Educational Attainment and Cognitive Change: A Life-Course Mediation Analysis of Lifestyle, Environment, and Health

1. Theoretical focus

As the global population continues to age, the prevalence of age-related conditions, including frailty and cognitive decline is arising. With the proportion of people aged 60 years and older projected to nearly double from around 12% to 22% by 2050 [1]. The promotion of healthy cognitive ageing has become a major public health priority.

Cognitive ageing is shaped by a complex interaction of biological, behavioural, and psychosocial factors such age, sex, education, lifestyle, psychosocial or environmental factors. Education is one of the most robust social determinants impacting cognitive functioning across the entire life span [2]. Overall cognitive ability increases with educational attainment, fostering neural processing and cognitive reserve that sustain during the life course. Longitudinal studies consistently show that while education is strongly associated with higher baseline cognitive ability, its effect on the rate of decline is more modest, suggesting that education primarily influences level rather than trajectory of cognitive aging.

Despite this fact, early-life education continues to shape cognitive aging indirectly. It has been suggested that higher educated individuals tend to seek in more cognitively stimulating activities and occupations, maintain healthier lifestyle, live in more advantaged environments and are more socially engaged in midlife compared to their less educated peers [3,4].

Lifestyle factors and long-term exposures to disadvantaged environment may influence brain health both directly and indirectly through physical and mental health. Accordingly, our study aims to examine the complex interplay between the education, lifestyle, environmental, psychosocial and health-related factors, and to explore how these factors jointly influence cognitive aging in later life.

2. Data

For this particular analysis, we utilized data from the HAPIEE (Health, Alcohol and Psychosocial Factors in Eastern Europe) study. Czech sub-cohort included participants recruited in seven cities. At baseline, participants completed a questionnaire survey and underwent a detailed medical examination, including blood sampling. Since then, questionnaire surveys were conducted regularly every 2-3 years to sustain longitudinal design of the study. The institutional ethics committees approved the study in all participating centres and the University College London. All participants provided informed consent.

3. Methods

Outcome

Cognitive function was evaluated using four neuropsychological tests, including verbal memory (immediate and delayed), verbal fluency, and processing speed. Cognitive functions were assessed at baseline (Wave 1; 2002-2009) and during the most recent follow-up (Wave 3; 2022-2024).

Predictors

Education was assessed at baseline and was categorized into four categories – primary or less, vocational, secondary and university. Marital status classified into three categories – married/cohabiting, single/divorced and widowed, and loneliness measured using the 3-item UCLA scale (range 3–9; cut-off ≥6) [5] were included in the analysis as late-life psychosocial predictors of cognitive change.

Mediators and covariates

Lifestyle factors included diet, physical activity, and smoking, all reported at baseline. Diet was evaluated using a Mediterranean diet score (MDS) [6] consisting of nine components (including alcohol) with scoring system 0, 1 or 2 points for each. MDS ranged from 0 to 17 points (olive oil usage was scored 0 or 1 point based on usage). Physical activity was measured by the number of hours per week engaged in sports, games or hiking and categorized into four categories – 0 hours, 1-2 hours, 3-4 hours and >4 hours. We defined smoking behaviours using three categories - a smoker, ex-smoker and non-smoker.

Environmental exposures included air pollution and neighborhood socioeconomic deprivation (nSED). Four-year average concentrations of $PM_{2.5}$ were estimated using a Europe-wide land-use regression model [7] and assigned to participants' residential addresses. The nSED was derived from census-based indicators including % of the unemployed population, % of the population with university education, and % of the population with less than secondary education. We used principal component analysis to derive nSED and assigned factor scores to all participants; with higher factor scores indicating greater deprivation.

Health status was evaluated using self-rated health (SRH). We recategorized five points Likert scale into three categories – very good/good, average, poor/very poor. The presence of depression was assessed using Centre for Epidemiological Studies-Depression Scale including a battery of 10 statements (CESD-10) with maximum 30 points [8], with a cut-off of ≥10 indicating the presence of depression. Both variables were measured during Wave 2 follow-up (2014-2015). Finally, we assessed sex and age as possible covariates.

Statistical analysis

We estimated a latent change score model (LCSM) to examine change in cognitive functioning across two measurements (Wave 1 and Wave 3). This longitudinal approach allowed us *a)* to estimate the reliable average change from T_1 to T_2, and *b)* to examine the extent to which individuals differ in the change they manifest over time. Four cognitive domains (immediate memory, verbal fluency, processing speed and delayed memory) constructed a latent factor of global cognition at each wave. The global cognition at Wave 3 (η_2) was defined as sum of the global cognition at Wave 1 (η_1) and a cognitive change ($\Delta\eta$). The mean of $\Delta\eta$ represents the average change in global cognition across two measurements, and the variance of $\Delta\eta$ captures inter-individual variability in change. A regression path from $\eta_1 \rightarrow \Delta\eta$ was freely estimated to test whether baseline cognitive level predicted the magnitude or direction of change.

Next, to examine the longitudinal pathways linking educational attainment to late-life cognitive change, we specified a three-wave multiple mediation model using a structural equation modelling (SEM) including time-invariant predictors and mediators. Education attainment reported at baseline (Wave 1) was modelled as predicting variable of lifestyle factors and environmental exposures measured at Wave 1, which in turn predicted SRH and depression assessed at Wave 2. Global cognition measured at Wave 1 (η_1) and cognitive change ($\Delta\eta$) were considered as outcome variables. We estimated direct effects of education attainment, lifestyle factors and environmental exposures on both global cognition and cognitive change. Direct effects of SRH, depression, marital status and loneliness were estimated for cognitive change, but not to global cognition to preserve the temporal ordering of the effects. Indirect effects were tested using bias-corrected bootstrapped 95% confidence intervals (5,000 resamples). Sex and age reported at Wave 1 were included as potential covariates of the associations.

Model fit was assessed using fit indices, including confirmatory fit index (CFI; CFI $\geq$ 0.90) and root mean square error of approximation (RMSAE $\leq$ 0.08). To maximize all available data points, we used full information maximum likelihood, to manage missing data. Standardized β coefficients are reported. All statistical analyses were performed using Mplus 8.6, Muthen & Muthen, CA, USA).

4. Results

Study sample included 8,810 participants (53.5% women) aged 58.19 years at baseline. Latent variables of global cognition measured at two time points were adequately loaded by the cognitive domains. On average, cognitive performance significantly decreased over time ($p<.001$). LCSM showed significant inter-individual variance of cognitive change (p<.001) and negative correlation between global cognition (η_1) and cognitive change ($\Delta\eta$) (β = -0.381; p<.001), indicating that individuals with initially higher cognitive performance changed less compared to those with initially lower cognitive performance.

Multiple mediation model provided acceptable model fit: CFI = 0.844, RMSEA = 0.049 (90% CI RMSEA: 0.047-0.050). The results revealed that higher level of education predicted increased cognitive performance at Wave 1 (β = 0.349; p<.001), while no direct effect between education and cognitive change was observed (β = -0.030; p=.367). Nevertheless, SEM identified a small, marginally significant indirect pathway linking education and cognitive change through physical activity and SRH (β = 0.001; p=.050).

Additionally, several indirect pathways were observed, connecting environmental exposures and lifestyle factors to cognitive change, primarily through SRH and depression. For instance, increased exposure to $PM_{2.5}$ was indirectly associated with greater cognitive decline (total indirect effect: β = -0.005; p=.037), whereas non-smoking behaviour indirectly predicted lower cognitive decline (total indirect effect: β = 0.006; p=.025).

Finally, our results revealed significant direct associations between environmental exposures, lifestyle factors and cognitive change. Specifically, living in higher nSED (β = -0.275; p=.047) predicted faster cognitive decline, whereas higher level of physical activity (β = 0.169; p=.031) and MDS (β = 0.048; p=.018) were positively associated with slower cognitive decline. No associations were observed between marital status (β = -0.037; p=.258), loneliness (β = 0.049; p=.104) and cognitive change.

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