

Level and Change in Cognitive Functioning in Later Life and Principal Life-Time Career: The Role of Occupational Complexity and Physical Job Demands

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ABSTRACT

Very little is known of the long-term protective association between previous occupational activity and age-related cognitive decline. The present study sought to address this gap by investigating whether and how complex occupational activities at midlife predict age-associated cognitive decline in late life. In line with the *differential preservation* hypothesis, it was expected that older adults who previously engaged in occupations with higher levels of complexity would experience slower rates of cognitive decline in later life. The associations between physical job demands and age-associated cognitive decline were also explored.

In Study 1, the associations between occupational complexity (involving data, people, and things) and level of, and rate of change in, cognitive functioning (using the Mini Mental Status Examination [MMSE] as outcome) was examined. Participants were initially aged 65 to 98 years ($M = 78.71$) and from the Dynamic Analyses to Optimise Ageing project ($n = 1,714$). In Study 2, the associations of occupational complexity and physical job demands (movement- and strength-related) with level of, and rate of change in, cognitive domains during normal ageing were examined. Participants were initially aged 65 to 98 ($M = 78.09$) and from the Australian Longitudinal Study of Ageing ($n = 1,059$). In both datasets, cognition was assessed four times over an 11 year interval.

In multilevel models adjusted for age, gender, education, and more proximal influences on cognitive performance and change, higher occupational complexity involving data was associated with higher initial levels of perceptual speed ($\beta = 0.61$, $p < .001$) and verbal reasoning ($\beta = 0.64$, $p < .001$), but not slower rates of decline in any cognitive domain. The associations remained robust even in light of differences in age at retirement, occupational status, and the other occupational demands. Strength-related job demand was associated with lower initial levels of perceptual

speed ($\beta = -2.21, p < .001$) and immediate memory ($\beta = -1.44, p < .05$), but not differential rates of cognitive decline. The associations were also independent of age at retirement, occupational status, and movement-related job demand. The associations between the predictor variables and trajectories of cognitive change did not vary according to differences in education, gender, or age at time of retirement.

The results support the *preserved differentiation* hypothesis, and indicate the associations between previous occupational activity demands and later life cognitive functioning reflect long-term individual differences in average levels of cognitive ability. In the context of the social and economic challenges posed by an ageing population, further inquiry into the nature of the associations between occupational activity demands and cognitive development in both current and former workers is warranted. Future research will benefit from a focus on complex activities involving data or people; using outcome measures in multiple cognitive domains and from the pre- and post-retirement periods. As the nature of work becomes increasingly sedentary, future research on the long-term effects of prolonged sitting on age-related cognitive decline will also become increasingly important. Currently, a long-term protective association between previous occupational activity demands and cognitive outcomes in late life have not been fully established.

DECLARATION

I certify that this thesis does not incorporate without acknowledgment any material previously submitted for a degree or diploma in any university; and that to the best of my knowledge and belief it does not contain any material previously published or written by another person except where due reference is made in the text.

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