<0.001					<0.001
<4 nights/month	239 (49.2%)	836 (44.6%)		700 (51.9%)	64 (35.6%)	112 (45.5%)	199 (34%)		503 (57.6%)	73 (34.6%)	131 (48.9%)	368 (36.5%)		719 (51.4%)	84 (42.4%)	127 (45.8%)	145 (29.8%)	
4–14 nights/month	125 (25.7%)	527 (28.1%)		355 (26.3%)	54 (30%)	65 (26.4%)	178 (30.4%)		207 (23.7%)	61 (28.9%)	71 (26.5%)	313 (31.1%)		374 (26.7%)	50 (25.3%)	79 (28.5%)	149 (30.7%)	
>14 nights/month	121 (24.9%)	495 (26.4%)		286 (21.2%)	61 (33.9%)	68 (27.6%)	201 (34.4%)		161 (18.4%)	75 (35.5%)	64 (23.9%)	316 (31.3%)		301 (21.5%)	61 (30.8%)	69 (24.9%)	185 (38.1%)	
No answer		16 (0.9%)							-	-	-	11 (1.1%)		-	-	-	-	
Sociodemographic - covariates																		
Retirement age (SD)	63.1 (3)	63.1 (2.7)		63.2 (2.4)	63 (2.7)	63 (2.6)	62.8 (3.5)		63.2 (2.4)	63 (2.3)	63.2 (2.3)	62.9 (3.3)		63.1 (2.5)	63.2 (2.1)	63 (2.6)	62.9 (3.7)	
Age at follow-up (phase IV) (SD)	70.1 (4)	69.7 (3.9)		69.2 (3.7)	70.3 (4)	70.5 (3.9)	71 (3.9)		68.8 (3.7)	69.4 (4)	70 (4)	70.7 (3.8)		69.3 (3.8)	70.1 (4.2)	70.5 (3.6)	70.9 (3.9)	
Retirement period years (phase IV) (SD)	7 (4.9)	6.7 (4.8)		6 (4.5)	7.2 (4.8)	7.5 (4.8)	8.1 (5.4)		5.6 (4.3)	6.4 (4.7)	6.8 (4.8)	7.9 (5.1)		6.1 (4.5)	6.9 (4.6)	7.6 (4.6)	8 (5.6)	
Gender (phase I)			<0.001					<0.001					0.1841					0.1342
Men	486 (100%)	0 (0%)		232 (17.2%)	57 (31.7%)	51 (20.7%)	146 (25%)		161 (18.4%)	50 (23.7%)	54 (20.1%)	221 (21.9%)		271 (19.4%)	51 (25.8%)	64 (23.1%)	100 (20.6%)	
Women	0 (0%)	1874 (100%)		1117 (82.8%)	123 (68.3%)	195 (79.3%)	439 (75%)		712 (81.6%)	161 (76.3%)	214 (79.9%)	787 (78.1%)		1128 (80.6%)	147 (74.2%)	213 (76.9%)	386 (79.4%)	
Education (phase I)			<0.001					0.0053					<0.001					<0.001
Basic	170 (35%)	776 (41.4%)		499 (37%)	75 (41.7%)	106 (43.1%)	266 (45.5%)		303 (34.7%)	85 (40.3%)	99 (36.9%)	459 (45.5%)		498 (35.6%)	89 (44.9%)	110 (39.7%)	249 (51.2%)	
Secondary	112 (23%)	525 (28%)		370 (27.4%)	46 (25.6%)	75 (30.5%)	146 (25%)		233 (26.7%)	63 (29.9%)	80 (29.9%)	261 (25.9%)		388 (27.7%)	57 (28.8%)	87 (31.4%)	105 (21.6%)	
Higher	204 (42%)	573 (30.6%)		480 (35.6%)	59 (32.8%)	65 (26.4%)	173 (29.6%)		337 (38.6%)	63 (29.9%)	89 (33.2%)	288 (28.6%)		513 (36.7%)	52 (26.3%)	80 (28.9%)	132 (27.2%)	
Occupational class (phase I)			<0.001					0.1074					0.0011					<0.001
Managers and professionals	267 (54.9%)	660 (35.2%)		557 (41.3%)	67 (37.2%)	90 (36.6%)	213 (36.4%)		380 (43.5%)	83 (39.3%)	108 (40.3%)	356 (35.3%)		600 (42.9%)	66 (33.3%)	105 (37.9%)	156 (32.1%)	
Semi-professionals	92 (18.9%)	301 (16.1%)		225 (16.7%)	35 (19.4%)	41 (16.7%)	92 (15.7%)		154 (17.6%)	36 (17.1%)	43 (16%)	160 (15.9%)		237 (16.9%)	35 (17.7%)	49 (17.7%)	72 (14.8%)	

(*continued on next page*)

Table 1 (*continued*)

Statutory retirees	Gender (phase I)			Changes in memory (phases IV → V)					Changes in learning (phases IV → V)					Changes in concentration (phases IV → V)				
	Male	Female		Stable good	Improving	Declining	Stable poor		Stable good	Improving	Declining	Stable poor		Stable good	Improving	Declining	Stable poor	
(*N* = 2360)	(*N* = 486)	(*N* = 1874)		(*N* = 1349)	(*N* = 180)	(*N* = 246)	(*N* = 585)		(*N* = 873)	(*N* = 211)	(*N* = 268)	(*N* = 1008)		(*N* = 1399)	(*N* = 198)	(*N* = 277)	(*N* = 486)	
Routine non-manual workers	31 (6.4%)	723 (38.6%)		426 (31.6%)	59 (32.8%)	79 (32.1%)	190 (32.5%)		262 (30%)	63 (29.9%)	89 (33.2%)	340 (33.7%)		433 (31%)	65 (32.8%)	78 (28.2%)	178 (36.6%)	
Manual workers/no answer	96 (19.8%)	190 (10.1%)		141 (10.5%)	19 (10.6%)	36 (14.6%)	90 (15.4%)		77 (8.8%)	29 (13.7%)	28 (10.4%)	152 (15.1%)		129 (9.2%)	32 (16.2%)	45 (16.2%)	80 (16.5%)	
Marital status (phase IV)			<0.001					0.7482					0.9592					0.0044
Other/no answer	81 (16.7%)	772 (41.2%)		481 (35.7%)	61 (33.9%)	94 (38.2%)	217 (37.1%)		313 (35.9%)	76 (36%)	94 (35.1%)	370 (36.7%)		471 (33.7%)	73 (36.9%)	101 (36.5%)	208 (42.8%)	
Co-habiting/married	405 (83.3%)	1102 (58.8%)		868 (64.3%)	119 (66.1%)	152 (61.8%)	368 (62.9%)		560 (64.1%)	135 (64%)	174 (64.9%)	638 (63.3%)		928 (66.3%)	125 (63.1%)	176 (63.5%)	278 (57.2%)	
Health-related behaviors - covariates																		
Smoking (phase IV)			<0.001					0.6234					0.7795					0.2762
Never smoker	220 (45.3%)	1135 (60.6%)		777 (57.6%)	99 (55%)	150 (61%)	329 (56.2%)		505 (57.8%)	120 (56.9%)	153 (57.1%)	577 (57.2%)		830 (59.3%)	106 (53.5%)	160 (57.8%)	259 (53.3%)	
Ex-smoker	163 (33.5%)	399 (21.3%)		318 (23.6%)	47 (26.1%)	60 (24.4%)	137 (23.4%)		208 (23.8%)	43 (20.4%)	66 (24.6%)	245 (24.3%)		319 (22.8%)	49 (24.7%)	69 (24.9%)	125 (25.7%)	
Current smoker	103 (21.2%)	340 (18.1%)		254 (18.8%)	34 (18.9%)	36 (14.6%)	119 (20.3%)		160 (18.3%)	48 (22.7%)	49 (18.3%)	186 (18.5%)		250 (17.9%)	43 (21.7%)	48 (17.3%)	102 (21%)	
Alcohol consumption (phase IV)			<0.001					0.1217					0.0555					0.6154
No consumption	50 (10.3%)	282 (15%)		175 (13%)	24 (13.3%)	42 (17.1%)	91 (15.6%)		113 (12.9%)	25 (11.8%)	42 (15.7%)	152 (15.1%)		183 (13.1%)	33 (16.7%)	42 (15.2%)	74 (15.2%)	
Moderate consumption	286 (58.8%)	1369 (73.1%)		956 (70.9%)	124 (68.9%)	166 (67.5%)	409 (69.9%)		634 (72.6%)	147 (69.7%)	183 (68.3%)	691 (68.6%)		1005 (71.8%)	131 (66.2%)	187 (67.5%)	332 (68.3%)	
High consumption	47 (9.7%)	130 (6.9%)		115 (8.5%)	10 (5.6%)	19 (7.7%)	33 (5.6%)		74 (8.5%)	18 (8.5%)	20 (7.5%)	65 (6.4%)		104 (7.4%)	18 (9.1%)	21 (7.6%)	34 (7%)	
High risk consumption	103 (21.2%)	93 (5%)		103 (7.6%)	22 (12.2%)	19 (7.7%)	52 (8.9%)		52 (6%)	21 (10%)	23 (8.6%)	100 (9.9%)		107 (7.6%)	16 (8.1%)	27 (9.7%)	46 (9.5%)	
Fruit and vegetable consumption (phase IV)			<0.001					<0.001					0.1444					0.0425
Daily consumer both	224 (46.1%)	1144 (61%)		829 (61.5%)	87 (48.3%)	143 (58.1%)	309 (52.8%)		541 (62%)	122 (57.8%)	159 (59.3%)	546 (54.2%)		852 (60.9%)	99 (50%)	161 (58.1%)	256 (52.7%)	
Daily consumer of either	123 (25.3%)	438 (23.4%)		287 (21.3%)	55 (30.6%)	62 (25.2%)	157 (26.8%)		191 (21.9%)	46 (21.8%)	63 (23.5%)	261 (25.9%)		316 (22.6%)	51 (25.8%)	65 (23.5%)	129 (26.5%)	
Non-daily consumer	135 (27.8%)	273 (14.6%)		220 (16.3%)	38 (21.1%)	41 (16.7%)	109 (18.6%)		132 (15.1%)	41 (19.4%)	44 (16.4%)	191 (18.9%)		219 (15.7%)	45 (22.7%)	48 (17.3%)	96 (19.8%)	
No answer	4 (0.8%)	19 (1%)		13 (1%)	0 (0%)	0 (0%)	10 (1.7%)		-	-	-	10 (1%)		12 (0.9%)	-	-	-	
Physical activity (phase IV)			0.7214					<0.001					<0.001					<0.001
Inactive (MET<14)	103 (21.2%)	381 (20.3%)		231 (17.1%)	54 (30%)	61 (24.8%)	138 (23.6%)		146 (16.7%)	37 (17.5%)	54 (20.1%)	247 (24.5%)		246 (17.6%)	52 (26.3%)	57 (20.6%)	129 (26.5%)	
Active (MET≥ 14)/no answer	383 (78.8%)	1493 (79.7%)		1118 (82.9%)	126 (70%)	185 (75.2%)	447 (76.4%)		727 (83.3%)	174 (82.5%)	214 (79.9%)	761 (75.5%)		1153 (82.4%)	146 (73.7%)	220 (79.4%)	357 (73.5%)	
Health factors - covariates																		
Current pain (phase IV)	146 (30%)	722 (38.5%)	0.0023	447 (33.1%)	67 (37.2%)	98 (39.8%)	256 (43.8%)	<0.001	286 (32.8%)	74 (35.1%)	90 (33.6%)	418 (41.5%)	<0.001	475 (34%)	76 (38.4%)	100 (36.1%)	217 (44.7%)	<0.001
Cardiovascular risk disease (phase IV)	304 (62.6%)	1143 (61%)	0.3052	787 (58.3%)	109 (60.6%)	158 (64.2%)	393 (67.2%)	0.0018	495 (56.7%)	129 (61.1%)	153 (57.1%)	670 (66.5%)		821 (58.7%)	117 (59.1%)	173 (62.5%)	336 (69.1%)	<0.001

(*continued on next page*)

Table 1 (*continued*)

Statutory retirees	Gender (phase I)			Changes in memory (phases IV → V)					Changes in learning (phases IV → V)					Changes in concentration (phases IV → V)				
	Male	Female		Stable good	Improving	Declining	Stable poor		Stable good	Improving	Declining	Stable poor		Stable good	Improving	Declining	Stable poor	
(*N* = 2360)	(*N* = 486)	(*N* = 1874)		(*N* = 1349)	(*N* = 180)	(*N* = 246)	(*N* = 585)		(*N* = 873)	(*N* = 211)	(*N* = 268)	(*N* = 1008)		(*N* = 1399)	(*N* = 198)	(*N* = 277)	(*N* = 486)	
Pulmonary disease (phase IV)	47 (9.7%)	249 (13.3%)	0.0029	155 (11.5%)	24 (13.3%)	28 (11.4%)	89 (15.2%)	0.0556	120 (13.7%)	17 (8.1%)	37 (13.8%)	122 (12.1%)	0.0273	168 (12%)	25 (12.6%)	32 (11.6%)	71 (14.6%)	0.0622
Psychiatric disease (phase IV)	26 (5.3%)	195 (10.4%)	<0.001	99 (7.3%)	24 (13.3%)	20 (8.1%)	78 (13.3%)	<0.001	59 (6.8%)	27 (12.8%)	24 (9%)	111 (11%)	0.0048	90 (6.4%)	25 (12.6%)	28 (10.1%)	78 (16%)	<0.001
Sleep apnoea (phase IV)	43 (8.8%)	71 (3.8%)	<0.001	50 (3.7%)	11 (6.1%)	10 (4.1%)	43 (7.4%)	0.0039	36 (4.1%)	14 (6.6%)	-	55 (5.5%)	0.0752	55 (3.9%)	-	-	41 (8.4%)	<0.001

SD standard deviation.
P-value from the chi-square test.
MET metabolic equivalent.
Phases 1–5 (2000–2002, 2007, 2012, 2017, 2022)
- a cell contains less than 10 individuals

insomnia symptoms. In the fully adjusted model, no statistically significant associations with the BMI trajectory groups were detected.

In dual trajectories, there were no statistically significant differences between the different BMI trajectories with changes in subjective cognitive functioning among those with stable low insomnia symptoms. In the fully adjusted model, those with increasing insomnia symptoms and overweight were more likely to report poor memory (OR 2.0, 95% CI 1.3–3.0), poor learning (OR 2.3, 95% CI 1.5–3.6), and poor concentration (OR 2.4, 95% CI 1.5–3.8) than those with stable low insomnia symptoms and healthy weight. Those with increasing insomnia symptoms and healthy weight were more likely to report poor memory (OR 2.3, 95% CI 1.5–3.5), poor learning (OR 3.3, 95% CI 2.2–5.0), and poor concentration (OR 3.2, 95% CI 2.1–4.8). Those with decreasing insomnia symptoms and overweight more often reported poor memory (OR 1.5, 95% CI 1.0–2.2), poor learning (OR 2.2, 95% CI 1.4–3.2), and poor concentration (OR 2.2, 95% CI 1.4–3.4). Finally, those with decreasing insomnia symptoms and healthy weight were more likely to report poor memory (OR 1.9 95% CI 1.3–2.9), poor learning (OR 1.7 95% CI 1.1–2.5), and poor concentration (OR 2.1 95% CI 1.4–3.3). In the obesity dual trajectories, none of the studied associations were statistically significant.

4. Discussion

4.1. Main findings

We sought to identify the individual and dual trajectories of insomnia symptoms and BMI before and after statutory retirement and to investigate their associations with changes in subjective cognitive functioning post-retirement across a 20- to 22-year follow-up. We selected a model with three latent group trajectories of insomnia symptoms (stable low, decreasing and increasing symptoms) and BMI (stable healthy weight, stable overweight, and stable obesity) over the follow-up period.

Our main finding was that belonging to the trajectory of increasing or decreasing insomnia symptoms was associated with poor subjective cognitive functioning after retirement. In the dual models, the accumulation of insomnia symptoms explained most of the effect on the poor subjective cognitive functioning at all levels of BMI, whereas the effect of BMI was negligible.

4.2. Interpretation

SCD is common (ranging from 20% to 35%) in ageing populations (Minett et al., 2008; van Harten et al., 2018) The development of SCD varies according to the background mechanism: reversible SCD might be caused by depression, some medications or insomnia symptoms; slightly declined but stable SCD might be caused by normal ageing; and progressive SCD may be due to neurodegenerative diseases that cause dementia (Jessen et al., 2020). The associations between sleep, BMI and cognitive functioning is highly complex. This study enables us to speculate on some of the mechanisms behind these associations.

The accumulation of insomnia symptoms was associated with declined subjective cognitive functioning. As discussed earlier, the effect on cognition can be reversible and the explanation might be factors that impair the effective functioning of the hippocampus, such as depression, insomnia symptoms and pain (Elcombe et al., 2015; Ezzati et al., 2019; Saletin et al., 2016). However, it is also possible that the mechanism is irreversible and can lead to Alzheimer's disease or to other types of dementia. In sleep, the brain cleans away β-amyloid (Lucey et al., 2018). When a person has sleep problems, β-amyloid accumulates in the brain, which might accelerate the formation of β-amyloid plaques associated with Alzheimer's disease (Lucey et al., 2018; Fenton et al., 2021). During sleep deprivation, the levels of tau protein increase in the brain and this might lead to the formation of neurofibrillary tangles related to Alzheimer's disease (Holth et al., 2019). However, the association may

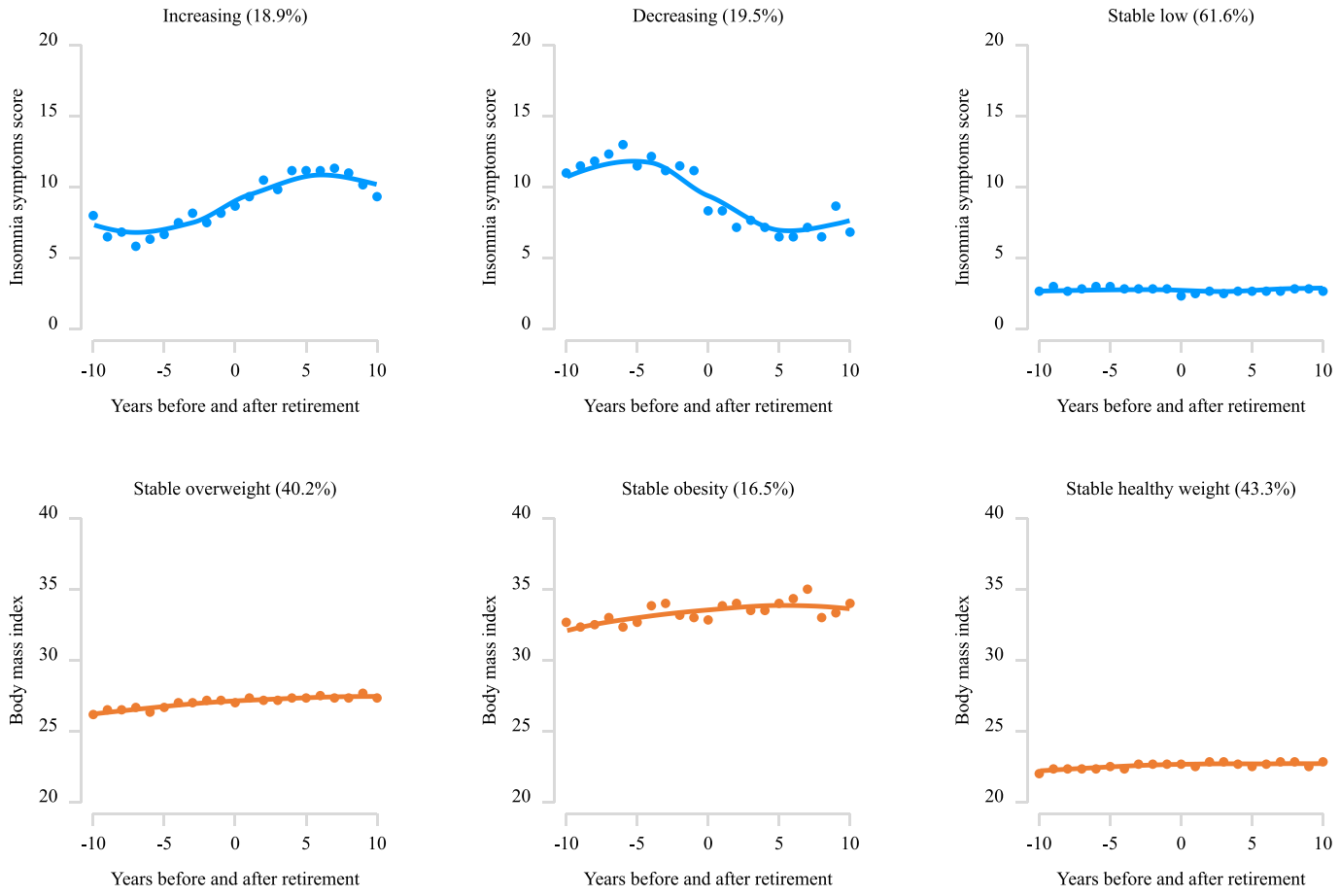

Fig. 2. Selected dual trajectories of insomnia symptoms and body mass index to show development pattern years before and after retirement in group-based trajectory modelling. Total sample size $N = 2360$.

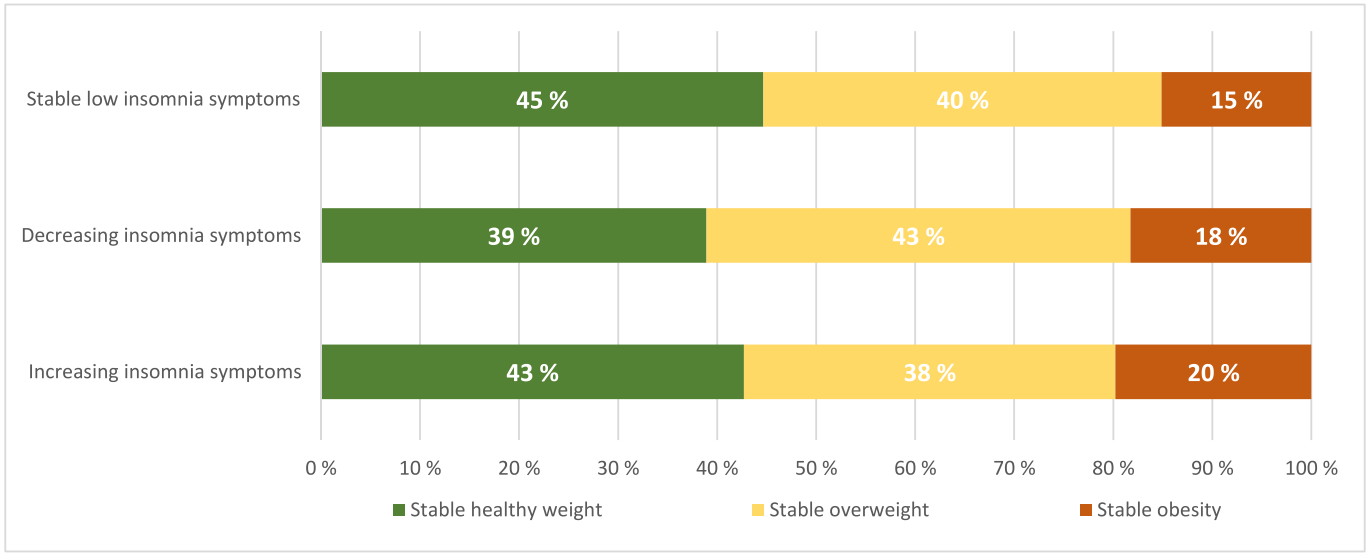

Fig. 3. Cross tabulation between latent insomnia symptoms (stable low, decreasing and increasing symptoms) and body mass index (stable healthy weight, stable overweight, and stable obesity) trajectory groups showing 100% scaled percentages of BMI trajectory groups within each insomnia symptom trajectory. Total sample size $N = 2360$.

be bidirectional, and sleeping problems may also be a predisposing sign or preclinical symptom of Alzheimer's disease (Nedelec et al., 2022).

Obesity can independently affect cognitive functioning for many reasons, for example neuroinflammation, insulin, ghrelin, leptin, and gut microbiome (Cholerton et al., 2013; Willmann et al., 2020; Spyridaki et al., 2016; Lauridsen et al., 2017; Samara et al., 2020; Ghosh-Swaby et al., 2022; Kim et al., 2020b; Macaluso et al., 2022). However, in our 22-year follow-up we found no association with changes in subjective

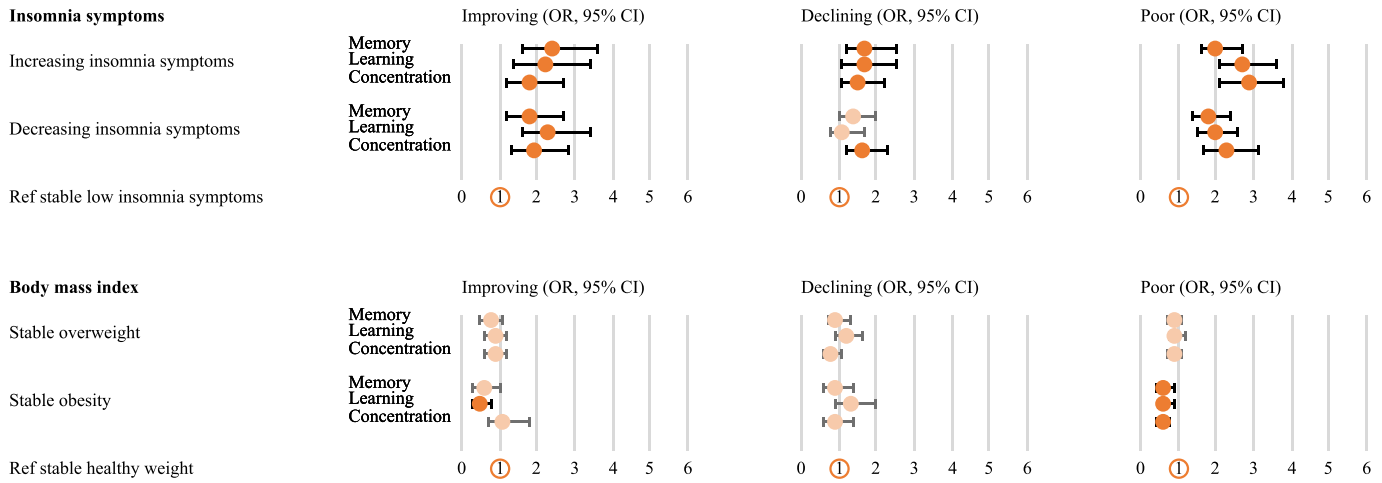

Fig. 4. Multinomial logistic regression full model (adjusted for age, gender, other socio-demographic and healthrelated covariates) to compare associations between individual latent insomnia symptoms and body mass index trajectory groups and changes in subjective cognitive functioning in the domains of memory, learning and concentration. OR = odds ratios. CI = confidence interval. Ref = reference group. Total sample size *N* = 2360?

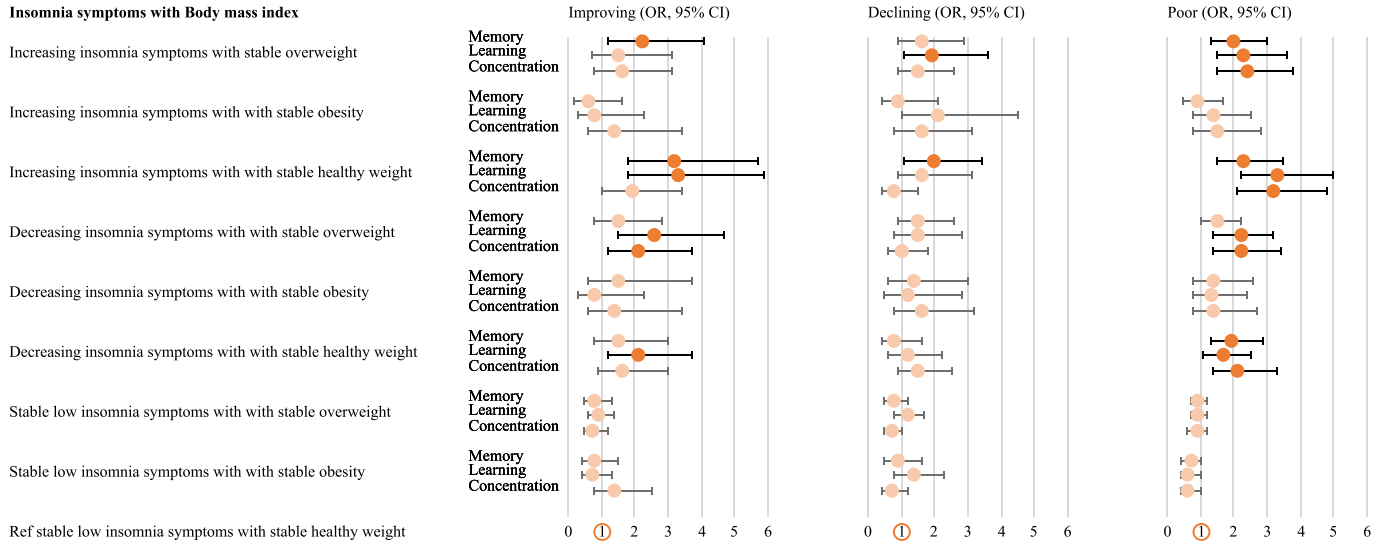

Fig. 5. Multinomial logistic regression full model (adjusted for age, gender, other socio-demographic and health-related covariates) to compare associations between dual latent insomnia symptoms with body mass index trajectory groups and changes in subjective cognitive functioning in the domains of memory, learning and concentration. OR = odds ratios. CI = 95% confidence interval. Ref = reference group. Total sample size *N* = 2360.

cognitive functioning in our univariate BMI trajectories. This could be because our study population consisted of mainly young- old adults (mean age 75 years in Phase 5). Another reason could be that for those aged over 65, the recommended normal healthy weight is 23–29 kg/m^2 and a slightly higher weight may actually be a protective factor (Kim et al., 2020a).

In our dual models, insomnia symptoms explained most of the effect on poor subjective cognitive functioning. The explanation for this might be that insomnia affects subjective cognitive functioning so strongly in comparison to BMI that it hinders this joint effect. Obesity caused by unhealthy nutrition affects memory and the function of the hippocampus, but the effect might be different for subjective cognitive functioning (Akbaraly et al., 2018; Taylor et al., 2021; Lee and Yau, 2020). However, even short sleep deprivation has been shown to affect memory and learning (Cullen et al., 2019).

In clinical practice, decreased subjective cognitive functioning may lead a physician to initiate wider-ranging memory tests such as the MMSE (Mini-Mental State Examination) or the CERAD (Consortium to Establish a Registry for Alzheimer's Disease), etc. (Folstein et al., 1975; Moms et al., 1989) SCD adversely affects the quality of life (Hill et al., 2017). Subjective cognitive complaints might be influenced by depressive symptoms and unawareness of cognitive symptoms due to anosognosia (Crumley et al., 2014; Brailean et al., 2019). Affective symptoms and negative perceptions are also related to cognitive complaints (McWhirter et al., 2020). Objective measures might more accurately detect memory disorders such as MCI, Alzheimer's disease, vascular dementia, or other types of dementia. However, measuring subjective cognitive functioning is inexpensive and more practical, particularly in large population studies. In addition, increasing evidence suggests that subjective cognitive difficulties might be a potential first symptom of dementia and may begin years before the disease onset. However, the majority of SCD cases do not progress to dementia (Jessen et al., 2020). Early treatment is critical, and more treatment options will be available in the future.

4.3. *Limitations and strengths of the study*

Our study had some limitations. First, we showed in our attrition

analysis (Supplementary Table S5) that those who had poorer subjective cognitive functioning in Phase 4 were more likely to drop out in Phase 5. However, this also indicates that we did not underestimate our results. Second, cognitive functioning was assessed using self-reports and therefore no interpretations of the association between insomnia symptoms, BMI and clinically diagnosed dementia can be made on the basis of our findings. Third, we only asked about insomnia symptoms in the last four weeks. A three-month period would have been better synchronized with the definition of insomnia (American Psychiatric Association, 2013). Moreover, this score is not specific to insomnia; for example, daytime effects were not included, and normal night-time waking cannot be ruled out. Fourth, Insomnia and body mass index measurements were based on self-report and the classification (measurement) error cannot be totally ruled out. Fifth, Although the regression analyses were adjusted for multiple confounders, residual confounding remains always a possibility in an observational study. Sixth, We were not able to consider the effects of medications to changes in cognitive functioning, sleep and BMI in this study. Seventh, the cohort was limited to employees of the City of Helsinki at baseline. Thus, our results cannot be generalised to the entire ageing population. In addition, person-oriented approach in a different population would likely produce different latent groups, and therefore caution is warranted in comparisons with other studies.

Despite these limitations, our study also had significant strengths. First, our over 20-year follow-up had moderate to excellent response rates in all five phases, and we also conducted thorough non-response analyses showing that the data fairly represented the target population (Lahelma et al., 2013). Second, the response rates for the surveyed outcome variables were extremely high. Third, we used a person-orientated approach. The advantage of this approach is that it enables the identification of latent groups without a priori assumptions. Moreover, the person-oriented approach better takes into account the developmental pattern of the individuals over time than the traditional variable-based methods, which may be open to bias caused by predefined cut-points. Fourth, the questions on insomnia symptoms and BMI were identical in all four phases. Fifth, our data included many covariates (sociodemographic, health-related behaviors, health factors), which enabled proper adjustment in the analysis.

5. Conclusions

We found that insomnia symptoms cumulatively increased the risk of cognitive problems after retirement, whereas BMI played a smaller role. Although insomnia symptoms and BMI can develop together, this study suggests that the higher likelihood of declined memory, concentration, and learning ability is explained by insomnia symptoms at all BMI levels.

A potential intervention point to prevent or postpone cognitive decline in later life usually starts years or even decades before retirement, when risk factors emerge or start to increase. Further research could examine the neurological changes that can occur years before changes in cognition. Longer follow-up times and more detailed and objective measures of cognitive functioning are also needed.

Funding

TL and AE are supported by the Research Council of Finland (Grant #330527). AE is supported by the Emil Aaltonen Foundation. AK is supported by the Research Council of Finland (grants #312310 and #336669 for the Centre of Excellence for Research on Ageing and Care, RG 3 Migration, Care and Ageing). OR is supported by the Juho Vainio Foundation (Grant #202300041) and by the Ministry of Education and Culture, Finland. JK is supported by the Ministry of Education and Culture, Finland and Research Council of Finland (Grant #355265).

Patient consent

Not required.

Ethical approvals

The Helsinki Health Study has received ethical approval from the City of Helsinki health authorities, and the ethics committee of the Department of Public Health, University of Helsinki.

CRediT authorship contribution statement

Antti Etholén: Data curation, Formal analysis, Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Anne Kouvonen:** Conceptualization, Supervision, Writing – review & editing. **Mirja Hänninen:** Conceptualization, Writing – original draft, Writing – review & editing. **Jenni Kulmala:** Conceptualization, Supervision, Writing – review & editing. **Ossi Rahkonen:** Conceptualization, Supervision, Writing – review & editing. **Minna Mänty:** Conceptualization, Supervision, Writing – review & editing. **Tea Lallukka:** Conceptualization, Supervision, Writing – review & editing.

Declaration of Competing Interest

Financial Disclosure: none.
Non-financial Disclosure: none.

Data availability statement

Data are available upon reasonable request. Data cannot be made publicly available due to strict data protection laws, but access to data can be applied for from the Helsinki Health Study group.

Acknowledgments

n/a

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ypmed.2023.107830.

References

Akbaraly, T., Sexton, C., Zsoldos, E., et al., 2018. Association of long-term diet quality with hippocampal volume: longitudinal cohort study. Am. J. Med. 131 (11), 1372–1381.e4. https://doi.org/10.1016/j.amjmed.2018.07.001.

Albanese, E., Hardy, R., Wills, A., Kuh, D., Guralnik, J., Richards, M., 2012. No association between gain in body mass index across the life course and midlife cognitive function and cognitive reserve—the 1946 British birth cohort study. Alzheimers Dement. 8 (6), 470–482. https://doi.org/10.1016/j.jalz.2011.09.228.

Albanese, E., Davis, B., Jonsson, P.V., et al., 2015. Overweight and obesity in midlife and brain structure and dementia 26 years later. Am. J. Epidemiol. 181 (9), 672–679. https://doi.org/10.1093/aje/kwu331.

American Psychiatric Association, 2013. Diagnostic and Statistical Manual of Mental Disorders, Fifth edition. American Psychiatric Association. https://doi.org/10.1176/appi.books.9780890425596.

Blackwell, T., Yaffe, K., Laffan, A., et al., 2014. Associations of objectively and subjectively measured sleep quality with subsequent cognitive decline in older community-dwelling men: the MrOS sleep study. Sleep. 37 (4), 655–663. https://doi.org/10.5665/sleep.3562.

Brailean, A., Steptoe, A., Batty, G.D., Zaninotto, P., Llewellyn, D.J., 2019. Are subjective memory complaints indicative of objective cognitive decline or depressive symptoms? Findings from the English Longitudinal Study of Ageing. J. Psychiatr. Res. 110, 143–151. https://doi.org/10.1016/j.jpsychires.2018.12.005.

Carroll, S., Turkheimer, E., 2018. Midlife risk factors for late-life cognitive decline. Dev. Rev. 48, 201–222. https://doi.org/10.1016/j.dr.2018.01.001.

Chernenko, A., Meeks, H., Smith, K.R., 2019. Examining validity of body mass index calculated using height and weight data from the US driver license. BMC Public Health 19 (1), 100. https://doi.org/10.1186/s12889-019-6391-3.

Cholerton, B., Baker, L.D., Craft, S., 2013. Insulin, cognition, and dementia. Eur. J. Pharmacol. 719 (1–3), 170–179. https://doi.org/10.1016/j.ejphar.2013.08.008.

Crumley, J.J., Stetler, C.A., Horhota, M., 2014. Examining the relationship between subjective and objective memory performance in older adults: a meta-analysis. Psychol. Aging 29 (2), 250–263. https://doi.org/10.1037/a0035908.
Cullen, T., Thomas, G., Wadley, A.J., Myers, T., 2019. The effects of a single night of complete and partial sleep deprivation on physical and cognitive performance: a Bayesian analysis. J. Sports Sci. 37 (23), 2726–2734. https://doi.org/10.1080/02640414.2019.1662539.
Cummings, J., Lee, G., Ritter, A., Sabbagh, M., Zhong, K., 2019. Alzheimer's disease drug development pipeline: 2019. Alzheim. Demen. Transl. Res. Clin. Interven. 5 (1), 272–293. https://doi.org/10.1016/j.trci.2019.05.008.
Elcombe, E.L., Lagopoulos, J., Duffy, S.L., et al., 2015. Hippocampal volume in older adults at risk of cognitive decline: the role of sleep, vascular risk, and depression. JAD. 44 (4), 1279–1290. https://doi.org/10.3233/JAD-142016.
Elgar, F.J., Stewart, J.M., 2008. Validity of self-report screening for overweight and obesity: evidence from the Canadian community health survey. Can. J. Public Health 99 (5), 423–427. https://doi.org/10.1007/BF03405254.
Eliassen, C.F., Reinvang, I., Selnes, P., Grambaite, R., Fladby, T., Hessen, E., 2017. Biomarkers in subtypes of mild cognitive impairment and subjective cognitive decline. Brain Behav. 7 (9), e00776 https://doi.org/10.1002/brb3.776.
Etholén, A., Pietiläinen, O., Kouvonen, A., Hänninen, M., Rahkonen, O., Lallukka, T., 2022. Trajectories of insomnia symptoms among aging employees and their associations with memory, learning ability, and concentration after retirement – a prospective cohort study (2000–2017). J. Aging Health. https://doi.org/10.1177/08982643221078740. Published online April 28. 089826432210787.
Exalto, L.G., Hendriksen, H.M.A., Barkhof, F., et al., 2022. Subjective cognitive decline and self-reported sleep problems: the SCIENCe project. Alz Dem. Diag. Ass. Dis. Monit. 14 (1) https://doi.org/10.1002/dad2.12287.
Ezzati, A., Zammit, A.R., Lipton, M.L., Lipton, R.B., 2019. The relationship between hippocampal volume, chronic pain, and depressive symptoms in older adults. Psychiatry Res. Neuroimaging 289, 10–12. https://doi.org/10.1016/j.pscychresns.2019.05.003.
Fenton, L.E., Albrecht, D.S., Isenberg, L., et al., 2021. Sleep efficiency is associated with amyloid burden, cerebral blood flow, and cognition in healthy older adults. Alzheimers Dement. 17(S10). https://doi.org/10.1002/alz.055596.
Folstein, M.F., Folstein, S.E., McHugh, P.R., 1975. Mini-mental state. J. Psychiatr. Res. 12 (3), 189–198. https://doi.org/10.1016/0022-3956(75)90026-6.
Ghosh-Swaby, O.R., Reichelt, A.C., Sheppard, P.A.S., Davies, J., Bussey, T.J., Saksida, L. M., 2022. Metabolic hormones mediate cognition. Front. Neuroendocrinol. 66, 101009 https://doi.org/10.1016/j.yfrne.2022.101009.
Hao, L., Xing, Y., Li, X., et al., 2019. Risk factors and neuropsychological assessments of subjective cognitive decline (plus) in Chinese memory clinic. Front. Neurosci. 13, 846. https://doi.org/10.3389/fnins.2019.00846.
Hill, N.L., McDermott, C., Mogle, J., et al., 2017. Subjective cognitive impairment and quality of life: a systematic review. Int. Psychogeriatr. 29 (12), 1965–1977. https://doi.org/10.1017/S1041610217001636.
Holth, J.K., Fritschi, S.K., Wang, C., et al., 2019. The sleep-wake cycle regulates brain interstitial fluid tau in mice and CSF tau in humans. Science. 363 (6429), 880–884. https://doi.org/10.1126/science.aav2546.
Jack, C.R., Knopman, D.S., Jagust, W.J., et al., 2013. Tracking pathophysiological processes in Alzheimer's disease: an updated hypothetical model of dynamic biomarkers. Lancet Neurol. 12 (2), 207–216. https://doi.org/10.1016/S1474-4422(12)70291-0.
Jack, C.R., Bennett, D.A., Blennow, K., et al., 2018. NIA-AA research framework: toward a biological definition of Alzheimer's disease. Alzheimers Dement. 14 (4), 535–562. https://doi.org/10.1016/j.jalz.2018.02.018.
Jessen, F., Amariglio, R.E., Buckley, R.F., et al., 2020. The characterisation of subjective cognitive decline. Lancet Neurol. 19 (3), 271–278. https://doi.org/10.1016/S1474-4422(19)30368-0.
Johnson, D.K., Wilkins, C.H., Morris, J.C., 2006. Accelerated weight loss may precede diagnosis in Alzheimer disease. Arch. Neurol. 63 (9), 1312. https://doi.org/10.1001/archneur.63.9.1312.
Jones, B.L., Nagin, D.S., 2013. A note on a Stata plugin for estimating group-based trajectory models. Sociol. Methods Res. 42 (4), 608–613. https://doi.org/10.1177/0049124113503141.
Kim, S., Kim, Y., Park, S.M., 2016. Body mass index and decline of cognitive function. Rosenfeld CS PLoS One 11 (2). https://doi.org/10.1371/journal.pone.0148908. e0148908.
Kim, G., Choi, S., Lyu, J., 2020a. Body mass index and trajectories of cognitive decline among older Korean adults. Aging Ment. Health 24 (5), 758–764. https://doi.org/10.1080/13607863.2018.1550628.
Kim, S., Nam, Y., Shin, S.J., et al., 2020b. The potential roles of ghrelin in metabolic syndrome and secondary symptoms of Alzheimer's disease. Front. Neurosci. 14, 583097 https://doi.org/10.3389/fnins.2020.583097.
Kivimäki, M., Luukkonen, R., Batty, G.D., et al., 2018. Body mass index and risk of dementia: analysis of individual-level data from 1.3 million individuals. Alzheimers Dement. 14 (5), 601–609. https://doi.org/10.1016/j.jalz.2017.09.016.
Knapp, M., Iemmi, V., Romeo, R., 2013. Dementia care costs and outcomes: a systematic review: costs and outcomes-review. Int. J. Geriatr. Psychiatry 28 (6), 551–561. https://doi.org/10.1002/gps.3864.
Koolhaas, C.M., Kocevska, D., te Lindert, B.H.W., et al., 2019. Objectively measured sleep and body mass index: a prospective bidirectional study in middle-aged and older adults. Sleep Med. 57, 43–50. https://doi.org/10.1016/j.sleep.2019.01.034.
Kouvonen, A., Kemppainen, T., Taipale, S., Olakivi, A., Wrede, S., Kemppainen, L., 2022. Health and self-perceived barriers to internet use among older migrants: a population-based study. BMC Public Health 22 (1), 574. https://doi.org/10.1186/s12889-022-12874-x.
Kulmala, J., Ngandu, T., Kivipelto, M., 2018. In: Perry, G., Avila, J., Moreira, P.I., Sorensen, A.A., Tabaton, M. (Eds.), Prevention Matters: Time for Global Action and Effective Implementation, Vol. 64. JAD, pp. S191–S198. https://doi.org/10.3233/JAD-179919 (s1).
Lahelma, E., Aittomäki, A., Laaksonen, M., et al., 2013. Cohort profile: the Helsinki health study. Int. J. Epidemiol. 42 (3), 722–730. https://doi.org/10.1093/ije/dys039.
Lauridsen, J.K., Olesen, R.H., Vendelbo, J., et al., 2017. High BMI levels associate with reduced mRNA expression of IL10 and increased mRNA expression of iNOS (NOS2) in human frontal cortex. Transl. Psychiatry 7 (2). https://doi.org/10.1038/tp.2016.259 e1044.
Lee, T.H. yin, Yau, S. yu, 2020. From obesity to hippocampal neurodegeneration: pathogenesis and non-pharmacological interventions. IJMS. 22 (1), 201. https://doi.org/10.3390/ijms22010201.
Lucey, B.P., Hicks, T.J., McLeland, J.S., et al., 2018. Effect of sleep on overnight cerebrospinal fluid amyloid β kinetics: disrupted sleep and amyloid β. Ann. Neurol. 83 (1), 197–204. https://doi.org/10.1002/ana.25117.
Macaluso, F., Weber, K.M., Rubin, L.H., et al., 2022. Body mass index and leptin are related to cognitive performance over 10 years in women with and without HIV infection. J. Clin. Endocrinol. Metab. 107 (3), e1126–e1135. https://doi.org/10.1210/clinem/dgab759.
McWhirter, L., Ritchie, C., Stone, J., Carson, A., 2020. Functional cognitive disorders: a systematic review. Lancet Psychiatry 7 (2), 191–207. https://doi.org/10.1016/S2215-0366(19)30405-5.
Minett, T.S.C., Da Silva, R.V., Ortiz, K.Z., Bertolucci, P.H.F., 2008. Subjective memory complaints in an elderly sample: a cross-sectional study. Int. J. Geriat. Psychiatry 23 (1), 49–54. https://doi.org/10.1002/gps.1836.
Mitchell, E., Walker, R., 2020. Global ageing: successes, challenges and opportunities. Br. J. Hosp. Med. 81 (2), 1–9. https://doi.org/10.12968/hmed.2019.0377.
Mitchell, A.J., Beaumont, H., Ferguson, D., Yadegarfar, M., Stubbs, B., 2014. Risk of dementia and mild cognitive impairment in older people with subjective memory complaints: meta-analysis. Acta Psychiatr. Scand. 130 (6), 439–451. https://doi.org/10.1111/acps.12336.
Moms, J.C., Heyman, A., Mohs, R.C., et al., 1989. The consortium to establish a registry for Alzheimer's disease (CERAD). Part I. Clinical and neuropsychological assesment of Alzheimer's disease. Neurology. 39 (9), 1159. https://doi.org/10.1212/WNL.39.9.1159.
Morys, F., Dadar, M., Dagher, A., 2021. Association between midlife obesity and its metabolic consequences, cerebrovascular disease, and cognitive decline. J. Clin. Endocrinol. Metab. 106 (10), e4260–e4274. https://doi.org/10.1210/clinem/dgab135.
Nagin, D.S., Odgers, C.L., 2010. Group-based trajectory modeling in clinical research. Annu. Rev. Clin. Psychol. 6 (1), 109–138. https://doi.org/10.1146/annurev.clinpsy.121208.131413.
Nagin, D.S., Tremblay, R.E., 2001. Analyzing developmental trajectories of distinct but related behaviors: a group-based method. Psychol. Methods 6 (1), 18–34. https://doi.org/10.1037/1082-989X.6.1.18.
Nagin, D.S., Jones, B.L., Passos, V.L., Tremblay, R.E., 2018. Group-based multi-trajectory modeling. Stat. Methods Med. Res. 27 (7), 2015–2023. https://doi.org/10.1177/0962280216673085.
Nandi, A., Counts, N., Chen, S., et al., 2022. Global and regional projections of the economic burden of Alzheimer's disease and related dementias from 2019 to 2050: a value of statistical life approach. eClinicalMedicine. 51, 101580 https://doi.org/10.1016/j.eclinm.2022.101580.
Nebes, R.D., Buysse, D.J., Halligan, E.M., Houck, P.R., Monk, T.H., 2009. Self-reported sleep quality predicts poor cognitive performance in healthy older adults. J. Gerontol. B Psychol. Sci. Soc. Sci. 64B (2), 180–187. https://doi.org/10.1093/geronb/gbn037.
Nedelec, T., Couvy-Duchesne, B., Monnet, F., et al., 2022. Identifying health conditions associated with Alzheimer's disease up to 15 years before diagnosis: an agnostic study of French and British health records. Lancet Dig. Health 4 (3), e169–e178. https://doi.org/10.1016/S2589-7500(21)00275-2.
R Core Team, 2021. A Language and Environment for Statistical Computing. Published online. https://www.R-project.org/.
Rahe, C., Czira, M.E., Teismann, H., Berger, K., 2015. Associations between poor sleep quality and different measures of obesity. Sleep Med. 16 (10), 1225–1228. https://doi.org/10.1016/j.sleep.2015.05.023.
Rao, M.N., Blackwell, T., Redline, S., et al., 2009. Association between sleep architecture and measures of body composition. Sleep. 32 (4), 483–490. https://doi.org/10.1093/sleep/32.4.483.
Sabia, S., Fayosse, A., Dumurgier, J., et al., 2021. Association of sleep duration in middle and old age with incidence of dementia. Nat. Commun. 12 (1), 2289. https://doi.org/10.1038/s41467-021-22354-2.
Saletin, J.M., Goldstein-Piekarski, A.N., Greer, S.M., Stark, S., Stark, C.E., Walker, M.P., 2016. Human hippocampal structure: a novel biomarker predicting mnemonic vulnerability to, and recovery from, sleep deprivation. J. Neurosci. 36 (8), 2355–2363. https://doi.org/10.1523/JNEUROSCI.3466-15.2016.
Samara, A., Murphy, T., Strain, J., et al., 2020. Neuroinflammation and white matter alterations in obesity assessed by diffusion basis Spectrum imaging. Front. Hum. Neurosci. 13, 464. https://doi.org/10.3389/fnhum.2019.00464.
Singh-Manoux, A., Dugravot, A., Shipley, M., et al., 2018. Obesity trajectories and risk of dementia: 28 years of follow-up in the Whitehall II Study. Alzheimers Dement. 14 (2), 178–186. https://doi.org/10.1016/j.jalz.2017.06.2637.
Smagula, S.F., Stone, K.L., Fabio, A., Cauley, J.A., 2016. Risk factors for sleep disturbances in older adults: evidence from prospective studies. Sleep Med. Rev. 25, 21–30. https://doi.org/10.1016/j.smrv.2015.01.003.

Spyridaki, E.C., Avgoustinaki, P.D., Margioris, A.N., 2016. Obesity, inflammation and cognition. Curr. Opin. Behav. Sci. 9, 169–175. https://doi.org/10.1016/j.cobeha.2016.05.004.

Taylor, Z.B., Stevenson, R.J., Ehrenfeld, L., Francis, H.M., 2021. The impact of saturated fat, added sugar and their combination on human hippocampal integrity and function: a systematic review and meta-analysis. Neurosci. Biobehav. Rev. 130, 91–106. https://doi.org/10.1016/j.neubiorev.2021.08.008.

Tsapanou, A., Vlachos, G.S., Cosentino, S., et al., 2019. Sleep and subjective cognitive decline in cognitively healthy elderly: results from two cohorts. J. Sleep Res. 28 (5) https://doi.org/10.1111/jsr.12759.

van Harten, A.C., Mielke, M.M., Swenson-Dravis, D.M., et al., 2018. Subjective cognitive decline and risk of MCI: the Mayo Clinic study of aging. Neurology. 91 (4), e300–e312. https://doi.org/10.1212/WNL.0000000000005863.

Verlinden, V.J.A., Geest, J.N., Bruijn, R.F.A.G., Hofman, A., Koudstaal, P.J., Ikram, M.A., 2016. Trajectories of decline in cognition and daily functioning in preclinical dementia. Alzheimers Dement. 12 (2), 144–153. https://doi.org/10.1016/j.jalz.2015.08.001.

Wen, C., Hu, H., Ou, Y.N., et al., 2021. Risk factors for subjective cognitive decline: the CABLE study. Transl. Psychiatry 11 (1), 576. https://doi.org/10.1038/s41398-021-01711-1.

Whitmer, R.A., Sidney, S., Selby, J., Johnston, S.C., Yaffe, K., 2005a. Midlife cardiovascular risk factors and risk of dementia in late life. Neurology. 64 (2), 277–281. https://doi.org/10.1212/01.WNL.0000149519.47454.F2.

Whitmer, R.A., Gunderson, E.P., Barrett-Connor, E., Quesenberry, C.P., Yaffe, K., 2005b. Obesity in middle age and future risk of dementia: a 27 year longitudinal population based study. BMJ. 330 (7504), 1360. https://doi.org/10.1136/bmj.38446.466238.E0.

Willmann, C., Brockmann, K., Wagner, R., et al., 2020. Insulin sensitivity predicts cognitive decline in individuals with prediabetes. BMJ Open Diabetes Res. Care 8 (2), e001741. https://doi.org/10.1136/bmjdrc-2020-001741.

World Health Organization Regional Office for Europe, 2021. Body Mass Index - BMI. Accessed November 4, 2022. https://www.who.int/europe/news-room/fact-sheets/item/a-healthy-lifestyle—who-recommendations.

Zitser, J., Anatürk, M., Zsoldos, E., et al., 2020. Sleep duration over 28 years, cognition, gray matter volume, and white matter microstructure: a prospective cohort study. Sleep. 43 (5) https://doi.org/10.1093/sleep/zsz290 zsz290.