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 (β = 0.61, p<.001) and verbal reasoning (β = 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 (β = -2.21, p<.001) and immediate memory (β = -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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CHAPTER 1: AN OVERVIEW OF THIS THESIS

1.1 Aims of this thesis

The purpose of this thesis is to investigate whether and how complex and physical demands in the main lifetime occupation are associated with initial levels of, and rates of change in, cognitive functioning in later life. Whether the associations between occupational complexity, physical job demands, and cognitive ageing (a) differ by education, gender, and age at the time of retirement, and (b) hold when the influence of other correlates of age-associated cognitive decline are statistically controlled, are also explored.

1.2 Focus of this thesis

Australians are living longer and the population is getting older. Over the last century, life expectancy at birth has increased almost 25 years and most Australians can now expect to live into their late eighties (Australian Bureau of Statistics, 2014). Projections presented in the 2010 Intergenerational Report (Commonwealth of Australia, 2010) indicate the proportion of the population aged 85 years and over will increase rapidly over the next half century. Whilst this age group made up 1.8 per cent of Australia's population in 2010, it is expected to account for about 5.1 per cent of the population in 2050 (Commonwealth of Australia, 2010).

Cognition is a key resource for realising a productive, independent, and engaged lifestyle, and older age is a significant risk factor for cognitive impairment and dementia. Consequently, Australians are increasingly concerned with optimising cognitive health. To develop strategies for optimising cognitive health, a better understanding of the determinants of cognitive health, or the risk factors for cognitive impairment and dementia, is necessary (Hughes & Ganguli, 2009). Therefore, the Australian Government has suitably identified *Promoting and Maintaining Good Health* as a national research priority, and *Ageing Well, Ageing*

Productively as a priority goal (National Health and Medical Research Council, 2006).

Cognitive development is a lifelong, dynamic process determined by a diverse array of genetic and contextual factors (Baltes, 1987, 1993; Baltes, Staudinger, & Lindenberger, 1999). As genetic factors are relatively fixed, environmental or behavioural strategies to optimise cognitive health have received great interest from researchers and from older people (Hughes & Ganguli, 2009). Also, midlife has been identified as a critical period for strategic intervention because people have greater control over their lives in mid- compared to early-life, and cognitive plasticity may be greater during this period and prior to disease onset (Hughes & Ganguli, 2009; MacDonald, Karlsson, Fratiglioni, & Bäckman, 2011; Willis, Martin, & Rocke, 2010).

Cognitively stimulating leisure-time activity engagement and physical exercise have been identified as possible strategies for optimising cognitive health and have received considerable empirical attention (for a comprehensive review, see Hertzog, Kramer, Wilson, & Lindenberger, 2008). In contrast, the potential benefits of complex occupational activity and physical job demands for age-associated cognitive decline are underexplored (Finkel, Andel, Gatz, & Pedersen, 2009; Gow, Avlund, & Mortensen, 2012; Marquié et al., 2010). This research gap is all the more surprising because occupational activity can be readily modified and is a normative part of the life course that encompasses midlife (Finkel et al., 2009; Gow, Avlund, et al., 2012; Marquié et al., 2010).

The *environmental complexity* (Schooler, 1984) hypothesis suggests that a long-term engagement in a complex, cognitively stimulating occupation may act to promote cognitive functioning and lessen age-related cognitive decline by increasing *cognitive reserve* (Stern, 2002). Some evidence in support of *differential* *preservation* demonstrates a positive and reciprocal association between *substantively complex work* and cognitive functioning in current workers (Schooler, 2009b; Schooler, Mulatu, & Oates, 1999). Some evidence also demonstrates a long-term protective association between previous occupational complexity and dementia risk in later life (Andel et al., 2005; Stern et al., 1995). By comparison, little is known about the long-term protective association between previous occupational complexity and normative, non-pathological, cognitive decline (Finkel et al., 2009; Gow, Avlund, et al., 2012). Even less is known about the associations between physically demanding work and later life cognitive functioning. Addressing this knowledge gap is the main focus of this thesis and as such it fits well within the Government's national research priority - *Promoting and Maintaining Good Health* - and associated goal - *Ageing Well, Ageing Productively*.

1.3 Importance of this thesis

A better understanding of the association between occupational activity and cognitive ageing will have practical implications for meeting the challenges of an ageing population. Dementia is a leading contributor to *burden of disease*[1] and in the absence of any intervention, predictions indicate the number of Australian with dementia will increase threefold to 900,000 by 2050 (AIHW, 2012). An increase in the prevalence of cognitive impairment and dementia will place a huge burden on individuals, families, communities, and the health system (AIHW, 2012). Consequently, the optimising of cognitive health in old age is an important societal and public health goal.

The occupational context may be a potential point of intervention for achieving public health goals. As a normative part of the life course (Elder & Johnson, 2003), many people in a population engage in paid occupational activity.

[1] "…the amount of healthy life lost due to premature death and prolonged illness or disability" (AIHW, 2012, p. ix).

They typically enter the workforce in early adulthood after a period of formal education and retire around the pension eligibility age. Hence, the health and wellbeing of many people in a population are potentially affected by their occupational context. People can also exert some control over the activities they perform in their jobs. So, job design and workplace health promotion policy may provide ways of realising cognitive wellbeing for many (Jex, Wang, & Zarubin, 2007; Krain, 1995; Marquié et al., 2010). To inform the design of jobs and workplace interventions to promote cognitive health, we need to better understand the occupational activity and cognitive ageing relationship.

In the context of current labour force trends, a better understanding of the occupational activity and cognitive ageing relationship is also increasingly relevant. To manage the costs of an ageing population, the Australian government is encouraging older workers to delay their retirement. They are doing this by gradually increasing the qualifying age for the pension to 67 by 1 July 2023 and encouraging employers to retain and recruit older workers (Commonwealth of Australia, 2010). However, if some occupational activity is detrimental to cognitive functioning, these strategies may have unintended adverse health outcomes. For example, the nature of work has become increasingly sedentary and many workers engage in *prolonged sitting* (Rovio et al., 2007). Research (see Brown, Bauman, Bull, & Burton, 2012, for a review of the evidence) has linked physical inactivity and prolonged sitting at work to risk factors for cognitive impairment and dementia, such as obesity, diabetes, and cardiovascular disease (Deary et al., 2009; Hughes & Ganguli, 2009). Consequently, understanding whether and how sedentary and physical job demands are associated with cognitive functioning is increasingly topical (Rovio et al., 2007).

Understanding the occupational activity and cognitive ageing relationship is also relevant to theoretical debates about the causes of cognitive decline and impairment (Anstey, Hofer, & Luszcz, 2003). To date, research initiatives have tended to focus disproportionately on how the socio-economic aspects of occupations predict cognitive ageing. That is, studies have measured occupational status or attainment, or included occupational information in measurement models of socio-economic status (e.g., Dartigues, Gagnon, Mazaux, et al., 1992; Evans et al., 1997; Frisoni, Rozzini, Bianchetti, & Trabucchi, 1993; Fritsch, McClendon, Smyth, & Ogrocki, 2002; Karp et al., 2004; Lee, Back, Kim, & Byeon, 2010; Qiu et al., 2003; Wilson et al., 2009). However, occupations also have functional aspects. In addition to providing people with incomes that enable healthy lifestyles, occupation is a form of activity that can be characterised by a variety of functional demands. To clarify, measures of occupational status or attainment reflect the characteristics of the workers within an occupational category (Cain & Treiman, 1981). In contrast, measures such as occupational complexity reflect the functional requirements of occupations[2] (Cain & Treiman, 1981). Each aspect of occupation (the socio-economic and the functional) has implications for cognitive ageing. For example, a number of studies on the socio-economic aspects of occupations have reported negative associations between blue-collar occupation and dementia or age-related cognitive decline (e.g., Dartigues, Gagnon, Letenneur, et al., 1992; Dartigues, Gagnon, Mazaux, et al., 1992; Frisoni et al., 1993; Qiu et al., 2003). Whether these associations are due to reduced opportunities for education and training, lower incomes, unhealthy lifestyles, adverse working conditions, or a lack of cognitive stimulation, is unclear. For a more complete understanding of the nature of the association between occupation and cognition, knowledge of how the socio-

[2] A distinction is made in this thesis between the terms *occupation* and *job*. An occupation refers to a category of similar jobs. A job refers to a combination of tasks that an individual performs (Cain & Treiman, 1981).

economic and functional aspects of occupations are associated with cognitive ageing is needed. In addition, Hertzog, Hultsch, and Dixon (1999, p. 531) has suggested “a focus on intellectual activities rather than on SES is both justified and prudent”. Therefore, this thesis focuses on the comparatively neglected area of research that concerns the functional or demand aspects of occupational activity.

1.4 Methodological approach of this thesis

The research aims are addressed in two studies using longitudinal data from the Dynamic Analyses to Optimise Ageing (DYNOPTA: Anstey, Byles, et al., 2010) and the Australian Longitudinal Study of Ageing (ALSA: Luszcz et al., 2007). The DYNOPTA is a collaborative project concerned with the analyses of pooled data from nine Australian longitudinal studies of ageing to better understand interrelationships between demographic, social, lifestyle, economic, and health factors that underpin development in adulthood and ageing. (Anstey, Byles, et al., 2010) The ALSA is an ongoing longitudinal project that aims to investigate how bio-psycho-social factors are associated with age-related changes in the health and wellbeing of older Australians (Luszcz et al., 2007).

The DYNOPTA and the ALSA each have their individual strengths and together they enable a comprehensive examination of the research questions. A key strength of the DYNOPTA is its large sample size and geographical heterogeneity. The larger sample size afforded by the DYNOPTA provides statistical power for examining the potentially subtle associations between the occupational activity demands and rates of cognitive change, especially in low prevalence groups (e.g., women who previously held occupations higher in complexity with things) (Aguinis, Beaty, Boik, & Pierce, 2005; Anstey, Byles, et al., 2010). Also, as Burns et al. (2012, p. 6) notes: “The harmonization of existing studies, by pooling data or parallel analysis, is increasingly recognised as an important method that adds value to and addresses the limitations of investment in individual longitudinal studies" (see also, Hofer, 2009; Hofer & Piccinin, 2010).

A key strength of the ALSA is the depth and breadth of its measures. For example, the ALSA contains data on peoples' perceptions of the physical demands of their jobs, and data from a range of cognitive tests. To date, no study has examined the association between previous movement-related job demand (i.e., sitting versus moving around a lot) and cognitive ageing and only one study (Finkel et al., 2009) has examined change in multiple cognitive domains. Thus, the capacity to comprehensively examine the associations between occupational activity demands[3] and cognitive ageing is enhanced by the use of two datasets.

1.5 Chapter summary

In the context of the social and economic challenges posed by an ageing population, research that informs strategies at midlife for cognitive health in late life is increasingly important. Engaging in complex, cognitively stimulating work tasks is purported to be one possible strategy that promotes cognitive functioning among current workers and protects against dementia among former workers. Physical job activities may also have implications for later life cognitive functioning. However, the long-term protective association between previous occupational activity demands and cognitive performance and change in old age is largely underexplored. Moreover, few studies have considered education, gender, and age at time of retirement as possible moderators of the association between occupational activity and cognitive ageing. This gap is addressed in this thesis via a comprehensive examination of the associations between occupational complexity (involving data, people, and things), physical job demands (movement- and strength-related), and

[3] The term 'occupational activity demands' is used throughout this thesis to refer to complex occupational demands involving data, people, and things, and physical job demands.

cognitive ageing. This thesis also addresses the theoretical underpinnings of these relationships and their practical consequences for an ageing population.

1.6 Overview of subsequent chapters

Chapter 1 provided an overview of the aims, focus, importance, and methods of this thesis. A brief description of each of the following chapters is provided next. In Chapter 2, general patterns of cognitive ageing and a correlational, individual differences approach to explaining cognitive ageing are discussed. Theoretical perspectives that provide insights into the long-term protective associations between previous occupational activity demands and cognitive ageing are reviewed. Next, the empirical literature is summarised and evaluated in relation to general methodological issues, and the present investigation is outlined.

In Chapter 3, the concept and measurement of occupational complexity is reviewed. The original source of the complexity ratings, the U.S. Dictionary of Occupational Titles (DOT), is described. The various methods used to estimate complexity ratings for occupations in the U.S, Swedish, Canadian, and Australian census classifications (where the bulk of relevant studies were conducted), are discussed and compared. Measurement issues for the complexity types are also discussed.

Study 1 is presented in Chapter 4. Using 11-year data from the DYNOPTA, Study 1 provides an examination of the associations between occupational complexity and cognitive performance and change. The Mini Mental Status Examination (MMSE) is used as the cognitive outcome measure. Study 2 is presented in Chapter 5. Using 11-year data from the ALSA, Study 2 provides an examination of the associations of occupational complexity and physical job demands with cognitive performance and change. Tests of perceptual speed, immediate and delayed episodic memory, and verbal reasoning are used as cognitive outcomes measures. In chapters 4 and 5, the results are interpreted in relation to the empirical literature reviewed in Chapter 2.

In the final chapter, Chapter 6, the purpose, aims, and methods of this thesis are reiterated and the main findings are summarised. The findings are interpreted in relation to the theoretical perspectives presented in Chapter 2. Practical implications of the findings are also discussed. Finally, the strengths and limitations of this thesis are described and recommendations for future research are outlined.

CHAPTER 2: THEORETICAL PERSPECTIVES AND LITERATURE REVIEW

2.1 Chapter overview

The theoretical and empirical foundations of this thesis are presented in this chapter. The chapter comprises four parts; beginning with an overview of the kinds of changes that are expected during normal cognitive ageing and a summary of two lines of research explaining individual differences in cognitive ageing in terms of individual-level characteristics. Next, the environmental complexity and cognitive reserve hypotheses are described. These theoretical perspectives offer insights into the possible protective associations between previous occupational activity demands and cognitive outcomes in later life. The empirical literature, comprising 20 studies on the associations between previous occupational activity demands and dementia or age-associated cognitive decline, is then reviewed. The literature is summarised first, then evaluated in relation to a number of general methodological issues. The chapter concludes by outlining how this thesis makes a unique contribution to the current body of knowledge.

2.2 Cognitive ageing

In this section, the focus of the thesis is situated within the broader cognitive ageing literature. The nature of age-related cognitive decline is summarised and a correlational, individual differences approach to explaining age-related cognitive decline is outlined. In addition, two main research designs in the study of cognitive ageing are discussed. Cognitive ageing is a complex phenomenon (King & Suzman, 2008) and the cognitive ageing literature is extensive. Consequently, this review is selective and, for illustrative purposes, draws on evidence in select key studies.

2.2.1 General trends

Cognitive development is characterised by an average pattern of growth in the first half of the lifespan, and by an average pattern of decline in the second half of the lifespan. This general trend are demonstrated in Schaie's seminal work with the Seattle Longitudinal Study (SLS: Schaie, 1994; Schaie, 2005). The SLS began in the late 1950s with 500 participants aged 22 to 67 years. Every seven years, participants were assessed and a new cohort of participants was recruited with the aim of examining ageing and cohort effects. At each wave of assessment, participants completed a battery of standardised tests measuring, for example, verbal meaning, spatial orientation, inductive reasoning, word fluency, and processing speed. Research from the SLS shows that for most individuals cognitive development peaks about the fourth decade, stabilises until the sixth decade, then declines modestly though the eighth decade (Schaie, 1994, 2005).

Cognition is a multifaceted construct and age-related decline is not uniform across cognitive domains. Schaie's (Schaie, 1994, 2005) research program revealed differential changes in abilities over time. For example, growth in processing speed was shown to peak earlier and then decline faster compared to verbal meaning. The findings from other longitudinal studies of ageing (with participant samples aged 65 years and over at baseline) have also demonstrated heterogeneity in change trajectories across cognitive domains (e.g., Anstey et al., 2003; Christensen, 2001; Lövdén, Ghisletta, & Lindenberger, 2004; Wilson et al., 2002). For example, research from the Australian Longitudinal Study of Ageing (e.g., Anstey et al., 2003; Bielak, Gerstorf, Anstey, & Luszcz, 2014; Gerstorf, Hoppmann, Anstey, & Luszcz, 2009), where data for the current study are sourced, has demonstrated reliable declines in performances on tests of processing speed and episodic memory with increasing age, but stability in performances on tests of vocabulary and verbal reasoning.

There exists a consensus amongst cognitive ageing researchers about two average patterns of relations between age and cognition (Salthouse, 2010). On one hand, process-based abilities, such as speed of processing, working memory, and inhibitory function, or performances “on measures representing efficiency or effectiveness of processing carried out at the time of assessment” (Salthouse, 2010, p. 754) are considered “aging-sensitive” (Ghisletta & Lindenberger, 2003, p. 696) and demonstrate decline across old age. By contrast, culture-based abilities or performances on “measures representing products of processing carried out in the past” (Salthouse, 2010, p. 754), such as vocabulary, general knowledge, and implicit memory, are thought to be “aging-resilient” (Ghisletta & Lindenberger, 2003, p. 696) and demonstrate maintenance across old age.

The terminology of the dual-component models of intellectual development (Baltes, 1987; Baltes et al., 1999; Horn & Cattell, 1966) has been adopted by researchers to summarise which cognitive abilities decline and which abilities are maintained with increasing age (Finkel, Reynolds, McArdle, & Pedersen, 2007). They distinguish between *fluid* and *crystallized* ability (Horn & Cattell, 1966) and the *mechanics* and *pragmatics* of cognition (Baltes et al., 1999). Fluid ability (the mechanics) is concerned with reasoning and novel problem solving, and crystallized ability (the pragmatics) refers to the use of knowledge that is culturally acquired and transferred. Growth in fluid ability is thought to precede growth in crystallized ability, developing rapidly during childhood and early adolescence. Additionally, fluid ability is thought to decline beginning around late adulthood whilst crystallized ability is maintained well into late old age.

The dual-component model assumes that fluid ability is determined largely by biological or genetic factors. As the integrity of the brain deteriorations and thus the efficiency of fluid ability declines, the assumption is that individuals become more reliant on crystallized ability to accomplish everyday tasks (Baltes et al., 1999). The model also assumes that fluid ability drives the development of crystallized ability, and that as fluid ability declines it places increasing limits upon the growth or maintenance of crystallized abilities. However, research does not tend to support this hypothesis. For example, using sophisticated bivariate dual change score models, and data from the Swedish Adoption/Twin Study of Aging, e.g., Finkel et al. (2007) showed that changes in processing speed (broadly defined as a fluid ability) led to subsequent changes in memory and spatial ability, but not verbal ability (i.e., crystallized ability). As Salthouse (2010) has pointed out, fluid and crystallized abilities are likely to be determined by both biological and contextual factors.

2.2.2 Individual differences

Age-associated cognitive decline is not uniform across individuals. Schaie (Schaie, 1994, 2005) reported that whilst some individuals in the SLS showed change that approximated the average, others did not. Instead, some individuals showed steady declines beginning earlier in their lifespan (i.e., in their 40s), some showed steady declines in some abilities but not in others, and some showed little change in most abilities or even slight improvement in some. Individual heterogeneity is also evidenced in the onset and prevalence of neurodegenerative diseases such as Alzheimer's disease (AD), the extreme end of cognitive decline (e.g., Anstey, Burns, et al., 2010; Lobo et al., 2000).

Researchers have sought to explain individual differences in trajectories of cognitive ageing by differences in the characteristics of individuals. Individual level characteristics include both cognitive and contextual variables, and the cognitive ageing literature can be divided broadly along these lines (Hultsch, Hertzog, Small, & Dixon, 1999). The current study is situated within the literature focused on contextual variables.

The skills that people call upon to perform cognitive tasks vary between individuals and this may account for differences in performances between individuals (Hultsch et al., 1999). Several cognitive processes, including processing speed, working memory, and attention, are purported to be fundamental resources for successful performance on a range of cognitive tasks (Park, 2000). Individual differences in the efficiency and of these fundamental resources is also thought to account for heterogeneity in performances on a range of cognitive tasks (Park, 2000).

Processing speed refers to the rate at which mental processes are executed, and it is the dominant construct, perhaps, within the cognitive ageing literature (Park & Reuter-Lorenz, 2009). Many early cross-sectional studies showed processing speed mediated age differences in a number of cognitive tests, including tests of working memory, recall, and verbal fluency (e.g., Bryan & Luszcz, 1996; Bryan, Luszcz, & Crawford, 1997; Hultsch, Hertzog, & Dixon, 1990; Luszcz, Bryan, & Kent, 1997; Park et al., 1996; Salthouse, 1996a, 1996b). A meta-analysis of cross-sectional studies (Verhaeghen & Salthouse, 1997), for example, showed that processing speed explained over 70 per cent of the age-related variance in a range of cognitive tasks. Salthouse (1996b) suggested that processing speed represented a single, fundamental resource or primitive of the cognitive system (Luszcz et al., 1997) and that declines in processing speed with increasing age could explain cognitive deficits in all other cognitive domains. Salthouse (1996b) also suggested two ways in which slowing could lead to decrements in cognitive function. First, the *limited time mechanism*, whereby cognitive deficits arise from an inability to efficiently execute the processes involved in a cognitive task within a limited time frame. Second, the *simultaneity mechanism,* whereby cognitive deficits arise because the information from previous processing needed for current processing have decayed.

Longitudinal studies do not support the general slowing theory of cognitive ageing (e.g., Hertzog, 2004; Lemke & Zimprich, 2005; Sliwinski & Buschke, 1999).

Sliwinski and Buschke (1999), for instance, demonstrated how cross-sectional studies have overestimated the amount of age-related variance shared between processing speed and other cognitive abilities. In longitudinal analyses they found processing speed accounted for about 6 to 26 per cent of the variance in a number of cognitive tasks whilst in cross-sectional analyses this amount increased to more than 70 percent. However, some longitudinal studies, that have applied more sophisticated modelling techniques, have found a temporal association between age-related declines in processing speed and changes in other abilities. For example, Finkel et al. (2007) applied bivariate dual change score models to longitudinal data from participants who were aged 50 to 88 years at baseline and from the Swedish Adoption/Twin Study of Aging. They found processing speed predicted subsequent change in spatial and memory ability. Overall, the literature suggests that processing speed can explain some but not all age-related changes in some cognitive domains (Drag & Bieliauskas, 2010). This thesis does not seek to examine the processing speed theory of cognitive ageing. Given the status of processing speed as a cognitive primitive (Luszcz & Bryan, 1999) and a sensitive measure of age-associated cognitive decline (Lövdén et al., 2004), it is used as a cognitive outcome measure in the current study.

A number of factors “reflective of the individual’s exposure to various events and environments” (Hultsch et al., 1999, p. 245) have been proposed as predictors of individual differences in age-related cognitive decline. Although some debate still remains about the contribution of contextual factors to trajectories of cognitive decline, a comprehensive review of the literature concluded that engaging in mental, social, and physical activities does play a beneficial role in age-associated cognitive decline (Hertzog et al., 2008). There is even a growing body of evidence that suggests leisure-time activity at midlife is associated with favourable cognitive outcomes in later life (e.g., Crowe, Andel, Pedersen, Johansson, & Gatz, 2003; Friedland, Fritsch, & Smyth, 2001; Kåreholt, Lennartsson, Gatz, & Parker, 2011). For example, Kåreholt et al. (2011) found that engagement in leisure-time mental activities at midlife (mean age 57 years) was associated with better cognition performance 23 years later. Their results remained significant even after statistical control for other types of leisure-time activities and a range of socio-demographic, medical and health factors. Also, Crowe et al. (2003) observed an association between participating in intellectual/cultural leisure activities 20 years earlier and a reduced risk of AD in older women. However, these studies have only examined cognitive performance or clinical outcomes in late life, they have not examined whether activity engagement at midlife is associated with cognitive change in late life. Nevertheless, they provide an empirical justification for examining the associations between previous occupational activity and later life cognitive function. The literature on occupational activity and cognitive ageing is reviewed in Section 2.4.

There is also some evidence that suggests physical activity at midlife can have favourable cognitive outcomes in late life (e.g., Andel et al., 2008; Dik, Deeg, Visser, & Jonker, 2003; Rovio et al., 2005). For example, Dik, Deeg, Visser and Jonker (2003) found that regular physical activity in early adulthood (15-25 years) was associated with higher levels of processing speed in older men (55-85 years), independent of current physical activity. However, they also reported a negative association between high intensity physical activity (i.e., activity that makes a person sweat) and cognition. They suggested this finding might be explained by the large proportion of people in the high intensity group who reported they were physically active at work, because heavy physical work may not convey cardiovascular fitness. Also workers performing heavy physical work may be exposed to environmental pollutants that are detrimental to cognitive function. Thus, although some studies have demonstrated positive associations between physical activity at midlife and cognitive outcomes in late life, whether and how work-related physical activity is associated with late life cognitive functioning is unclear.

Whilst vascular pathways have been proposed to explain how physical activity impacts cognition functioning (Marmeleira, 2012), the mechanisms via which cognitively stimulating activity impacts cognition is less clear (Bielak, 2010). One hypothesis is that mental exercise strengthens cognitive processes and builds cognitive reserve (Stern, 2002). The cognitive reserve hypothesis is discussed in Section 2.3.

2.2.3 Research designs

Cross-sectional and longitudinal research designs are commonly used to study cognitive ageing. Cross-sectional research involves the comparison of groups of people at different ages assessed at one point in time. Thus, cross-sectional studies provide information on age-differences in cognitive performance but they do not provide information on age-changes (Hofer & Sliwinski, 2006). Longitudinal studies, by contrast, provide information on age-related changes in cognition because they measure the same people repeatedly over time (Hofer & Sliwinski, 2006).

A further limitation of cross-sectional studies is that they confound age with cohort effects (Hofer & Sliwinski, 2006). In a cross-sectional study, it is assumed that when the older people were younger, they resembled the younger people in the study (Cavanaugh & Blanchard-Fields, 2006). However, each generation develops within a specific historical context, so this assumption is unlikely to be true. As a result, differences in cognitive performances might be attributed to age when in fact they reflect differences in historical contexts such as access to, or quality of, schooling (Rizzuto, Cherry, & LeDoux, 2012). By following a single cohort over time, longitudinal research designs can effectively eliminate cohort effects as a cause of cognitive decline (Gow, Avlund, et al., 2012). However, most longitudinal studies track people who vary widely by age at study baseline. For example, participants in the ALSA were aged 65 to 103 years at baseline. Also, the range of between-person age differences is often wider than the range of within-person age changes (i.e., ageing) over the duration of the study (Hofer, Rast, & Piccinin, 2012). Thus, confounding of age and ageing can be an issue in longitudinal studies.

Selective attrition and practice effects are also potential problems for longitudinal studies (Hofer et al., 2012). Selective attrition refers to the phenomenon whereby those individuals who are most likely to drop out of a study are also those individuals most likely to experience cognitive decline or impairment. Consequently, rates of cognitive decline may be underestimated because the continuing participants are a healthier subset of the baseline sample (Sliwinski & Buschke, 1999). Practice effects may also attenuate estimated rates of cognitive decline in longitudinal studies (Hofer et al., 2012; Sliwinski & Buschke, 1999). Practice effects refer to the phenomenon whereby people who repeatedly perform a task become better at that task such that their performance improves over time (Hofer et al., 2012).

Even though longitudinal studies are complicated by a range of methodological issues, they are recognised as the best approach for understanding cognitive ageing (Hofer et al., 2012; Hofer & Sliwinski, 2006). This awareness is evidenced by the growing number of longitudinal studies in the field of cognitive ageing, including the current study.

2.2.4 Summary

In summary, heterogeneity of age-associated decline across cognitive domains and individuals is a central feature of normal cognitive ageing and explaining this heterogeneity is a key challenge for researchers. Whilst some researchers have focused their attention on basic processing resources as explanations for individual differences in cognitive ageing, other researchers have focused on contextual factors. This thesis takes a contextual perspective and examines whether and how midlife occupational activity is associated with individual differences in cognitive performance and change in late life. Two theoretical perspectives linking contextual factors to cognitive performance and change are discussed next.

2.3 Theoretical perspectives

The environmental complexity and the cognitive reserve hypotheses underpin the empirical literature on occupational complexity and cognitive ageing. These theoretical perspectives are based on the notion that cognitive functioning is not fixed, but can be enhanced across the life span and within the realms of genetic possibility, by contextual factors (Hertzog et al., 2008).

2.3.1 Environmental complexity

The environmental complexity theory (Schooler, 1984) invokes psychological processes to explain the link between environmental conditions and cognitive development. It theorises that, to the extent to which environments characterised by diverse stimuli and complex demands reward cognitive effort, then people in such environments will be motivated to exercise their cognitive skills, whereby increasing them to a higher level, and to further exercise and develop their enhanced skills in other situations (Schooler et al., 1999). Regarding the occupational environment, the hypothesis of environmental complexity states that occupational conditions which involve dealing with complex demands will enhance cognitive capacity, whereas conditions that limit occupational complexity will weaken cognitive processes.

The hypothesis of environmental complexity is analogous to the *use it or lose it* hypothesis (Salthouse, 2006), which has been applied perhaps more broadly to explain associations between mental, social, and physical activity engagement and cognitive ageing (Bielak, 2010; Hultsch et al., 1999). The use it or lose it hypothesis states that cognitive processes can be strengthened via their exercise and weakened by their disuse. It follows, therefore, that the rate of cognitive decline will be reduced for individuals who are more mentally active across the life course (Salthouse, 2006). This pattern, where activity engagement alters the course of cognitive development, is commonly referred to as *differential preservation* (Bielak, Anstey, Christensen, & Windsor, 2012; Salthouse, 2006). It is distinguished from *preserved differentiation* where more mentally active people also have higher levels of ability and the advantage is maintained over time (Bielak et al., 2012; Salthouse, 2006). In the current study, differential preservation would be supported if people who previously held a main lifetime occupation characterised by higher levels of complexity had slower rates of cognitive decline. By contrast, preserved differentiation would be supported if higher occupational complexity in the main lifetime occupation was associated only with higher levels of cognitive ability.

The environmental complexity theory evolved from Kohn and Schooler's (1973, 1978, 1983) research project about the effects of *occupational self-direction* on *intellectual flexibility*. Occupational self-direction referred to "the conditions that facilitate … the use of initiative, thought and independent judgement at work" (Kohn & Schooler, 1973, p. 104). Intellectual flexibility was defined as "cognitive flexibility in coping with the intellectual demands of a complex situation" (Kohn & Schooler, 1983, p. 112). The project applied structural equation modelling techniques to longitudinal data from a U.S. population-based sample of 3,101 men, aged 16 or more, who were employed at least 25 hours per week in 1964. The participants were interviewed three times (in 1964, 1974, and 1994/5) and the wives of the male participants were interviewed twice (in 1974 and 1994/5). The main finding in Kohn and Schooler's research project was a reciprocal relationship between occupational self-direction and intellectual flexibility. Specifically, occupational conditions providing the opportunity to do self-directed, substantively complex work increased intellectual flexibility, whereas occupational conditions limiting the same opportunity decreased intellectual flexibility (Schooler et al., 1999). The finding was replicated in sub-samples of younger and older workers (Schooler et al., 1999; Schooler, Mulatu, & Oates, 2004), and in males and females (Schooler et al., 1999).

Another key finding from Kohn and Schooler's research project was the primacy of *substantively complex work* for intellectual flexibility compared to the other two components of occupational self-direction, namely routinization and closeness of supervision. Substantively complex work referred to "work that in its very substance requires thought and independent judgement" and "by its very nature requires making many decisions involving ill-defined and apparently contradictory contingencies" (Kohn & Schooler, 1983, p. 106). The construct was measured with information obtained from participants about the nature of their work tasks involving data, people, and things, as well as participant estimates of time spent working with data, people, and things (Schooler et al., 1999). Kohn and Schooler's research revealed substantive complexity was the "key source of environmental complexity on the job" (Schooler, 2001, p. 369). The present investigation also uses a measure of complexity involving work with *data* (information, facts, and statistics), *people* (interactions between people, and between people and animals), and *things* (physical interactions with machines, tools, equipment, and work aids) that is available for occupations in the 1971 Australian Classification and Classified List of Occupations

(CCLO: Australian Bureau of Statistics, 1971). Kohn and Schooler's research extends findings from early studies (e.g., Avolio & Waldman, 1990; Avolio & Waldman, 1994) which found positive cross-sectional associations between occupational complexity and cognitive functioning among workers, but did not examine the reciprocal effects of occupational complexity and cognitive function. The present investigation extends this prior research by examining whether and how previous occupational complexity is associated with cognitive performance and change in former workers. If engaging in complex occupational activity at midlife changes the course of cognitive development, as Kohn and Schooler's research suggests, then higher complexity in the main lifetime occupation should be associated with a slower rate of decline in later life.

Kohn and Schooler's research findings have been critiqued by other researchers, most notably Salthouse (2006), and subsequently defended (Schooler, 2007). Salthouse questioned the construct validity of intellectual flexibility, because, unlike other standard measures of cognition that are commonly used in studies of cognitive ageing, it was not negatively correlated with age. He also suggested that measurement invariance in the latent construct across waves might have impacted on the integrity of the research findings. Kohn and Schooler measured intellectual flexibility from a number of items including: scores on the Embedded Figures Test, interviewer appraisals of participant intelligence, and participant responses to a number of hypothetical problems (Schooler et al., 1999). In response to the criticism, Schooler and colleagues (Schooler et al., 1999) evaluated the validity of the intellectual flexibility construct by comparing it with a construct based on more standard measures of cognition. They found the cognitive construct to be highly correlated with intellectual flexibility. Although, as Gow, Avlund, et al. (2012) point out, the analysis was performed with data collected at the final wave and thus validity cannot be reliably established at earlier waves. Nevertheless, Kohn and Schooler's findings have been validated in cross-national contexts (Kohn, Naoi, Schoenbach, Schooler, & Slomczynski, 1990; J. Miller, Slomczynski, & Kohn, 1985; Naoi & Schooler, 1985). Their findings have also been independently validated by Hauser and colleagues (Hauser, 2010; Hauser & Roan, 2007) using a similar methodological approach but with different data and statistical control for the confounding effects of cognitive ability in adolescence.

The underlying mechanisms via which complex occupational activity contributes to cognitive functioning is not well understood. One suggestion is that complex occupational activity that affords sufficient stimulation, promotes active and/or passive reserve capacity (Finkel et al., 2009).

2.3.2 Cognitive reserve

Cognitive reserve (Stern, 2002, 2012) describes brain plasticity and the hypothesis of cognitive reserve states that the detrimental effects of age-associated and pathological brain changes on cognitive functioning can be buffered by structural (passive) and functional (active) aspects of reserve. The hypothesis was originally advanced to account for differences in clinical outcomes between people with similar levels of neuropathology. For example, Stern, Alexander, Prohovnik, and Mayeux (1992) found that in AD patients with similar degrees of disease severity, those with higher levels of education had more severe neuropathology than those with lower levels of education. Similar findings had also been observed in post-mortem and prevalence studies of dementia and education (e.g., Katzman, 1993; Katzman et al., 1988; Roth, Tomlinson, & Blessed, 1967). Stern surmised that education represented a reserve capacity that somehow delayed the clinical manifestations of AD, and therefore neuropathology was necessarily greater in those patients with higher levels of education (Richards & Deary, 2005). Since cognitive reserve capacity cannot be readily measured, education and other life experiences such as occupational attainment and occupational complexity have served as proxy measures of cognitive reserve (Richards & Deary, 2005).

Stern (2002, 2009) proposed two types of reserve - passive and active - to explain how cognitive functioning can be maintained, or cognitive decline attenuated, with increasing age. The passive model emphasises neuroanatomical structures, including cortical volume, neuronal density, dendritic branching, and synaptic connectivity, as reserve mechanisms. It asserts that older adults with greater passive reserve have higher levels of cognitive ability, compared to older people with lesser reserve, and take longer to reach a threshold below which cognitive functioning is considered impaired and dementia is diagnosed[4]. The active model, on the other hand, emphasises neural organisation and processing efficiency as reserve mechanisms. It states that in older adults with greater active reserve the brain uses existing neural networks more efficiently, and uses alternative or compensatory neural networks in response to brain pathology (Stern, 2002). In this way, age-related decline is attenuated in people with higher levels of reserve capacity.

Although cognitive reserve is determined by genetics, particularly the passive component, there is some evidence to suggest that reserve may also be influenced by contextual factors (Bielak, 2010; Hughes, 2010). Basic evidence in support of this notion is available from experimental animal studies. For example, laboratory studies with rodents have shown that enriched environments, as indexed by cages adorned with running wheels, toys, and other stimuli, induce neurogenesis (Kempermann, Gast, & Gage, 2002), promote dendritic lengthening and branching, and stimulate beneficial neurochemical changes (for reviews, see Kramer, Bherer, Colcombe, Dong, & Greenough, 2004; Petrosini et al., 2009). Evidence is also

[4] This model has also been referred to as a *functional threshold model* of reserve (Tucker-Drob, Johnson, & Jones, 2009)

available from brain imaging studies with humans. For example, over a four year period, Woollett and Maguire (2011) examined changes in brain function in trainee taxi drivers learning the layout of London's streets. Among those trainees who subsequently qualified for a taxi license they found evidence of brain and cognitive plasticity: a “selective increase in gray matter volume in their posterior hippocampi and concomitant changes to their memory profile” (Woollett & Maguire, 2011, p. 2109). In contrast, they observed no brain-related changes in trainees who failed to qualify for a license. Thus, complex occupational activity that affords sufficient cognitive effort may contribute to passive and active reserve capacity, which protects against the detrimental effects of age-associated brain changes.

2.3.3 Summary

The environmental complexity and cognitive reserve hypotheses provide a psychological and a neurobiological basis, respectively, for linking occupational activity to age-related cognitive decline. They suggest cognitive reserve capacity can be built by engaging in activities that afford sufficient cognitive stimulation, and that the course of cognitive development may be altered by participating in, or refraining from, cognitively stimulating occupational activity. This prediction, termed differential preservation, is examined in this thesis. Evidence about whether and how occupational complexity and other occupational demands are associated with favourable cognitive outcomes in later life, is reviewed in the next section.

2.4 Literature review

The literature review is presented in two parts. First, the main findings from studies that have investigated the associations of occupational complexity and other occupational demands with cognitive ageing are summarised. Then, the literature is evaluated on the basis of a number of methodological issues relating to sample characteristics, measurement of occupational activity demands, the “choice of cognitive outcome measure", and confounding by prior ability (Anstey & Christensen, 2000, p. 164). The purpose of the summary is to provide an account of the general pattern of findings in the current literature. The evaluation, presented in Section 2.4.2, provides greater detail on the summarised studies.

2.4.1 Summary of the empirical literature

A search of the published literature identified 20 studies on the associations between occupational activity demands and cognitive ageing. Peer reviewed studies were identified using searches on PsycInfo and Scopus. The main predictor variables in this thesis are occupational complexity and physical job demands. Occupation complexity is a rating of the intellectual demands in work tasks involving data, people, and things. Since there is some overlap between complexity with data and mental job demand variables, and complexity with people and social job demand variables (Andel et al., 2005), mental, intellectual, and social demands were also included in the list of search terms. For studies to be identified, the predictor variables had to be mentioned in the title or abstract (Anstey & Christensen, 2000).

As discussed in Chapter 1 (also see Chapter 3), the focus of this thesis is on the functional aspects of occupations. Therefore, the related literature examining the socio-economic aspects of occupations (i.e., occupational status or attainment) was not reviewed. Nor was the literature on the psychosocial aspects of occupations (i.e., work load, time pressures, job control, social support at work, etc.) reviewed. A review study (Then, Luck, et al., 2013, p. 1) of the "effect of the psychosocial working environment on cognition and dementia" considered many of the same studies reviewed in this thesis. However, a distinction was drawn in this thesis between occupational activity demands and psychosocial work conditions because the literatures rest on separate theoretical foundations (Rijs et al., 2013). Karasek's *job strain model* (Karasek, 1979; Karasek & Theorell, 1990) supports the literature on psychosocial work conditions and cognitive ageing. The job strain model proposes that workers in jobs with high work demands and pressures combined with low control in meeting those demands (high-strain jobs) face greater mental health risks due to work-stress (Andel, Crowe, Kåreholt, Wastesson, & Parker, 2011). Finally, the vast body of literature from Kohn and Schooler's research project on occupational self-direction and intellectual flexibility was excluded because it was discussed in relation to the environmental complexity theory (see Section 2.3.1). Also, their research project considered the "contemporaneous reciprocal pathways" (Gow, Avlund, et al., 2012, p. 1) via which substantively complex work might influence cognitive functioning. That is, they focused on the associations between substantively complex work and cognitive change among current workers not former workers, and the latter group is the focus of this thesis.

Age-associated cognitive decline is the outcome investigated in this thesis, therefore studies were included in the review if the participant samples comprised mostly older adults (i.e., aged 65 years and over). Hertzog et al. (2008) highlighted the value of considering evidence across the entire spectrum of cognitive ageing outcomes. Therefore, studies on dementia, representing the extreme end of cognitive decline (Deary et al., 2009), were also included in the review.

Occupational activity demands and dementia

Eleven studies were identified that examined occupational complexity or other occupational demands as predictors of dementia, and they are summarised in Table 2.1. Overall, these studies suggest that higher occupational complexity involving data or people (Andel et al., 2005; Andel, Vigen, Mack, Clark, & Gatz, 2006; Karp et al., 2009; Kröger et al., 2008) and higher mental[5] or social[6]

[5] The term *mental demand* is used throughout this review to refer to demand factors that have intellectual-type elements.

[6] The term *social demand* is used loosely to refer to demand factors that have social or people-type elements.

occupational demands (Bosma, van Boxtel, Ponds, Houx, Burdorf, et al., 2003; Potter, Helms, Burke, Steffens, & Plassman, 2007; Seidler et al., 2004; Smyth et al., 2004; Stern et al., 1995; Then, Luppa, et al., 2013) are protective of dementia. Only Smyth et al. (2004) and Potter et al. (2007) reported no association between social demands or complexity with people and dementia risk.

Upon close inspection, it was apparent that in relation to occupational complexity involving data and people, findings were more complex and to a certain extent, equivocal. In analyses in which the three complexity types were examined separately, higher complexity with people and data was shown to be associated with reduced dementia risk (Andel et al., 2005; Karp et al., 2009). Similarly, Andel et al. (2006) found faster rates of MMSE decline in AD patients matched for severity, who previously held occupations higher in complexity with data and people. This finding is consistent with the hypothesis that people with greater cognitive reserve are better able to compensate for increasing neuropathology and thereby delay reaching the clinical threshold for dementia, but thereafter they decline more rapidly. However, when the three complexity types were analysed in the same model, Andel et al. (2005) reported that only higher complexity with people was protective of dementia whereas Andel et al. (2006) and Karp et al. (2009) both reported that only higher complexity with data was protected of dementia. Thus, it is unclear as to whether the cognitive stimulation provided by complex work demands involving data or people is central in protecting against dementia.

In relation to occupational complexity involving things, findings are inconsistent. Karp et al. (2009) and Potter et al. (2007) found no association between complexity with things and dementia risk. In contrast, Kröger et al. (2008) reported *higher* complexity with things was associated with a reduced risk of dementia, and Andel et al. (2005) reported *lower* complexity with things was marginally associated with a reduced risk of dementia. However, Karp et al.'s (2009) findings were conditional on the presence in their analyses of the other complexity measures (i.e., data and people) and work-related physical activity. Thus, the nature of the relationship between occupational complexity with things and dementia risk is ambiguous.

Four studies examined associations between occupational physical demands and dementia outcomes, and their findings are also equivocal. For instance, Stern et al. (1995) reported that higher physical demands were associated with reduced perfusion in the parietal region in AD patients matched for severity, but only after analyses controlled for education. In contrast, Karp et al. (2009) reported work-related physical activity was associated with increased dementia risk, AD risk, and VaD risk in an unadjusted model. Moreover, Smyth et al. (2004) found higher physical demands were associated with dementia occurrence, and at least two other studies reported no associations between physical demands and dementia risk (Potter et al., 2007; Rovio et al., 2007).

Table 2.1

Methods and Findings from Previous Studies of Occupational Demands and Dementia

Author and publication date	Sample, n, Age, % female	Occupation measure	Statistical methods	Main findings
Andel, Crowe, Pedersen, Mortimer, Crimmins, Johansson, & Gatz (2005)	Swedish HARMONY (65+) study. $N_{controls}$ = 10,079, M_{age} = 72.5 (6.0), 52% female. N_{cases} = 225, M_{age} = 82 (6.7), 58% female	Complexity with data, people, and things (DOT)	Case and Co-twin control. Logistic regression	No associations between complexity with data and odds of dementia in case control analyses. Higher complexity with data associated with lower risk of AD in cotwin control analyses. Higher complexity with people associated with lower risk of dementia and AD only, controlling for age, gender and education in case control analyses. Higher complexity with people associated with lower risk of dementia and AD in co-twin control analyses. Lower complexity with things associated with reduced risk of dementia, controlling for age, gender and education (case control analyses).
Andel, Vigen, Mack, Clark, & Gatz (2006)	Longitudinal study of aging and dementia, University of Southern California, AD Research Center; N=171 AD cases; M_{age}=76.5 (8.7)	Complexity with data, people, and things. (DOT) Substantive complexity (DOT)	Multilevel modelling	High substantive complexity, high complexity with data and people associated with faster rates of MMSE decline, controlling for age, gender, native language, education, dementia severity and entry into the analyses at initial v's follow-up testing.
Bosma, van Boxtel, Ponds, Houx, Burdorf, & Jolles (2003)	Maastricht Aging Study (MAAS); N = 630; $M_{age\ at\ 3\text{-}yr\ follow\text{-}up}$ = 61.8 (8.8); 41.6% female	Mental demands Task complexity (rated by job experts)	Logistic regression, 3 year follow up	High mental demands associated with lower odds of cognitive impairment, independent of age, sex, education level, employment status, follow-up interval and additional covariates. Excluding people with incident dementia did not affect the results. Task complexity not associated with cognitive impairment.
Karp, Andel, Parker, Wang, Winblad, & Fratiglioni (2009)	Kungsholmen Project, Stockholm (75+); N = 931; 76.6% female	Complexity with data, people, and things (DOT)	Cox proportional hazards models.	High complexity with data or people associated with lower dementia and AD risk, adjusting for age and gender, 6 years later, but not when controlling for education. Complexity with things not associated with dementia or AD risk. Significant interaction between complexity with people and education in relation to AD risk.
Kröger, Andel, Lindsay, Benounissa, Verreault, & Laurin (2008)	Canadian Study of Health and Aging; N = 3,557; M_{age} = 73; 51.2% female	Complexity with data, people, and things (DOT) Work related physical activity (WPA)	Cox proportional hazards models	High complexity with data, people, and things not associated with lower dementia risk after adjusting for gender and education. In models comprising all three complexity variables, and adjusting for gender, education and WPA, higher complexity with people or things associated with lower risk of dementia. WPA associated with increased dementia risk, AD risk, and VaD risk in an unadjusted model. Effect mediation by occupational duration and gender, but not by education.

Potter, Helms, Burke, Steffens, & Plassman (2007)	Duke Twins Study of Memory and Aging; Male WWII veterans; $N_{controls}$ = 6075; N_{cases} = 425	Complexity with data, people, and things (DOT) Physical strength (DOT)	Case and Co-twin control. Cox proportional hazard model	High complexity with data associated with reduced dementia risk in case-control models and covarying for education. High complexity with data associated with reduced dementia risk in analysis of twin pairs discordant for dementia for at least 6 years and covarying for education. No significant interaction effects by zygosity. No associations between complexity with people and things or strength-demands and dementia risk.
Rovio, Kåreholt, Viitanen, Winblad, Tuomilehto, Soininen, Nissinen, & Kivipelto (2007)	Cardiovascular Risk Factors, Aging, and Dementia (CAIDE) study. N=1449; M_{age} = 71.3 (4.0); 62.1% female	Occupational physical activity	Logistic regression	Frequency of dementia and AD lower in sedentary occupations. No association between occupational physical activity and risk of dementia 21 years later, after adjusting for age, sex, education, follow-up time and locomotor symptoms.
Siedler, Nienhaus, Bernhardt, Kauppinen, Elo, & Frölich (2004)	$N_{controls}$ = 229, Aged 60-94. N_{cases} = 195 M_{age} = 79.5 (8.4)	Challenge at work, and social demands at work (Finnish Job Exposure Matrix)	Logistic regression	High challenge at work associated with lower odds of dementia, and AD. High social demands at work associated with lower odds of dementia and VaD; controlling for age, region, gender, dementia in parents, education, smoking and psychosocial network at age 30.
Smyth, Fritsch, Cook, McLendon, Santillan, & Friedland (2004)	AD Research Center Registry of University Hospitals of Cleveland/Case Western Reserve University; $N_{controls}$ = 253; N_{cases} = 122	Mental, social, physical, and motor demands (DOT)	ANOVA pairwise comparisons	Mental demands were lower, and physical demands were higher, for cases than for control subjects. Case/control differences in mental demand scores were not found in their 20s but only in later decades. Differences in physical demands were found in all decades but their 30s. Social and motor demands did not differ between cases and controls overall or by decade.
Stern, Alexander, Prohovnik, Stricks, Link, Lennon, & Mayeux (1995)	Patient sample. N = 51 AD cases; M_{age} = 67.3 (9.6)	Substantive complexity, motor skills, physical demands, management, and interpersonal skills (DOT)	Multiple regression	High substantive complexity associated with greater deficits of parietal blood flow, controlling for age, clinical dementia severity. High interpersonal skills and physical demands associated with greater deficits of parietal blood flow, controlling for age, clinical dementia severity, and education.
Then, Luppa, Schroeter, König, Angermeyer, & Riedel-Heller (2013)	Leipzig Longitudinal study of the Aged (75+); N = 903	Novelty, executive, verbal, fluid demands	Logistic regression	Executive demands, only, associated with lower risk of dementia, adjusting for age, and education

Notes. DOT: factor items were sourced from the Dictionary of Occupational Titles. Some studies provided mean age for subsamples only. Potter et al. (2007) provided mean age for subgroups only. Bosma et al. (2003) and Siedler et al. (2004) also examined psychosocial work variables, for example, social climate at work, control possibilities at work, work load, concentration, time pressure and precision, perceived risks for error at work, and supervisor support. However, these factors did not meet the inclusion criteria for the review thus they are not presented. Bosma et al. (2003) examined cognitive impairment as outcome.

Occupational activity demands and normal cognitive ageing

Four cross-sectional studies and five longitudinal studies that examined occupational complexity and other occupational demands as predictors of normal cognitive ageing were identified, and they are summarised in Table 2.2. The findings from cross-sectional studies suggest that occupational complexity involving data (Andel, Kåreholt, Parker, Thorslund, & Gatz, 2007; Correa Ribeiro, Lopes, & Lourenço, 2013) might be central to promoting cognitive function.

In relation to complexity with people and things, findings are inconsistent. For example, Andel et al. (2007) examined the associations between occupational complexity involving data, people, and things with MMSE scores in a sample of 386 participants aged on average 85 years and from the Swedish Panel Study of Living Conditions of the Oldest Old. They found higher complexity with people was associated with higher MMSE scores even after controlling for age, sex, childhood socioeconomic status, and education. They also reported no association between complexity with things and MMSE scores. Correa Ribeiro et al. (2013) also examined the associations between occupational complexity and MMSE scores in later life. They examined the associations in a sample of 624 older adults aged over 65 years and from the Study of Fragility in Brazilian Older Adults. In contrast to Andel et al., they found complexity with people was not associated with MMSE scores, and *intermediate* levels of complexity with things was associated with higher MMSE scores in models adjusting for age, education, income, and duration in occupation.

Regarding other occupational demands, findings from cross-sectional studies are also inconsistent. For example, Potter, Helms, and Plassman (2008) reported higher mental and social demands were associated with higher levels of cognitive ability (measured using the Modified Telephone Interview for Cognitive Status

[TICS-m]), and higher physical demands were associated with lower levels of general cognitive ability. By contrast, Fritsch et al. (2007) reported mental, social, and physical occupational demands were not reliably associated with cognition in late life. Fritsch et al. (2007) collected retrospective data on early life variables (parents' SES, adolescent IQ, and education), and midlife occupational activity from a sample of 349 individuals aged 75 years. They used path analysis to examine the direct and indirect associations of these variables with memory, verbal fluency, and processing speed. They regressed each cognitive outcome measure on all the antecedent variables and found no direct association between the occupational demands and any of the cognitive outcome measures.

Findings from longitudinal studies are equivocal about the nature of the associations between occupational activity demands and cognitive decline. Some studies (Marquié et al., 2010; Potter, Plassman, Helms, Foster, & Edwards, 2006) found higher mental demands to be associated with slower rates of cognitive decline. For example, in a sample of WWII male-twin veterans, aged 65 years on average, Potter and colleagues (2006) reported higher *general intellectual* demands were associated with "modest" improvement in residualised TICS-m change scores over a 7-year period. Marquié et al. examined the association of *cognitive stimulation at work* on level of, and change in, a composite score of cognitive ability. Their large population-based sample comprised current and former workers, aged 32 to 62 years at baseline. Using multilevel modelling techniques, and adjusting for age, sex, education, blood pressure, and social activities, they found cognitive stimulation at work was a significant predictor of patterns of cognitive change over a 10 year period. Specifically, lower cognitive stimulation at work was associated with lower levels of cognitive performance, less improvement over the first five years, and decline over the next 5 years. In contrast, higher cognitive stimulation at work was associated with a marked increase in performance over the first five years, and stability thereafter. Marquié et al.'s sample was relatively young and the study was focused primarily on current workers. Thus it does not strictly meet the inclusion criteria for this review, and is less comparable to the other studies reviewed. However, it was included because it does comprise some data from former workers and it is one of only a hand full of studies to have examined the associations between cognitively stimulating work and change in cognitive ability.

Other studies (Gow, Avlund, et al., 2012; Jorm et al., 1998) have found higher mental demands to be associated with high levels of cognitive ability, but not differential rates of cognitive decline. Gow and colleagues (2012) examined the associations of *intellectually challenging* occupations with a composite score of general cognitive ability. Cognition was assessed at ages 60, 70, and 80 years in a sample of men and women from the Glostrup 1914 Cohort Study. Latent growth curve analyses showed more intellectually challenging occupations were associated with higher levels of cognitive ability, even after adjusting for the influences of sex, education, and social class. Unusually, they also found the association was reversed after controlling for cognitive ability assessed at age 50, and suggested the finding may have been due to the earlier retirement of people in more intellectually challenging occupations.

One further longitudinal study (Finkel et al., 2009) reported that the relationships between occupational complexity and cognitive ageing varied across the complexity types, cognitive domains, and the pre- and post-retirement periods. Finkel et al. (2009) examined the associations of occupational complexity with data, people, and things with changes in four cognitive domains (verbal, memory, speed, and spatial), in a sample of 462 older adults, aged on average 64 years at baseline, and from the Swedish Adoption/Twin Study of Aging. Using latent growth curve models, they estimated cognitive change pre- and post-retirement (defined at age 64) and found that only complexity with people was associated with cognitive ageing in age and education adjusted models. They reported that higher occupational complexity with people was associated with higher levels of processing speed, but not differential rates of change in either the pre- or post-retirement periods. In addition, they found higher complexity with people was associated with increases in verbal ability pre-retirement but not post-retirement, and a faster rate of decline in spatial ability post-retirement. A faster rate of decline post-retirement is consistent with the disuse hypothesis, as the reduction in mental exercise resulting from retirement (i.e., the cessation of cognitively stimulating occupational activity) would be greater for people who held higher complexity occupations (Finkel et al., 2009). They concluded that engaging in a main lifetime occupation characterised by complexity has a role in the differential preservation of cognitive ability. However, their study found no evidence of a protective association between higher occupational complexity and age-related cognitive decline in the post-retirement period.

Table 2.2

Methods and Findings from Previous Studies of Occupational Demands and Cognitive Performance and Change

Author and publication date	**Sample, n, Age, % female**	**Occupation measure**	**Cognitive measure**	**Statistical Method**	**Main findings**
Andel, Kareholt, Parker, Thorslund, & Gatz (2007)	Swedish Panel Study of Living Conditions of the Oldest Old (SWEOLD) N = 386; M_{age} = 82.5 (3.9); 52% female	Complexity with data, people, and things (DOT)	MMSE score (ordinal) Cognitive impairment - MMSE cutoff <7 out of 11	Ordered and binary logistic regression	High complexity with data associated with higher MMSE scores, controlling for age, sex, childhood SES, and education or adult occupational status. High complexity with people associated with higher MMSE scores, controlling for age, sex, childhood SES and education. High complexity with data and people associated with lower odds of cognitive impairment, controlling for age, sex, and childhood SES. No associations between occupational complexity with things and MMSE scores or cognitive impairment.
Correa Ribeiro, Lopes, & Lourenço (2013)	Study of Fragility in Brazilian Older Adults (FIBRA-RJ). N = 624; Age = 65+; 67% female	Complexity with data, people, and things (DOT)	MMSE	Linear regression	Complexity with data and things associated with higher cognitive performance, independent of age, schooling, income, and duration of occupation. Complexity with people not associated with cognition.
Finkel, Andel, Gatz, & Pedersen (2009)	Swedish Adoption/Twin Study of Aging (SATSA). N = 462; M_{age} = 66.1 (7.5), 55% female	Complexity with data, people, and things (DOT)	Verbal, memory, speed, spatial factor scores	Latent growth curve analysis: change before retirement, change after retirement; 6 waves of data.	High complexity with people only associated with rates of cognitive change, controlling for age and education. High complexity with people associated with improvement in verbal skills up until retirement. Following retirement, high complexity with people associated with faster rate of decline on spatial ability, only. High complexity with people associated with higher levels of speed. Complexity with people not associated with memory.
Fritsch, McClendon, Smyth, Lerner, Friedland, & Larsen (2007)	Convenience sample from the Cleveland Longitudinal Aging Study of Students; N = 349; M_{age} = 74.8 (1.0); 57.6% female.	Mental, social, and physical demands (DOT)	TICS-m score; episodic memory; verbal fluency; speed	Path analysis	No significant associations between mental, physical, and social occupational demands and cognition, after controlling for education, gender, parents SES, and intelligence in adolescence.
[a]Gow, Avlund, & Mortensen (2012)	Glostrup 1914 Cohort, Demark; N = 483; $M_{age\ at\ baseline}$ = 60 (0.0); 34.4% female	Intellectual challenge and physical hazards	Cognitive ability factor: digit symbol, block design, digit span, picture completion	Latent growth curve analysis, 3 waves of data, 20 year period.	High intellectual challenge associated with higher levels of cognitive ability but not rates of change, adjusting for age, gender, education, and social class. High intellectual challenge associated with lower levels of cognitive ability after adjusting for ability at age 50. High physical hazards not associated with levels of cognitive ability, in models adjusting for age, gender, education, and social class.
Jorm, Rodgers, Henderson, Korten, Jacomb, Christensen, & Mackinnon (1998)	Canberra Longitudinal Study, Australia; Age ≥70. Male only	Realistic, investigative, artistic, social, enterprising, and conventional	MMSE, NART, Symbol-Letter, Episodic Memory, IQCODE.	One-way ANOVA; 2 waves of data, 3.6 year period.	Realistic occupations associated with lower performance on the memory, NART and symbol letter tests, and associated with a higher prevalence of dementia. No occupational differences in change in cognitive performance.

Marquié, Duarte, Bessiéres, Dalm, Gentil, & Ruidavets (2010)	VISAT longitudinal study. N = 3237; $M_{age\ at\ baseline}$ = 44.7 (10.2); 49.1% female	Cognitive stimulation at work	Cognitive ability composite: word-list learning/recall, digit symbol task, selective attention, delayed retrieval	Multilevel modelling, 3 waves of data, 10 year period	High cognitive stimulation associated with higher levels of cognitive ability, and improvement over 10 years, controlling for baseline age, gender, education, blood pressure, and social activity.
Potter, Plassman, Helms, Foster, & Edwards (2006)	Duke Twins Study of Memory and Aging; N = 3,880; M_{age} = 65.8 (2.7); Male WWII veterans; dementia cases excluded	General intellectual (GI); human interaction and communication (HC) physical exertion (PE) factor; visual attention (VA) demands (DOT)	Residualized TICS-m change score	Least-squares regression model, 3 waves of data, 7 year period	Higher GI associated with modest improvement, and higher PE and VA associated with modest decline in TICS-m scores, adjusting for education, age at testing, medical conditions, and initial TICS-m score. Significant interaction effect by zygosity - effects present among dizygotic twins only.
Potter, Helms, & Plassman (2008)	Duke Twins Study of Memory and Aging; N = 1036; M_{age} = 71.8 (2.4); Male WWII veterans; dementia cases excluded	General intellectual (GI); human interaction and communication (HC) physical exertion (PE) factor; visual attention (VA) demands (DOT)	TICS-m score	Linear regression	Higher GI and HC associated with higher TICS-m performance, and higher PE was associated with lower performance, adjusting for age, intelligence, and years of education. No interactions with education. An interaction between GI and intelligence - individuals with lower intellectual aptitude in early adulthood derived greater cognitive benefit from intellectually demanding work.

Notes: DOT: Dictionary of Occupational Titles. MMSE: Mini Mental Status Examination. TICS-m: Modified Telephone Interview for Cognitive Status. Not all studies gave a mean age for their sample. Gow, Avlund, et al. (2012) also examined psychological demands, which indexed work load stresses and the pace of work, and found no association with cognitive ability. However, this factor did not meet the inclusion criteria for the review thus the finding is not presented in the table.

2.4.2 Evaluation of the empirical literature

Comparisons across studies were complicated by differences in relation to sample characteristics, measures of occupational demands, choice of cognitive outcome measure, and confounding by prior ability (Anstey & Christensen, 2000, p. 164). These general methodological issues have implications for research integrity, thus the empirical literature is evaluated in relation to these issues[7].

Sample characteristics

The associations between occupational activity demands and cognitive ageing might depend on the amount of time people spent in their main lifetime occupation. For instance, Kröger et al. (2008) reported no associations between occupational complexity and dementia risk among people who held their principal occupation for less than 23 years. Some studies have not accounted for duration in the main lifetime occupation. For example, Andel et al. (2005) and Finkel et al. (2009) measured main lifetime occupation using answers to the following question in the Swedish Adoption/Twin Study of Aging (SATSA): “What kind of occupation did you have during the major part of your working life?”. Retirement information provided in Finkel et al.’s publication showed that some SATSA participants who answered this question had retired at ages as young as 23 years. Thus, their studies may have included data from people who spent as little as 8 years and as much as 50 years in their main lifetime occupation, but they did not take this variation into account in their analyses. Studies are limited somewhat by the available data in archival sources, so not all studies were able to account for occupational duration (e.g., Gow, Avlund, et al., 2012; Marquié et al., 2010). In this thesis, distribution information on age at time of retirement is used to exclude data from people who may have engaged in their main lifetime occupation for only a brief duration.

When studying the association between occupational demands and cognitive ageing, it may also be important to take into consideration when or if retirement has occurred. The use it or lose it hypothesis suggests that retirement may be detrimental to cognitive functioning because the retirement period may be associated with a reduction in mental exercise and some recent econometric evidence supports this proposition (e.g., Bonsang, Adam, & Perelman, 2012; Mazzonna & Peracchi, 2012; Rohwedder & Willis, 2010). Some evidence also suggests that the adverse effects of retirement on cognition may be greater for people who retired from a higher complexity occupation because the reduction in mental exercise would presumably be greater for those people (e.g., Finkel et al., 2009; Schaie, 2005). Furthermore, retirement is a major life course transition and research has shown it to be associated with both positive and negative changes in mental health and wellbeing (for reviews see, M. Wang, Henkens, & van Solinge, 2011; M. Wang & Shultz, 2010), which may in turn impact on cognitive functioning. Given the multiple possible interpretations of the associations between occupation, retirement, and cognition, it may be prudent to take into consideration when or if retirement has occurred. Yet, some studies (e.g., Gow, Avlund, et al., 2012) appear to have included data from people who retired during the period over which change was modelled and their results were usual (refer to Section 2.5.1). This thesis examines the associations of occupational activity demands with cognitive ageing in older adults who were retired at baseline.

In studies of normal cognitive ageing, inconsistent findings may be due to the inclusion of data from people with dementia. For example, Andel et al. (2006) found faster rates of cognitive decline in AD patients matched for severity, who previously held occupations higher in complexity. Thus, the beneficial effects of occupational complexity during normal cognitive ageing, which would be evidenced by a slower

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[7] This approach to evaluating the literature is similar to the approach used by Van Dijk, Van Gerven, Van Boxtel, Van der Elst, and Jolles (2008) in their study of the associations between

rate of cognitive decline, might be obscured if data from people with dementia are included in samples of healthy older adults (Van Dijk et al., 2008; Wilson et al., 2009). However, only some studies have excluded data from people with dementia (e.g., Finkel et al., 2009; Potter et al., 2006). In the data sources used in this thesis, information about dementia diagnoses is not available. So, information on pre-morbid ability (Study 1) and mental status (Study 2) is used to account for the possible inclusion of data, or to exclude data, from people with dementia.

Measures of occupational demands

Another key factor complicating research integrity is the reliability and validity of the diverse range of occupational demand measures that have been used. Studies can be categorised into three groups according to measurement: (a) studies using measures of occupational complexity involving data, people, and things (Andel et al., 2005; Andel et al., 2006; Andel et al., 2007; Correa Ribeiro et al., 2013; Finkel et al., 2009; Karp et al., 2009; Kröger et al., 2008; Potter et al. 2007); (b) studies using occupational demand factor scores (Fritsch et al., 2007; Jorm et al., 1998; Potter et al., 2006; Potter et al., 2008; Smyth et al., 2004; Stern et al., 1995; Then et al., 2013); and, (c) studies using self-report measures of job demands (Bosma et al., 2003; Gow, Avlund, et al., 2012; Marquié et al. 2010; Rovio et al., 2007; Siedler et al. 2004).

The crucial difference between the measures concerns the formal distinction between occupations and jobs. The term *occupation* refers to a group of jobs with similar work tasks and conditions (Cain & Treiman, 1981). Ratings for occupations are assigned by job analysts, who rate job conditions against objective criteria. In contrast, the term *job* refers to the activities performed by specific individuals (Cain & Treiman, 1981), and ratings for jobs are based on the perceptions of individuals

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education and cognitive decline.

about their own work activities. For example, Marquié et al.'s (2010) measured *cognitive stimulation at work* from peoples' perceptions about the cognitive challenge provided by their work content and the cognitive effort required to performed their work tasks.

Occupation and job ratings both have advantages and disadvantages. Job ratings are limited by individual biases because they capture information about the individual in addition to information about job tasks. However, they also provide rich information about the degree to which individuals are cognitively challenged in their jobs. By comparison, occupational ratings are considered more objective than self-reported ratings (Cain & Treiman, 1981; J.R. Hackman & Lawler, 1971). However, occupational ratings are limited by the assumption that all individuals characterised by the same occupational category experience the same level of cognitive challenge (Gow, Avlund, et al., 2012).

Measures of occupational demands are primarily sourced from the U.S. Dictionary of Occupational Titles (DOT: U.S. Department of Labor, 1965; U.S. Department of Labor, 1977). Chapter 3 describes in detail the DOT and the ratings it provides for occupations, including ratings of complexity. One exception is Jorm et al. (1998) who used John Holland's Taxonomy (Holland, 1985; Lokan, 1988) to classify occupations according to their psychological demands. Holland et al.'s measure is an all or nothing measure. For example, occupations might be described as either social or investigative, but not both. In contrast, the DOT classification system assumes all occupations require workers to performance tasks involving data, people, and things, and each task type is associated with varying levels of cognitive challenge (U.S. Department of Labor, 1977).

Inconsistent findings in studies of occupational complexity involving data, people, and things, may be due to measurement error. The occupational complexity measures were developed originally to describe occupations in the DOT (U.S. Department of Labor, 1965, 1977). They were later used to describe occupations in Sweden (Andel et al., 2005), Canada (Kröger et al., 2008), Brazil (Correa Ribeiro et al., 2013) and Australia (Broom, Duncan-Jones, Jones, & McDonnell, 1977a). Error introduced via the processes used to convert the ratings or differences in occupational contexts across countries, may account for inconsistent results across countries. These issues are discussed in greater detail in Chapter 3. This investigation uses scores estimated for Australian occupations. Thus, one of the strengths of this thesis is that it provides a cross-national validation of findings in relation to complexity with data, people, and things.

Different approaches to measurement have made it difficult to draw conclusions about the associations between occupational activity demands and cognition. For example, Potter et al.'s (2006) *general intellectual demands* factor was constituted by complexity with data and people (and a number of other items in the DOT), but Finkel et al. (2009) examined complexity with data and people separately. Whilst, Potter et al.'s findings suggest that general intellectual demands are predictive of cognitive function in late life, Finkel et al.'s findings suggest that only complex activities involving people are predictive of cognition. Thus, it is not clear whether complex work with data or people offers the greatest potential benefits to cognition. If complex work with data provides cognitive benefits then redesigning occupations to introduce greater complexity with people might have limited benefits for cognitive functioning. Clearly, conclusions about whether and how occupational activity demands might be related to cognition in late life are complicated by the different approaches to measurement.

Occupational physical demands

In relation to physical demands, it may be important to distinguish between sitting, moving, and heavy physical exertion. Studies do not appear to have done so and their findings are equivocal. For example, Potter and colleague's (Potter et al., 2007; Potter et al., 2008; Potter et al., 2006), Smyth and associate's (Fritsch et al., 2007; Smyth et al., 2004) and Stern et al.'s.(1995) physical demand factors were constituted by a number of occupational characteristics relating to strength, movement, and coordination (refer to Chapter 3, Section 3.4). Whereas, Potter et al. (2008) reported that higher physical demands were associated with decline in general cognitive ability over a 7-year period, Stern et al. (1995) reported higher physical demands were protective of dementia. Other studies have found no associations between physical demands and cognitive functioning (Fritsch et al., 2007) or dementia risk (Potter et al., 2007; Smyth et al., 2004). Also, Rovio et al. (2007) reported no association between physical job demands and dementia risk. However, they categorised jobs as either sedentary or active based on participants' responses to the question: "How physically heavy is your work?". Answers to this question are perhaps more valid as a measure of strength or physical exertion, rather than a reflection of movement.

The effects of occupational physical activity on cognitive ageing are thought to operate, in part, via the vascular system. Australia's Physical Activity and Sedentary Behaviour Guidelines (Department of Health, 2014) advises adults (i.e., those aged 18 to 64 years) to engage in 150 minutes of moderate intensity physical activity (e.g., walking briskly), or 75 minutes of vigorous intensity physical activity (e.g., tasks that involve lifting, carrying or digging) each week. Some occupations, such as landscape gardening, farming, or manual labouring, might provide levels of physical exertion that meet these guidelines. Therefore, to the extent to which physical work conveys cardiovascular fitness, physically demanding work may assist in building cognitive reserve capacity.

The Physical Activity and Sedentary Behaviour Guidelines also recommend that people reduce their amount of time spent in *prolonged sitting* and sedentary behaviour because these factors have been linked to obesity, diabetes, and cardiovascular disease (Brown et al., 2012). In a classic study, for example, Morris, Kagan, Pattison, and Gardner (1966) reported that conductors on London's double decker buses, who routinely walked up and down the bus stairs, had lower rates of coronary heart disease compared to bus drivers, who routinely sat behind a steering wheel. Given that obesity, diabetes, and cardiovascular disease are risk factors for cognitive impairment, prolonged sitting at work and sedentary work behaviour may be associated with poor cognitive outcomes in later life.

In sum, the Physical Activity and Sedentary Behaviour Guidelines suggest that different types of occupational physical demands might contribute to health in different ways. If this is so, then combining sitting, moving, and heavy job demands crudely into one measure may lead to ambiguous findings. In this thesis, the associations of movement-related (sitting versus moving) and strength-related (heavy versus non-heavy) job demands with cognitive ageing are examined.

Choice of cognitive outcome measure

The choice of cognitive outcome measures may also contribute to differences in study findings (Anstey & Christensen, 2000). As discussed in Section 2.2, abilities in the fluid and crystallized domains exhibit different average ageing trajectories. Whereas fluid abilities demonstrate an average pattern of age-related decline, crystallized abilities exhibited relative stability in old age. Also, some research has linked fluid ability to biological influences and crystallized abilities to cultural factors (e.g., Finkel & Pedersen, 2004; Lövdén et al., 2004). A meta-analysis

(Colcombe & Kramer, 2003) also suggested that physical exercise might have benefits for executive functioning and fluid abilities. Thus, different occupational demands may act to promote different cognitive abilities and a failure to observe an association between an occupational demand type and cognition might be due to the choice of cognitive outcome measure (Bielak, 2010; Van Dijk et al., 2008).

It has been recommended that studies examining contextual factors as predictors of cognitive ageing measure outcomes in multiple cognitive domains (Anstey & Christensen, 2000; Bielak, 2010; Gow, Bielak, & Gerstorf, 2012). As a minimum, Christensen et al. (2001) recommended studies incorporate measures of: (a) processing speed because it is a sensitive measure of cognitive ageing; (b) episodic memory because it shows declines with ageing and is a key symptom of cognitive impairment; and, (c) crystallized ability. However, only a handful of studies have examined cognitive outcomes in multiple domains (e.g., Finkel et al., 2009; Fritsch et al., 2007). Most studies have used a composite measure of general cognitive ability (e.g., Gow, Avlund, et al., 2012; Marquié et al., 2010), or measures of mental status, such as the MMSE or its telephone equivalent the TICS-m (e.g., Andel et al., 2007; Correa Ribeiro et al., 2013; Potter et al., 2008; Potter et al., 2006). Both the MMSE and the TICS-m were designed to detect cognitive impairment, not to measure variability in normal cognitive ageing. However, as Piccinin and colleagues (2013, p.375) point out there remains “substantial interest” amongst researchers in MMSE score decline because it is a dementia screening tool and diagnoses are “predicted on decline in functioning from a previous level”. In this thesis, decline in scores on the MMSE and tests of perceptual speed, immediate and delayed episodic memory, and verbal reasoning, are examined as outcomes.

Confounding by prior ability

Confounding by prior ability is a further limitation in the literature. Studies are limited somewhat in their capacity to control for the influence of prior ability on the associations between occupational activity and cognition by the available data. Consequently, some studies have used father's occupation (Andel et al., 2007) and education (Andel et al., 2007; Correa Ribeiro et al., 2013) as proxies for prior ability. Other studies (Gow, Avlund, et al., 2012; Potter et al., 2008) have made adjustments for prior ability and their results are inconsistent. For example, Gow, Avlund, et al. (2012) controlled for ability at age 50, as indicated by scores on a vocabulary test, in analyses of cognitive change from age 60 to age 80. They found that a positive association between intellectual work and cognitive functioning was reversed after controlling for ability at age 50. By contrast, Potter et al. (2008) reported that a positive association between previous intellectually demanding work and cognitive functioning in later life was independent of intellectual ability in early adulthood. Thus, results might depend on whether prior ability is assessed at early or late adulthood, and at different stages of a person's career. Even though some studies have been able to show that the associations between previous occupational activity and cognition is independent of prior ability, they typically have not been able to demonstrate causation (Schooler, 2009a). A measure of prior ability is not available in the data sources used in this thesis. However, education is included as a covariate in all analyses.

2.4.3 Summary

The empirical literature indicates that the long-term protective association between previous occupational activity demands and cognitive outcomes in late life have not been fully established. Moreover, the associations between occupational complexity, physical job demands, and age-related cognitive decline have not been sufficiently explored. The research is limited by a number of methodological issues relating to sample characteristics, the diversity of occupational activity demand measures, the choice of cognitive outcome measure, and confounding by prior ability. These issues are addressed, where possible, in this thesis. The next section presents an overview of the present investigation.

2.5 The present investigation

The overarching purpose of the thesis is to contribute new insights to the theoretical debate about the possible protective association between occupational complexity and cognitive ageing and the practical consequences of these associations for an ageing population. Therefore, using secondary data from the DYNOPTA and the ALSA, this thesis investigates whether and how complexity in the main lifetime occupation is associated with cognitive performance and change over an 11 year interval, among former workers. In line with differential preservation, it is expected that higher occupational complexity will be associated with slower rates of cognitive decline.

Using data from the ALSA, this thesis also explores whether and how movement- and strength-related demands in the main lifetime occupation are associated with cognitive performance and change in later life. Physical job demands have rarely been investigated in longitudinal research on normal cognitive ageing and the research measuring dementia outcomes is contradictory.

Consequently, no specific predictions are made about the nature of the association between physical job demands and cognitive ageing.

2.5.1 The modifying role of education, gender, and age at retirement

Education, gender, and age at retirement had been largely overlooked as possible moderators of the relationship between occupational activity and cognitive ageing. Therefore, a subsidiary aim of this thesis is to explore whether the associations between occupational complexity, physical job demands, and cognitive ageing vary by education, gender, and age at time of retirement.

Research has shown that people with lower levels of education (Bosma, van Boxtel, Ponds, Houx, & Jolles, 2003) or lower ability in early adulthood (Potter et al., 2008) derive greater cognitive benefits from cognitively demanding work or vocational training (Wight, Aneshensel, & Seeman, 2002). For example, Potter et al. examined the associations of occupational activity demands with TICS-m scores in a sample of WWII male-twin veterans. Their results showed a stronger positive association between intellectually demanding work and cognition during retirement for people with lower *intellectual aptitude*, as assessed by the Armed Services whilst the veterans were young adults. Some evidence also suggests that high occupational complexity may modify the increased dementia risk that has been shown to be associated with lower levels of education (Karp et al., 2009). Presumably, people at a lower starting level of ability have more to gain from engaging in complex activity than those with higher ability. However, the modifying role of education on the associations between occupational complexity and cognitive decline has not previously been examined. This thesis addresses this gap.

Gender may affect the type of occupation selected by people as well as occupational duration. Occupations and labour markets tend to be gender segregated, and the degree of the segregation was considerable in the period that the participants in the DYNOPTA and the ALSA were economically active. For example, women tended to work in different industries than men and they tended to be over-represented in lower paying occupations (Broom, Jones, & Zubrzycki, 1976; Workplace Gender Equality Agency, 2013). Moreover, women were not protected by anti-discrimination laws until the 1980s (Workplace Gender Equality Agency, 2013). Even today, women experience reduced employment opportunities or career disruptions because of family and caring responsibilities (Workplace Gender Equality Agency, 2013). Women are also eligible for the pension at younger ages than men, although this is changing (Commonwealth of Australia, 2010). Therefore, this thesis takes a *gender-sensitive* approach to the research question (Messing et al., 2003, p. 618; Moerman & van Mens-Verhulst, 2004) by exploring whether the associations between the occupational activity demands and cognitive ageing differ by gender.

The proposition that retirement timing plays a role in modifying associations between occupational activity demands and cognitive ageing was discussed by Gow, Avlund, et al. (2012) in relation to their findings. Gow, Avlund, et al. reported a positive association between intellectual challenging jobs and cognitive ability at baseline, when their participants were aged 60 years. However, this relationship became negative when they controlled for ability assessed at age 50. They suggested this finding might be explained by the earlier retirement of people in more complex occupations: “If those in more complex occupations were retiring earlier, then it might be expected that their cognitive decline would also be observed earlier” (Gow, Avlund, et al., 2012, p. 6). However, they were unable to examine this proposition because data about retirement was available for too few people in their sample. Similarly, Potter et al. (2007) suggested future studies should adjust for age at the time of retirement as they did not have the necessary data to do so. Whilst Finkel et al. (2009) modelled cognitive change pre- and post- mean retirement age, they did not consider individual differences in the timing of retirement. Therefore, the modifying role of age at time of retirement on the associations between the occupational activity demands and cognitive ageing is also explored in this thesis. This is a topical area of research as governments across the western world are increasing the pension eligibility age in an attempt to extend peoples' working lives.

2.5.2 Statistical control for correlates of cognitive ageing

Lifespan models of cognitive development (Baltes et al., 1999; Hertzog et al., 2008) and life course models of cognitive reserve (Anstey, 2014; Richards & Deary, 2005; Richards & Hatch, 2011) suggest that cognitive development is influenced by multiple biological, environmental, and behavioural variables, from conception to death. Therefore, a further aim of this thesis is to assess whether associations between occupational complexity, physical job demands, and cognitive ageing hold when the influence of other correlates of cognitive decline are statistically controlled.

Previously, Hertzog et al. (1999, p. 531) argued that research findings in support of the use it or lose it hypothesis would be received with greater confidence if "cognitively relevant activities have an effect on cognitive change, when controlling for social status". Therefore, in addition to age, education (as a proxy for prior ability), and gender, the potentially confounding influence of occupational status on the associations between the occupational activity demands and cognitive ageing is also statistically controlled.

Additional correlates of cognitive ageing, including physical health (Anstey & Christensen, 2000; Spiro III. & Brady, 2008), mental health (Bielak, Gerstorf, Kiely, Anstey, & Luszcz, 2011), smoking status (Anstey, von Sanden, Salim, & O'Kearney, 2007; Corley, Gow, Starr, & Deary, 2012), alcohol consumption (Bryan & Ward, 2002; Corley et al., 2011), and current activity engagement (Bryan & Ward, 2002; Hultsch et al., 1999; Lövdén, Ghisletta, & Lindenberger, 2005; Newson & Kemps, 2005) are also statistically controlled. Few studies (Marquié et al., 2010) have included such a broad range of potentially confounding covariates in their analyses.

2.6 Chapter summary

Age-related cognitive decline is characterised by individual variation, and some researchers have sought to explain this variation by contextual factors such as occupational activity demands. The environmental complexity hypothesis suggests that a long-term engagement in an occupation involving complex demands may act to promote cognitive functioning and possibly reduce age-related cognitive decline by building cognitive reserve. There is some empirical evidence linking complex occupational activity to improvements in cognitive functioning among current workers, and to a reduced risk of dementia among former workers. However, the long-term protective association of previous occupational complexity, and physical demands, with age-related cognitive decline is underexplored. This thesis aims to address this gap in the literature. Methodological issues relation to sample characteristics, measures of occupational demands, choice of cognitive outcome measure, and confounding by prior ability, have also complicated the integrity of the current literature. This thesis also addresses these issues, where possible, by comprehensively examining the associations of previous complex and physical occupational activity demands with performance and change in multiple cognitive domains in two samples of older, retired Australians. It also address gaps in the literature by exploring whether the associations between the occupational activity demands and cognitive ageing vary according to differences in education, gender, and age at time of retirement.

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CHAPTER 3: REVIEW OF OCCUPATIONAL COMPLEXITY

3.1 Chapter overview

In this chapter the concept and measurement of occupational complexity is reviewed and some inconsistencies in the empirical literature are resolved. The chapter begins with an outline of the measure's origin, namely the U.S. Dictionary of Occupational Titles (DOT: U.S. Department of Labor, 1965, 1977), and the meaning of the ratings. The second part of this chapter describes the methods used to estimate complexity ratings for occupations in Sweden, Canada, and Australia, where the bulk of relevant studies were conducted, and discusses some measurement issues that may account for inconsistencies in the literature. Finally, the measurement properties of the occupational complexity measures are discussed.

3.2 U.S. Dictionary of Occupational Titles (DOT)

Developed by the U.S. Employment Service principally for use as a job-worker matching tool, the DOT is both a dictionary and a functional classification of occupations in the U.S. (A. R. Miller, Treiman, Cain, & Roos, 1980). It was first published in 1939, with subsequent editions released in 1949, 1965 and 1977 (and a revised fourth edition in 1991), and ultimately replaced by the Occupational Information Network (O*NET) system (Peterson, Mumford, Borman, Jeanneret, & Fleishman, 1999).

The DOT classifies occupations with a nine digit code, comprised of three parts. The first three digits organise occupations into occupational groups according to the industrial aspects of the occupation, for example, industry type and the materials and equipment used (A. R. Miller et al., 1980). The middle three digits, referred to as the *worker function code*, describes how an occupation requires a worker to function in relation to *Data* (fourth digit), *People* (fifth digit), and *Things* (sixth digit). The last three digits serve to give each occupational title a unique code (A. R. Miller et al., 1980).

Worker functions are broad descriptions of activities that are performed by workers to achieve the main purpose of a particular occupation (U.S. Department of Labor, 1972). *Data* functions are activities involving information, facts, and statistics; *People* functions are interactions between people and also between people and animals; and, *Things* functions are activities involving physical interactions with machines, tools, equipment and work aids (U.S. Department of Labor, 1972).

As shown in Table 3.1, each worker function is represented by an action verb and a number. The action verb summarising what a worker does in the occupation (A. R. Miller et al., 1980), for example, compiling data, speaking with people, and operating-controlling things. The numbers reflect the complexity of the relationship between occupation and worker. The three worker functions (i.e., data, people, things) assigned to an occupation in the DOT reflect the most representative or characteristic, not necessarily the highest, worker function in relation to data, people, and things (U.S. Department of Labor, 1972). The worker functions are arranged in a hierarchy from the simple (indicated by higher numbers) to the complex (indicated by lower numbers) and each successive function includes those functions that are simpler and excludes those that are more complex (U.S. Department of Labor, 1965). In this way, the numbers represent ordinal level measures of occupational complexity (Fine, 1955; Fine & Getkate, 1995).

The worker functions differ somewhat between the third (U.S. Department of Labor, 1965) and fourth (U.S. Department of Labor, 1977) editions of the DOT. This difference is flagged here and discussed in the next section because the Australian complexity measures are reflective of the third edition whereas the Swedish and Canadian versions reflect the fourth edition.

Table 3.1

Worker Functions: Complexity Levels, Verbs, and Definitions

DATA	**Information, knowledge, and conceptions, related to data, people, or things, obtained by observation, investigation, interpretation, visualization, and mental creation, data are intangible and include numbers, words, symbols, ideas, concepts, and oral verbalization.**	
0	Synthesizing	Integrating analyses of data to discover facts and/or to develop knowledge concepts or interpretations.
1	Coordinating	Determining time, place, and sequence of operations or action to be taken on the basis of analysis of data; executing determinations and/or reporting on events
2	Analyzing	Examining and evaluating data. Presenting alternative actions in relation to the evaluation is frequently involved
3	Compiling	Gathering, collating, or classifying information about data, people, or things. Reporting and/or carrying out a prescribed action in relation to the information is frequently involved.
4	Computing	Performing arithmetic operations and reporting on and/or carrying out a prescribed action in relation to them. Does not include counting.
5	Copying	Transcribing, entering, or posting data.
6	Comparing	Judging the readily observable functional, structural, or compositional characteristics (whether similar to or divergent from obvious standards) of data, people, or things.
7/8	*No significant relationship*	*Appears in the 3rd edition only*
PEOPLE	**Human beings; also animals dealt with on an individual basis as if they were human beings.**	
0	Mentoring	Dealing with individuals in terms of their total personality in order to advise, counsel, and/or guide them with regard to problems that may be resolved by legal, scientific, clinical, spiritual, and/or other professional principles.
1	Negotiating	Exchanging ideas, information, and opinions with others to formulate policies and programs and/or arrive jointly at decisions, conclusions, or solutions.
2	Instructing	Teaching subject matter to others, or training others (including animals) through explanation, demonstration, and supervised practice; or making recommendations on the basis of technical disciplines.
3	Supervising	Determining or interpreting work procedures for a group of workers, assigning specific duties to them, maintaining harmonious relations among them, and promoting efficiency. A variety of responsibilities are involved in this function.
4	Diverting	Amusing others. (Usually accomplished through the medium of stage, screen, television, or radio.)
5	Persuading	Influencing others in favour of a product, service, or point of view.
6	Speaking - Signalling	Talking with and/or signalling people to convey or exchange information. Includes giving assignments and/or directions to helpers or assistants.
7	Serving	Attending to the needs or requests of people or animals or the expressed or implicit wishes of people. Immediate response is involved.
8	*Taking instructions - helping*	*Appears in the 4th edition only. Attending to the work assignment instructions or orders of supervisor (no immediate response required unless clarification of instruction or orders is needed).*
8	*No significant relationship*	*Appears in the 3rd edition only*

THINGS	Inanimate objects as distinguished from human beings, substances or materials; machines, tools, equipment and products. A thing is tangible and has shape, form, and other physical characteristics.	
0	Setting up	Adjusting machines or equipment by replacing or altering tools, jigs, fixtures, and attachments to prepare them to perform their functions, change their performance, or restore their proper functioning if they break down. Workers who set up one or a number of machines for other workers or who set up and personally operate a variety of machines are included here.
1	Precision working	Using body members and/or tool or work aids to work, move, guide or place objects or materials in situations where ultimate responsibility for the attainment for standards occurs and selection of appropriate tools, objects, or materials, and the adjustment of the tool to the task require exercise of considerable judgment.
2	Operating - Controlling	Starting, stopping, controlling, and adjusting the progress of machines or equipment. Operating machines involves setting up and adjusting the machine or material(s) as the work progresses. Controlling involves observing gages, dials, etc., and turning valves and other devices to regulate factors such as temperature, pressure, flow of liquids, speed of pumps, and reaction of materials.
3	Driving - Operating	Starting, stopping, and controlling the actions of machines or equipment for which a course must be steered, or which must be guided, in order to fabricate, process, and/or move things or people. Involves such activities as observing gauges and dials; estimating distances and determining speed and direction of other objects; turning cranks and wheels; pushing or pulling gear lifts or levers. Includes such machines as cranes, conveyor systems, tractors, furnace charging machines, such as hand trucks and dollies, and power assisted machines such as electric wheelbarrows and hand trucks.
4	Manipulating	Using body members, tools, or special devices to work, move, guide, or place objects or materials. Involves some latitude for judgment with regard to precision attained and selecting appropriate tool, object, or material, although this is readily manifest.
5	Tending	Starting, stopping, and observing the functioning of machines and equipment. Involves adjusting materials or controls of the machine, such as changing guides, adjusting timers and temperature gauges. Turning valves to allow flow of materials, and flipping switches in response to lights. Little judgment is involved in making these adjustments
6	Feeding - Offbearing	Inserting, throwing, dumping, or placing materials in or removing them from machines or equipment which are automatic or tended or operated by other workers.
7	Handling	Using body members, hand tools, and/or special devices to work, move or carry objects or materials. Involves little or no latitude for judgment with regard to attainment of standard or in selecting appropriate tool, object, or material.
8	*No significant relationship*	*Appears in the third edition only*

Notes. Lower numbers indicate higher complexity. "Although the 3rd edition uses both 7 and 8 for *Data*, there is no distinction between them" (Broom et al., 1977a, p. 140). Source: Dictionary of Occupational Titles, 4th edition (U.S. Department of Labor, 1977, pp. 1369-1371).

3.3 Complexity ratings for occupations in Sweden, Canada, and Australia

To facilitate the application of the complexity scores more broadly in research, they have been estimated for occupations in other national census classifications. The estimation methods used by various research groups are described and compared in this section. In addition, a cross-national comparison of complexity ratings for some typical occupations is presented.

3.3.1 1970 U.S. Census

To create complexity scores for occupation categories in the 1970 U.S. Census occupations, Roos and Treiman (1980) used data from the 1971 U.S. Current Population survey (CPS). The CPS includes both the 1970 U.S. Census occupation codes and the third edition DOT codes, and also links the third edition DOT codes to fourth edition DOT codes (Temme, 1975). Ross and Treiman computed a mean score for all the DOT occupations in each census occupation category using weights "proportional to the number of individuals holding each DOT occupation" in the U.S. labour market (Roos & Treiman, 1980, p. 337).

Correa Ribeiro et al. (2013) also sourced complexity scores from 1970 U.S Census to examine the associations of occupational complexity with cognition in a Brazilian sample. However, they did not provide any information on the processes used to match Brazilian occupations with the U.S. Census occupation categories.

3.3.2 1980 Swedish and Canadian census classifications

Andel et al. (2005) and Kröger et al. (2008) matched occupation categories in the 1970 U.S Census to occupation categories in the 1980 Swedish Population and Housing Census and the 1980 Canadian Standard Occupational Classification, respectively. The matching in each project was performed independently by two raters, one in Sweden / Canada and the other in the U.S. The two raters initially agreed on 90 per cent and 86 per cent of the matched codes, in the Swedish and

Canadian projects, respectively. The remaining codes were discussed until a consensus was reached about the most appropriate code. Then, Andel et al. and Kröger et al. applied the complexity scores that were developed by Roos and Treiman (1980) for the U.S Census.

3.3.3 1971 Australian CCLO

As part of a larger study on social mobility, Broom et al. (1977a) estimated third edition DOT (U.S. Department of Labor, 1965) complexity scores for occupations in the 1971 CCLO (Australian Bureau of Statistics, 1971). Complexity scores produced via this project were obtained by this researcher from the Australian Data Archive at the Australian National University. Broom et al. (1977a) described in detail the method they used to estimate complexity scores for the CCLO occupations. Briefly, the process involved two steps.

In the first step, they searched in the DOT (U.S. Department of Labor, 1965) for the 8,000 occupational titles listed in the CCLO's 358 civilian occupation categories (the DOT does not provide ratings for the armed services). In 1,812 cases Broom and colleagues were able to make an exact match of a CCLO title to a DOT title, and in 5,193 cases they were able to make a near match (Broom et al., 1977a). Thus, 88 per cent of the CCLO titles were given a complexity rating (Broom et al., 1977a). Unsurprisingly, many of the titles in the CCLO that were not located in the DOT fell into *not elsewhere classified (nec)* groups, which are "reserved for precisely defined occupations which are not sufficiently numerous in the labour force to be allocated a specific unit group code" (Australian Data Archive).

In a second step, Broom et al. (1977a) judged the consistency of the complexity ratings within the 358 occupation categories using a "two-thirds rule" (p. 135). If at least two-thirds of the located titles within a category had the same score then Broom et al. accepted that score. Using this rule, 51 per cent of the categories were assigned a complexity rating (Broom et al., 1977a). In 105 categories, the score for two of the three complexity dimensions met the two-thirds rule, and in 35 categories only one did (Broom et al., 1977a). These occupational categories were consequently assigned ratings for two complexity dimensions and one complexity dimension, respectively (Broom et al., 1977a). In 35 categories no ratings were produced by the two-thirds rule (Broom et al., 1977a). For the 175 categories where there was only partial or no agreement, three researchers re-examined the descriptive CCLO occupational titles with reference to the detailed descriptions provided for DOT occupations (Broom et al., 1977a). A further 26 per cent of all final complexity ratings were assigned on that basis (Broom et al., 1977a). Overall, 77 per cent of all required complexity ratings were produced using the two-thirds rule (Broom et al., 1977a).

3.3.4 Cross-national comparison

Estimation methods

Compared to the method used by Broom et al. (1977a), the method used by Andel et al. (2005) and Kröger et al. (2008) involved a number of adaptations. First, a mapping of third edition DOT scores to occupations in the 1970 U.S. Census, then a mapping of fourth edition DOT scores to third edition DOT scores, and finally a mapping of occupations in the 1980 Swedish and Canadian censuses to occupations in the 1970 U.S Census. Error may have been introduced during each mapping phase and distorted the meaning of the complexity ratings. Therefore, inconsistencies in the Swedish and Canadian studies (e.g., Andel et al., 2005; Andel et al., 2007; Finkel et al., 2009; Karp et al., 2009; Kröger et al., 2008) may be due to measurement error.

Broom et al. (1997a) examined whether the meaning of the complexity profiles (i.e., the worker function code) were distorted during their estimation process by comparing the distribution of scores within data, people, and things in the 100 DOT complexity profiles and the 53 CCLO complexity profiles. They found them to be similar (refer to Table 3.2). The interrelationships between the CCLO complexity profiles, the DOT profiles, and other ratings provided for occupations in the DOT were also examined by Broom et al. (1977a). They found that the pattern of relationships were similar for the DOT and the CCLO, and therefore concluded that their estimation method upheld the basic meaning of the complexity profiles.

Table 3.2

Distribution of Complexity Profiles by Complexity Level for Data, People and Things

Level of complexity	**Data**		**People**		**Things**	
	DOT (%)	**CCLO (%)**	**DOT (%)**	**CCLO (%)**	**DOT (%)**	**CCLO (%)**
0	12	9	3	2	4	0
1	18	19	2	2	17	15
2	15	11	5	4	7	11
3	16	24	9	7	10	8
4	9	6	5	4	10	9
5	5	4	8	7	5	2
6	5	2	18	21	1	2
7[a]	20	24	8	11	10	9
8			42	42	36	43
Total	**100**	**99**	**100**	**100**	**100**	**99**
N profiles	**100**	**53**	**100**	**53**	**100**	**53**

Notes. [a]The DOT does not distinguish between 7 and 8 on data. Table adapted from Broom et al. (1977a, p. 140).

Complexity ratings for the 1970 U.S. Census were weighted using U.S. labour market information (refer Section 3.3.1). Therefore, the complexity ratings for the 1980 Swedish and Canadian censuses may not directly reflect the Swedish or Canadian labour markets. The complexity ratings were also incorporated into the 1971 Canadian Classification and Dictionary of Occupations (Fine & Getkate, 1995), thus it is puzzling why Kröger et al. (2008) did not use scores from that source. Nevertheless, inconsistencies in the findings from the studies that used Swedish and Canadian samples (e.g. Andel et al., 2005; Andel et al., 2007; Finkel et al., 2009; Karp et al., 2009; Kröger et al., 2008) may be due to estimation bias.

Some limitations in the Australian complexity ratings should be noted. Specifically, the ratings represent an unweighted average score, and they are less detailed than those in the DOT. Although preferred, Broom et al. (1977a) were unable to produce a weighted score as the frequency with which occupational titles occurred within an occupational category in the Australian labour force was unknown. In effect, Broom et al. have assumed that each title within a given occupation occurs with equal frequency in the labour force, which is unlikely.

The conversion also resulted in a loss in variation in the complexity profiles. Only 53 of the 100 complexity profiles in the DOT persisted in the adaptation (Broom et al., 1977a; Broom, Duncan-Jones, Jones, & McDonnell, 1977b). This outcome was largely because the DOT is far more detailed than the CCLO. For instance, the CCLO comprises a large number of civilian occupational titles but it only classifies them using 358 occupation codes. So, complexity levels are distinguished for 358 occupation categories and not for the 8,000 occupational titles listed in the categories. By contrast, the third edition DOT distinguishes complexity levels within its 603 occupation categories (Broom et al., 1977a).

Complexity scores for typical occupations

As outlined in the sections above, the complexity scores in the third and fourth editions of the DOT differ somewhat, and whereas the complexity ratings in the Australian CCLO reflect the ratings in the third edition, the ratings in the Swedish and Canadian censuses reflect the ratings in the fourth edition. These differences may have resulted in some inconsistencies in complexity ratings across nations.

In the third edition DOT, the worker functions "included as the lowest response level a judgement that an occupation has no significant relationship to data, people, or things" (A. R. Miller et al., 1980, p. 188). In the fourth edition, *no significant relationship (8)* was dropped in response to criticism that the third edition undervalued jobs commonly held by women with respect to complexity with things (Miller et al., 1980). For example, *Typist*, an occupation more commonly held by women, was coded as having no significant relationship to things, whereas *Typesetting-Machine Tender*, an occupation more commonly held by men, was coded at a low but significant level of complexity, even though these occupations conceivably have similar levels of complexity in relation to things (A. R. Miller et al., 1980). In a review study, Cain and Treiman (1981, p. 272) recommended against the use of the third edition ratings for complexity with things to investigate gender differences in "occupational rewards", including presumably rewards relating to cognitive health.

Once dropped, the next lowest complexity level was redefined to include all occupations that did not score above the minimum level. Therefore, in the third edition, scores ranged from 0-8 for data, people, and things, whereas in the fourth edition they ranged from 0-6 for data, 0-8 for people, and 0-7 for things. The vast majority (about 70 per cent) of occupations that were classified as having *no significant relationship (8)* in the third edition were reassigned to the lowest (significant) level in the fourth edition (i.e., 6 for data, 8 for people, and 7 for things) (Cain & Treiman, 1981). Essentially, the *no significant relationship* category might accurately be conceptualised as the lowest level of complexity and this is the approach taken in the present investigation.

As Kröger et al. (2008) presented scores for the five most common occupations in their study, it was possible to compare scores for Canadian occupations with scores for similar occupations in the fourth edition DOT and the Australian CCLO. Scores for similar Swedish occupations were not available for comparison. The occupational titles and complexity scores for each country or source are presented in Table 3.3.

Table 3.3

Cross-National Comparison of Complexity Scores for Five Typical Occupations

Classification	**Occupational title**	**Data**	**People**	**Things**
Canada	Secretaries and stenographers	3.0	6.0	2.0
U.S. DOT	Secretary; Stenographer	5	8	2
U.S. DOT	Typist	3	6	2
Australia	Stenographer and typists	5	8	8
Canada	Farmers nec	1.5	6.2	1.5
U.S. DOT	Farmer, general; Farmer, vegetable, Farmer, diversified crops	1	6	1
Australia	Farmers and Farm managers nec; All mixed farmers;	1	8	2
Canada	Elementary and secondary school teaching and related occupations nec	0.9	2.2	3.8
U.S. DOT	Teacher, secondary school; Teacher, elementary school; Teacher, preschool	2	2	7
Australia	Secondary school teacher; primary school teacher; preschool teacher	2	2	8
Canada	Registered and graduate nurses and nurses in training	2.8	6.5	4.1
U.S. DOT	Nurse, licensed practical	3	7	4
Australia	Nurses certified, nurses probationer or trainee	3	8	7
Canada	General office clerks	3.8	6.2	3.4
U.S. DOT	Clerk, general	5	6	2
Australia	Clerical workers govt. nec; Clerical workers not govt. nec.	3	8	8

Notes. nec: not elsewhere classified. The occupations selected reflect the 5 most common occupations reported in the study by Kröger et al. (2008). US DOT: United States Dictionary of Occupational Titles, 4th edition (U.S. Department of Labor, 1977); Canada: 1980 Canadian Standard Occupational Classification (Kröger et al., 2008); Australia: 1971 Australian Classification and Classified List of Occupations (Broom, Duncan-Jones, Jones, McDonnell, & Willia, 1973).

They show that cross-national ratings for complexity with data and people are similar across all three countries. This is consistent with Cain and Treiman's (1981) finding that more than 93 per cent of the complexity ratings remained unchanged between the third and fourth editions. However, in relation to complexity with things, the ratings do vary. Consistent with the findings of Cain and Treiman on the effects of dropping the *no significant relationship* category, the ratings for complexity with things for stenographer/typist and clerical worker are higher in Australia and lower in the DOT and Canada. For example, *Typist* was coded as having *no significant relationship (8)* to things in the third edition of the DOT (not presented below) and in the Australian version. In the fourth edition of the DOT, it was recoded as involving the *operating-controlling (2)* of things and was similarly rated in the Canadian version. Thus, in relation to complexity with things, some caution is taken when comparing the results from this thesis to the results from studies by Andel and colleagues (e.g., Andel et al., 2007; Finkel et al., 2009).

3.4 Measurement issues of complexity with data, people, and things

As outlined in Chapter 2, measures vary with respect to their reliability and validity and this may explain differences in study findings. So, measurement issues relating to occupational complexity with data, people, and things, are discussed in this section.

Cain and Green (1983) tested the reliability of the complexity ratings in the fourth edition DOT and found that complexity with things was unreliably estimated and that this could be attributed, in part, to the job descriptions used to assign ratings to occupations. They suggested that perhaps jobs vary more widely in their complexity with respect to things or that job descriptions are less adequate for rating things. By contrast, Cain and Green found the estimated reliabilities for data and people to be high. The reported median reliability estimates were 0.85 for data (range = 0.84 – 0.90), 0.87 for people (range = 0.80 – 0.91), and 0.46 for things (range = 0.25 – 0.65).

Estimates from the third edition DOT might be more reliable than those in the fourth edition because the production of the third edition ratings were more centralised. In the third edition, complexity ratings were assigned by personnel at the national headquarters of the U.S. Employment Service using job descriptions from job analysts who had observed jobs on-site and as they were performed (A.R. Miller et al., 1980). In the fourth edition, job analysts rated each job with respect to complexity. Consequently, the decentralised processes used to construct the fourth edition may have introduced error into the ratings (A. R. Miller et al., 1980).

The ratings for the worker functions are considered an ordinal level measure of occupational complexity because they are arranged in a hierarchy and each successive function can include those functions that are simpler and exclude those that are more complex (Fine, 1955; Fine & Getkate, 1995). However, the U.S. Handbook for Analyzing Jobs (U.S. Department of Labor, 1972), which accompanies the DOT, cautioned that the arrangement of the people functions are somewhat arbitrary. A. R. Miller et al. (1980) noted that despite this disclaimer, studies have tended to use the rating as an interval scale. This was certainly true with respect to the literature reviewed in Chapter 2 and the findings do not appear to depend on whether the measure is used as a continuous or binary variable. Therefore, complexity with people was treated as a continuous variable in this thesis.

The U.S. Handbook for Analyzing Jobs (U.S. Department of Labor, 1972, p. 4) states that the worker functions: “express the total level of complexity of the job-worker situation”. Sidney Fine , who was largely responsible for developing the worker functions for use in the DOT, wrote that each successive level of complexity implies a “successively greater degree of involvement and hence skill on the part of the worker” (Fine & Getkate, 1995, p. 2). Fine also wrote that they reflect the extent to which workers are engaged in “prescribed versus discretionary duties” (Fine, 1968, p. 7, as cited in Miller et al. (1980)). Andel et al. (2005, p. 252) wrote that the worker functions reflect “three types of intellectual demands”. J. R. Hackman and

Oldham (1980) described complexity as the level of stimulating and challenging demands associated with a particular occupation. Therefore, the complexity ratings have been used by researchers to operationalise cognitively stimulating occupational activity.

Compared to complexity with data and people, complexity with things may be a relatively poor representation of cognitively stimulating occupational activity (Andel et al., 2005; Schooler et al., 2004). The factor structures of other occupational demands (e.g., Andel et al., 2006; Fritsch et al., 2007; Potter et al., 2008; Potter et al., 2006; Smyth et al., 2004; Stern et al., 1995) supports this suggestion. In addition to the complexity ratings, the DOT provides occupations with scores on 41 other characteristics. These items include measures of training time, aptitudes, temperaments, interest factors, physical demands, and environmental working conditions. Consistent with the complexity ratings, these characteristics also describe the demands or requirements placed on workers for achieving a job's purpose (Cain & Treiman, 1981). Research groups (e.g., Andel et al., 2006; Fritsch et al., 2007; Potter et al., 2008; Potter et al., 2006; Smyth et al., 2004; Stern et al., 1995) have factor analysed these items to produce factor scores of other occupational demands.

Table 3.4 presents the DOT items which constitute Stern et al.'s (1995) occupational demand factors. The table shows that complexity with data loaded on *substantive complexity*, complexity with people loaded on *management*, and complexity with things loaded on *motor skills*. Potter and colleagues (Potter et al., 2008; Potter et al., 2006) also measured *general intellectual demands, human interaction and communication*, *physical exertion,* and *visual attention demands*. Information provided by Potter and colleagues showed that complexity with data and with people loaded positively on general intellectual demands, and complexity with things loaded negatively on human interaction and communication. Thus, occupational complexity with things may be a comparatively weak representation of cognitively simulating occupational activity.

Table 3.4

Item Composition of Stern and Colleague's (1995) Occupational Demand Factors

Factor 1	**Factor 2**	**Factor 3**	**Factor 4**	**Factor 5**	**Factor 6**
[a]Substantive complexity	**Motor Skills**	**Physical Demands**	**Management**	**Interpersonal Skills**	**Undesirable Working Conditions**
General educational development Intelligence Specific vocational preparation ***Complexity of function in relation to data*** Verbal aptitude Numerical aptitude	Finger dexterity Motor coordination ***Complexity of function in relation to things*** Manual dexterity Form perception Seeing	Climbing, balancing Eye-hand-foot coordination Outside working conditions Stooping, kneeling, crouching, crawling Lifting, carrying, pulling, pushing	Talking Dealing with people Scientific, technical activities vs. business contact Direction, control, planning ***Complexity of function in relation to people***	Sensory or judgmental criteria Feelings, ideas, facts Influencing people Activities involving processes, machines vs. social welfare	Fumes, odours, dusts, poor ventilation Hazardous conditions Extreme heat, cold, noise, humidity

Notes. [a] The term *substantive complexity* was coined by Kohn and Schooler (1978). Source. Stern et al. (1995).

3.5 Chapter summary

Complexity is a term that describes how an occupation requires a worker to function in relation to activities or tasks involving data, people, or things, and ratings of complexity were originally provided for occupations in the U.S. DOT. Since its introduction, the classification system has been updated and changed, and although it has been applied in other countries, it may not be entirely legitimate to do so. Indeed, it may be that some of the equivocal results outlined in the previous chapter arose because of imprecision in the way in which the classification schemes have evolved. Findings in relation to complexity with things seem to necessitate caution in interpretation. Particularly in studies with the fourth edition DOT scores, discrepancies might be explained by the low reliability of this measure. In addition, complex work with things might be a poor representation of cognitive stimulation than complex work with data or people. The next chapter presents Study 1.

CHAPTER 4: OCCUPATIONAL COMPLEXITY AND COGNITIVE AGEING: 11-YEAR EVIDENCE FROM THE DYNOPTA

4.1 Overview of Study 1

The aim in Study 1 is to investigate whether and how complex occupational demands involving data, people, and things are associated with levels of, and rates of change in, MMSE scores using longitudinal data from the DYNOTPA. In line with the differential preservation hypothesis, it is expected that higher occupational complexity will be associated with slower rates of MMSE score decline.

In addition, whether the associations between occupational complexity and cognitive ageing (a) differ by education, gender, and age at the time of retirement, and (b) hold when the influence of age, gender, education, age at time of retirement, occupational status, pre-morbid ability, and current medical conditions and symptoms of depression are statistically controlled, are explored.

4.2 Method

In this section the methodology is presented. The DYNOPTA is described first, then the sample and measures selected from the DYNOPTA are defined. The statistical procedure and the preparation of the data are also outlined.

4.2.1 Procedure

Data were sourced from the DYNOPTA (Anstey, Byles, et al., 2010): a unique and new dataset created through the harmonization and pooling of data from nine Australian longitudinal studies of ageing (*n* = 50,652): the ALSA; the Australian Longitudinal Study of Women's Health; the Australian Diabetes, Obesity and Lifestyle study; the Blue Mountains Eye Study; the Canberra Longitudinal Study; the Household Income and Labour Dynamics in Australia Study; the Melbourne Longitudinal Study of Healthy Ageing; the PATH Through Life Study; and, the

Sydney Older Person Study (SOPS). The DYNOPTA project was approved by the Human Research Ethics Committee at the Australian National University.

Contributing study sample profiles

Two of the contributing studies, the ALSA (Luszcz et al., 2007) and the SOPS (Bennett et al., 2003) were included in the current analyses as each study provided data on occupational complexity as well as MMSE data on at least four occasions. The ALSA is an ongoing study following a sample of 2,087 men (50.6%) and women aged over 65 years at the time of recruitment in 1992, and residing in South Australia (Luszcz et al., 2007). The aim of the ALSA is to advance our understanding of how psychosocial, behavioural, biomedical and contextual variables are associated with age-related changes in the health and wellbeing of older Australians (Luszcz et al., 2007). Participants were randomly drawn from the South Australian Electoral Role, were proficient in English, and provided informed consent. The majority (94%) of the participants were residing in the community. Ethical approval for the ALSA was obtained from the Clinical Investigation Committee of Flinders Medical Centre in South Australia.

The SOPS is a non-ongoing study that followed a sample of 630 men (49.5%) and women aged 75 years or older at the time of recruitment in 1992, and residing in New South Wales (Bennett et al., 2003). The study was set up to examine the social, environmental and biological determinants of normal ageing and of age-related diseases (Bennett et al., 2003). Participants were randomly selected from a Department of Veteran's Affairs listing of war veterans and widows and by probability sampling from the Australian Bureau of Statistics' (ABS) selected census collection districts in the inner west of Sydney (Bennett et al., 2003). Eligibility criteria included non-institutional living, proficiency in English, and informed consent. The SOPS was approved by the Ethics Committee of the Concord Hospital, New South Wales.

For the DYNOPTA, occupational complexity data were taken from Baseline. MMSE data were taken from four waves of the ALSA (Waves 1 [Baseline], 3, 6, and 7) and four waves of the SOPS (Waves 1 [Baseline], 2, 4, and 5). Study details for the relevant waves appear in Table 4.1. Baseline assessments in each study occurred at approximately the same time, and Wave 7 of the ALSA and Wave 5 of the SOPS, occurred approximately 11 years later. Mean baseline ages in the ALSA and SOPS samples are 78.0 years (*SD* = 6.7) and 81.5 years (*SD* = 4.2), respectively. In both studies death is a key source of attrition (Anstey, Luszcz, Giles, & Andrews, 2001; Bennett et al., 2003)

Table 4.1

Summary of ALSA and SOPS Waves Analysed

Australian Longitudinal Study of Ageing (ALSA)					**Sydney Older Person Study (SOPS)**				
Wave	**Years**	**N**	**Age range**	**Deceased at wave**	**Wave**	**Year**	**N**	**Age range**	**Deceased at wave**
1	1992-93	2087	65-103		1	1991-93	630	75-97	
3	1994-95	1679	66-105	250	2	1994-96	449	78-99	123
6	2000-01	791	72-101	1248	4	1997-99	299	80-101	226
7	2003-04	487	75-102	1264	5	2001-03	62	84-106	318

Notes. Adapted from Anstey, Byles, et al. (2010).

The ALSA and the SOPS have similar commencement dates and sample age ranges, so it is likely their participants engaged in the labour market at approximately the same time and had historically similar labour market experiences. Additionally, they were employed during the period when the occupational complexity ratings were developed, adding to the contextual validity of the approach to coding described in Chapter 3.

4.2.2 Pooled sample profile

Participants were included in the present study if they provided data on occupational complexity, MMSE data for at least one time point (e.g. Piccinin et al., 2013), and were retired from the labour force at baseline. At baseline, 1,898 (1,271 males, 627 females) participants provided data on occupational complexity. Of these 1,789 participants (1,210 males, 579 females) had also provided MMSE data and were retired. Age at retirement ranged from 36 to 87 years (*M* = 63.02; *SD* = 5.02) for males and from 17 to 84 years (*M* = 55.51; *SD* = 12.02) for females. An inspection of the distribution of retirement ages revealed two distinct distributions: a ‘non-normative’ retirement sample comprised mostly of women who had retired before the age of 40, and a ‘normative’ sample. As their occupational duration may have been limited, data from people who retired at an age younger than 40 years[8] were excluded (refer to Section 2.4.2).

The final sample comprised 1,714 (1,201 male, 513 female) participants who provided valid data on occupational complexity and the MMSE, were completely retired at baseline, and also had complete baseline data for age, gender, education, and age at retirement. In order not to induce further sample selectivity, participants were not required to have complete baseline data on the time varying covariates (i.e., medical conditions and depression) or premorbid ability. The final sample represented 63% of the total combined ALSA/SOPS sample.

Sample selectivity analysis

To check for baseline differences between the study sample and the residuals (those not included in the sample), independent samples *t* tests were used for continuous variables and chi-square (χ^2) tests were used for categorical variables. Descriptive statistics are presented in Table 4.2.

As the study sample was selected of the basis of the occupational complexity and MMSE variables, participants were not compared on these variables. The study

[8] In their examination of the impact of retirement on cognition, Bonsang et al. (2012) restricted their sample to those who reported a retirement age of 50 or more. Also, the OECD (2005) characterises workers aged 50 years or more as older workers, and the Australian Bureau of Statistics defines mature aged workers as those aged 45 years or more (Productivity Commission, 2005). Thus, the approach used in the current study is in line with approaches in other studies.

sample and the residual were compared on the basis of the other study variables. Selectivity analyses showed the included participants were more likely to be male (*d* = 1.27) and to report fewer depressive symptoms (*d* = 0.17). At the same time, the two groups did not differ from each other with respect to age, education, or number of medical conditions. The analyses suggest that, with the exception of gender, baseline differences were small. Thus, sample selectivity effects may be considered marginal (Wagner, Gerstorf, Hoppmann, & Luszcz, 2013). The maleness of the sample is reflective of the gender composition of the labour market prior to the 1960s, the period when the cohort was chiefly employed (Broom et al., 1976).

Table 4.2

Baseline Descriptive Statistics for Sample Selectivity Analyses

	Excluded	**Included**	**Test statistic, *p* value**
Age, M (SD)	78.75 (6.63)	78.71 (6.06)	t(1947.78) = 0.16, p=.873
Male, n (%)	167 (17.7)	1201 (70.1)	χ^2(1, 2717) = 720.15, p= .000
Left school ≤ age 14 years, n (%)	546 (57.0)	960 (56.0)	χ^2(1, 2672) = 0.20, p=.652
No. of Medical Conditions, M (SD)	1.09 (0.95)	1.02 (0.92)	t(2618) = 1.77, p=.076
CES-D, M (SD)	9.19 (8.18)	7.90 (7.08)	t(1763.72) = 4.10, p=.000

Notes. Data missing on some variables. All χ^2 tests that were based on a 2 × 2 contingency table applied the Yates' continuity correction. Number of medical conditions from a list of six. Higher scores on the Centre for Epidemiological Studies – Depression (CES-D) indicate more depression symptoms.

4.2.3 Measures

Occupational complexity

Occupational complexity involving data, people, and things in the main lifetime occupation is the key independent variable. Occupational information from the ALSA and the SOPS was taken from baseline and was captured in the SOPS by the question: "What has been your main job during your working life?" and in the ALSA by the question: "What kind of work have you done most of your life?" For the DYNOPTA, occupational information was coded according to the 1971 CCLO (Australian Bureau of Statistics, 1971), and then occupational complexity scores were applied to the occupational code (Australian Data Archive; Broom et al., 1973). *To aid interpretation, complexity scores were reversed so that higher scores indicate* *higher levels of occupational complexity* (as per similar studies, e.g., Andel et al., 2007; Finkel et al., 2009). Coding was carried out by the thesis author, and a ten per cent sample of the data was also independently coded. There was a 91% agreement between the two raters.

Of the 2,087 ALSA participants, 1,429 had reported an occupation, 658 had not. Of the 1,429 who had reported an occupation, 4 had given an insufficient description of their occupation and thus could not be coded. Three participants had given their occupation as the armed forces, which could not be rated under the available coding scheme. Of the 658 participants who did not report an occupation, 405 were housewives and one had never worked. Finally, 252 were coded as missing as they did not answer the survey question. Occupational complexity data were provided by 468 of the 630 SOPS participants at baseline. Of the 630 SOPS participants, 480 responded to the occupation question. However, 4 had given insufficient information and 8 listed their occupation as armed services. Of the remaining 162 SOPS participants, 118 were housewives, 4 had never worked, and 24 did not provide valid data. Since occupational complexity is defined for paid employment only, housewives were not assigned complexity scores (as per similar studies, e.g., Andel et al., 2007; Finkel et al., 2009).

Table 4.3 provides descriptive statistics for the three occupational complexity measures. Mean occupational complexity was 3.33 for data (*SD* = 2.36; *Mdn* = 4; range = 0-7); 1.26 for people (*SD* = 2.18; *Mdn* = 0; range = 0-8); and, 2.36 for things (*SD* = 2.64; *Mdn* = 1; range = 0-6). The score distributions were consistent with previous studies (e.g., Andel et al., 2007; Cain & Treiman, 1981).

Table 4.3

Baseline Description Statistics for Occupational Complexity with Data, People, and Things by Gender

Complexity with Data				**Complexity with People**				**Complexity with Things**			
Function (Level)	**Total %**	**Males %**	**Females %**	**Function (Level)**	**Total %**	**Males %**	**Females %**	**Function (Level)**	**Total %**	**Males %**	**Female %**
No sig. relationship (0)	29.3	29.7	28.3	No sig. relationship (0)	64.4	70.9	49.1	No sig. relationship (0)	47.3	38.1	68.8
Comparing (1)	0.1	0.1	0.0	Serving (1)	9.6	2.2	26.9	Handling (1)	9.6	10.7	6.8
Copying (2)	2.5	0.2	7.8	Speaking/signalling (2)	5.3	6.2	3.1	Feeding/offbearing (2)	0.1	0.1	0.2
Computing (3)	5.8	4.1	9.9	Persuading (3)	7.6	8.2	6.0	Tending (3)	5.4	4.2	8.4
Compiling (4)	25.7	23.6	30.8	Diverting (4)	0.3	0.2	0.6	Manipulating (4)	5.6	7.1	2.1
Analysing (5)	13.7	14.5	11.9	Supervising (5)	2.5	3.2	0.8	Driving/operating (5)	4.5	6.4	0.0
Coordinating (6)	20.8	25.4	9.9	Instructing (6)	4.4	1.7	10.7	Operating/controlling (6)	27.5	33.4	13.6
Synthesising (7)	2.1	2.4	1.4	Negotiating (7)	4.7	5.7	2.3	Precision working (7)	0.0	0.0	0.0
				Mentoring (8)	1.3	1.7	0.4	Setting up (8)	0.0	0.0	0.0
M (SD)	3.33 (2.36)	3.49 (2.44)	2.97 (2.13)	**M (SD)**	1.26 (2.18)	1.19 (2.21)	1.41 (2.12)	**M (SD)**	2.36 (2.64)	2.84 (2.68)	1.23 (2.14)
Median	4	4	4	**Median**	0	0	1	**Median**	1	3	0
Skew	-.400	-.488	-.264	**Skew**	1.730	1.801	1.568	**Skew**	.434	.097	1.482
Kurtosis	-1.331	-1.334	-1.215	**Kurtosis**	1.708	1.997	1.075	**Kurtosis**	-1.633	-1.819	0.568
Test Statistic, p-value	U(df) = 254940, Z = -5.82, *p*=.000			**Test Statistic, p-value**	U(df) = 356,487, Z = 6.03, *p*=.000			**Test Statistic, p-value**	U(df) = 203592, Z = -11.92, *p*=.000		

Notes. Higher complexity levels/scores indicate higher complexity. Mann Whitney U tests were used to assess group differences in complexity as the variables were not distributed normally

Analyses comparing the occupational complexity scores by gender showed males were more likely to have held an occupation higher in complexity with data (*d* = 0.23), whereas females were more likely to have held an occupation higher in complexity with people (*d* = 0.10). Consistent with the gender bias for complexity with things in the third edition DOT (refer to Chapter 3) men were also more likely to have held an occupational higher in complexity with things (*d* = 0.63). Analyses comparing the occupational complexity scores by contributing study showed that the ALSA participants were more likely to have held occupations higher in complexity with data (*M* = 3.54, *SD* = 2.31, versus *M* = 2.65, *SD* = 2.31, *U*(df) = 208245, *Z* = -6.28, *p* =.000), and with things (*M* = 2.44, *SD* = 2.69, versus *M* = 2.08, *SD* = 2.42, *U*(df) = 243752, *Z* = -2.13, *p* =.033). There were no significant differences in complexity with people between the ALSA (*M* = 1.26, *SD* = 2.20) and the SOPS (*M* = 1.25, *SD* = 2.14, *U*(df) = 268534, *Z* = 1.03, *p* = .306).

Cognitive ability

Mini Mental State Examination (MMSE: Folstein, Folstein, & McHugh, 1975) was used as the cognitive outcome measure. The MMSE is a measure of global cognitive status or ability and is widely used in studies of ageing to measure cognitive performance and change (Anstey, Burns, et al., 2010; Piccinin et al., 2013). The MMSE comprises a series of questions addressing orientation, registration, immediate and delayed recall, comprehension of simple commands, naming ability, calculation or spelling, and spatial tasks. The DYNOPTA dataset includes one total MMSE score out of 30, with lower scores indicating lower cognitive ability.

For the DYNOPTA, total MMSE scores were computed from item level data in the nine contributing studies, as well as data on age, gender, education, and contributing study, using multiple imputation (Anstey, Burns, et al., 2010; Burns et al., 2011). Specifically, five imputed datasets were computed and total scores from those datasets were averaged to create a total MMSE score. Due to differences between studies in the coding of non-response, all missing data was imputed regardless of the nature of non-response (Anstey, Burns, et al., 2010).

Table 4.4 presents descriptive statistics for the MMSE (raw scores and *T* scores) across four time points. To aid interpretation, and for consistency across studies, MMSE scores were standardised to the *T* metric (*M* = 50, *SD* = 10) using scores from the combined ALSA/SOPS baseline sample (*M* = 26.68, *SD* = 3.33). This transformation maintains the "psychometric properties of the scores and the longitudinal changes in means and variances" (Gerstorf et al., 2009, p. 298). At baseline, mean MMSE score was 50.04 (*SD* = 9.68). MMSE scores were skewed (-1.900) and exhibited a slightly heavy tail (kurtosis = 5.766). However, the distributional properties of the scale improved over time because MMSE performance declined over subsequent occasions (Hofer et al., 2002).

Table 4.4

Descriptive Statistics for MMSE by Time

	MMSE	Time 1	Time 2	Time 3	Time 4
Sample, *n*	**n**	1698	1273	563	274
Raw score	**M(SD)**	26.69 (3.22)	26.26 (3.67)	25.90 (4.40)	22.94 (2.62)
T score	**M (SD)**	50.04 (9.68)	48.73 (11.03)	47.66 (13.20)	38.76 (7.86)
Males, *n*	**n**	1188	872	343	160
Raw Score	**M (SD)**	26.54 (3.26)	26.17 (3.64)	25.88 (4.13)	22.77 (2.63)
T score	**M (SD)**	49.56 (9.79)	48.48 (10.94)	47.60 (12.39)	38.25 (7.89)
Females, *n*	**n**	510	401	220	114
Raw score	**M (SD)**	27.06 (3.11)	26.44 (3.73)	25.90 (4.40)	22.94 (2.62)
T score	**M (SD)**	51.15 (9.34)	49.28 (11.21)	47.77 (14.40)	39.48 (7.78)

Notes. Higher scores indicate better cognitive performance. MMSE scores were standardised to the *T* metric (*M* = 50, *SD* = 10) using the combined ALSA/SOPS baseline sample.

Table 4.5 summarises the number of observations provided by the sample and by gender. The sample provided a total of 3,808 observations with 572 participants providing three or more observations. Males contributed almost twice as many observations as females. In relation to ceiling effects, 483 observations (or 12.7% of all observations) were recorded for the maximum score of 30. Also, 194 observations (or 18.3% of all observations) were recorded for scores less than 24.

By convention (Folstein, Anthony, Parhad, Duffy, & Gruenberg, 1985), scores less than 24 are often considered to be indicative of possible cognitive impairment or pre-clinical dementia (Anstey, Burns, et al., 2010).

Table 4.5

Number of MMSE Observations by Gender

Number of Observations	**Sample**	**Gender**	
		Males	**Females**
1	443	337	106
2	699	513	186
3	321	204	117
4	251	147	104
Total	**3808**	**2563**	**1245**

Time-invariant covariates

Age was a continuous variable. Mean age at baseline was 78.71 years (*SD* = 6.06; range = 65-101; skew = .261, kurtosis = -.291).

Gender was a binary variable coded as: 0 = male; 1 = female. At baseline, 70.1% (*n* = 1,201) of the sample was male.

Education was coded as: 0 = left school at age 14 or less; 1 = left school at age 15 or more. At baseline, 56% (*n* = 960) of the sample left school at age 14 years or less. In this study, the categories are referred to as low and high education, respectively. For the DYNOPTA dataset, education variables were computed based on similar question wording in the contributing studies. In the ALSA and the SOPS, participants were asked: "How old were you when you left school?". In the ALSA responses were coded into seven categories: never went to school; under fourteen years; fourteen years; fifteen years; sixteen years; seventeen years; eighteen or more years. In the SOPS, the raw ages were recorded. In both studies, 55% of the samples at baseline had left school at age 14 or younger. This cut point was used to create the binary education variable.

Age at retirement was indexed by self-report. For the DYNOPTA dataset, the age at retirement variable was computed based on similar question wording. In the ALSA, participants were asked: “In what year did you retire?” In the SOPS, participants were asked their age at retirement. At baseline, mean age at retirement was 61.75 (*SD* = 6.02; range = 40-87; skew = -.336, kurtosis = 1.798), the mean year at retirement was 1976 (range = 1945-1992), and the sample had been retired on average 16.95 years (*SD* = 6.84; range = 0-48).

Occupational status was indexed by the binary variable: 0 = blue-collar; 1= white-collar, using the ANU1 social-status group scale (IPUMS-International). The sixteen ANU1 occupation-based social status groups, which in rank order are: 1 = Upper Professional, 2 = Graziers, 3 = Lower Professional, 4 = Managerial, 5 = Shop Proprietors, 6 = Farmers, 7 = Clerical Workers, 8 = Armed Services and Police, 9 = Craftsmen, 10 = Shop Assistants, 11 = Operatives, 12 = Drivers and Transport Workers, 13 = Service Workers, 14 = Miners, 15 = Farm Workers, and 16 = Labourers; were divided between groups 8 and 9 to give a white-collar/non-manual versus blue-collar/manual distinction (Broom, Jones, & Zubrzycki, 1965; Broom et al., 1976). For the DYNOPTA dataset, the occupational status variable was obtained using a file linking the occupational titles in the CCLO to the ANU1 scale (Broom et al., 1973). Approximately, 60% (*n* = 990) of the participants were classified as blue-collar.

Premorbid ability was indexed by the National Adult Reading Test (NART: Nelson, 1982). The NART is an oral reading test comprising 50 words of irregular spelling which participants are asked to pronounce. The number of correctly pronounced words represents the final NART score. The NART correlates highly with general intelligence and is relatively resistant to the effects of mild dementia (Broe, Creasey, Jorm, Bennett, & et al., 1998). The NART was administered at baseline in the ALSA and at the first follow-up assessment in the SOPS. The first follow-up wave in the SOPS was approximately 2.9 years (*SD* = 0.3) after baseline.

For the SOPS, baseline NART scores were imputed by “conditional ordinary least squares mean imputation” (Kiely et al., 2011, p. 412). The mean NART score for the current study’s sample was 27.89 (*SD* = 8.86; range = 0-50; skew = -.027, kurtosis = -.318). Participants with missing data amounted to 581. These participants did not differ from those who contributed NART data with respect to the occupational complexity variables. However, they were slightly older at baseline ($t(1086.61) = 3.48$, $p<.01$; $M_{diff} = 1.10$) and they scored slightly lower on the MMSE at baseline ($t(939.99) = -4.15$, $p<.001$; $M_{diff} = -0.74$).

Contributing study was captured by the binary variable: 0 = ALSA; 1 = SOPS. Contributing study was used to control for findings that may be due to systematic differences in the sampling or methods of the ALSA and SOPS.

Time-varying covariates

Medical conditions were obtained by self-report and were measured as the total number of current medical conditions from a list of six: arthritis, diabetes mellitus, stroke, heart attack, hypertension, and other circulatory condition (Kiely, Gopinath, Mitchell, Luszcz, & Anstey, 2012; Ross et al., 2009). At baseline, observed scores ranged from 0 to 5 conditions with a mean of 1.02 (*SD* = 0.92). Participants with missing data across all testing occasions amounted to 20.

Depression was assessed using the Centre for Epidemiological Studies – Depression scale (CES-D: Radloff, 1977; Radloff & Teri, 1986), which was developed to measure depressive symptomology in community dwelling adults. The CES-D requires individuals to respond to 20 items referencing the way they felt in the last week on a 4-point Likert scale. The response scale ranges from, 0 = rarely or none of the time, to 3 = most or all of the time, and items are summed to give a total score ranging from 0 to 60. Higher scores indicate more depressive symptoms and scores greater than or equal to 16 reflect possible depression (Anstey, von Sanden, Sargent-Cox, & Luszcz, 2007). For the DYNOPTA, a total CES-D score ranging from 0 to 60 was computed from item level data provided by the ALSA and the SOPS because both studies used the 20-item scale (Burns, Butterworth, Luszcz, & Anstey, 2013; Burns et al., 2012). At baseline, observed scores ranged from 0 to 48 with a mean of 7.90 (*SD* = 7.08). Participants with missing data across all testing occasions amounted to 264. These participants did not differ from those who contributed CES-D data with respect to the occupational complexity variables. However, they were slightly older at baseline ($t(341.65) = -5.09$, $p<.001$; $M_{\text{diff}} = -2.23$).

Baseline descriptive statistics for the covariates are presented by gender in Table 4.6., below.

Table 4.6

Baseline Descriptive Statistics for the Covariates by Gender

	Total n = 1,714	**Males** n = 1,201	**Females** n = 513	**Test statistic, *p*-value**
Age, years, M (SD)	78.71 (6.06)	79.15 (5.77)	77.69 (6.58)	$t(864.17)= 4.34$, $p=.000$
Education, n (%)				
Age left school ≤ 14 years	960 (56.0)	705 (58.7)	255 (49.7)	$\chi^2(1, 1714) = 11.44$ $p=.001$
Age left school ≥ 15 years	754 (44.0)	496 (41.3)	258 (50.3)	
Age at Retirement, M (SD)	61.75 (6.02)	63.03 (4.89)	58.78 (7.26)	$t(718.01)= 1$, $p=.000$
Occupational status, n (%)				
Blue-collar	990 (57.8)	740 (61.6)	250 (48.7)	$\chi^2(1, 1714) = 23.93$, $p=.000$
White-collar	724 (42.7)	461 (38.4)	263 (51.3)	
NART, M (SD)	27.89 (8.86)	27.82 (8.87)	28.06 (8.83)	$t(1131)= -.420$, $p=.674$
No. of Medical Conditions, M (SD)	1.02 (0.92)	1.00 (0.92)	1.07 (0.93)	$t(1669)= -1.49$, $p=.136$
CES-D, M (SD)	7.90 (7.08)	7.87 (7.09)	7.97 (7.04)	$t(1680)= -.28$, $p=.782$
Contributing Study, n (%)				
ALSA	1318 (76.9)	942 (78.4)	376 (73.3)	$\chi^2(1, 1714) = 5.06$, $p=.024$
SOPS	396 (23.1	259 (21.6	137 (26.7)	

Notes. Higher scores on the NART indicate better performance. Higher scores on the Centre for Epidemiological Studies – Depression (CES-D) indicate more depression symptoms.

Gender differences at baseline were examined using independent samples *t* tests for continuous variables and chi-square (χ^2) tests for categorical variables. Analyses showed that, compared to males, females were younger (*d* = 0.24), had more years of schooling (*d* = 0.18), retired at a younger age (*d* = 0.69), and held white-collar occupations (*d* = 0.26). At the same time, the two groups did not differ in relation to premorbid ability, number of medical conditions or symptoms of depression. The large effect size in relation to age at retirement is consistent with the younger pension eligibility age for females and historical, gender-based patterns of retirement (Broom et al., 1976; OECD, 2005).

4.2.4 Statistical approach

The research questions were addressed using a standard multilevel growth modelling (MLM) approach (Raudenbush & Bryk, 2002; Singer & Willett, 2003). MLM provides estimates of within-person change across multiple occasions of measurement as well as estimates of between-person differences in within-person change (Ram & Grimm, 2007). By using all available information on outcome variables across occasions of measurement through maximum likelihood estimation, MLM have the capacity to deal with different patterns of *missingness* (Raudenbush & Bryk, 2002; Singer & Willett, 2003). This capacity of MLM was especially valuable in the current study because data were pooled from two longitudinal studies of ageing and consequently data in the DYNOPTA were unbalanced in terms of time of measurement. Models also included correlates that are known to be informative of attrition in the ALSA and the SOPS (Anstey et al., 2003; Bennett et al., 2003). They were included to help accommodate longitudinal selectivity under the assumption that incomplete data were missing at random (Anstey et al., 2003). A description of MLM is provided in Appendix A

Tobit models have been suggested as an alternative to standard multilevel growth models when the MMSE is the outcome measure, and the Tobit is suitable when more than 20 per cent of individuals score at the ceiling for at least one occasion (Piccinin et al., 2013; I. Wang, Zhang, McArdle, & Salthouse, 2008). In the present study, 14 per cent of individuals scored at ceiling any one occasion[9]. So, to

[9] Recently, Piccinin et al. (2013) used both Tobit and standard multilevel models to examine education as a predictor of MMSE change in six parallel studies (in which less than 20 per cent of individuals scored at ceiling at any one occasion) and reported the type of model had no effect on the estimates of the associations between education and MMSE decline.

allow for the ease of interpretation of parameter estimates, the present study applied a standard multilevel modelling approach.

Time was specified as years since baseline, and baseline age was included as a covariate in conditional growth models to separate the effects of age (between-person differences) and ageing (within-person changes). This type of time in study model has been recommended for samples that vary widely in age and where the effects of age and ageing may converge over the study interval (Hofer et al., 2012; Piccinin et al., 2013). Since data were collected from participants across varying time intervals, time was also treated as individual specific (Piccinin et al., 2013). This treatment of time provides models with additional information and has the effect of improving the precision of the parameter estimates and variance components (Bielak et al., 2012; Singer & Willett, 2003).

MMSE score trajectories were assessed in a series of unconditional models. In a first step, an unconditional means model was estimated to assess the amount of variation in MMSE scores at the between-person and within-person levels, and to determine whether there was sufficient variation at each level to warrant further analysis. In a second step, unconditional growth models were fit to the data. In order to select a suitable level-1 (within-person) change trajectory, linear and non-linear (quadratic) change were estimated and models were compared using relative model fit indices (Singer & Willett, 2003). Differences in deviance (-2 Log Likelihood [-2LL]) and change in Pseudo R^2 were used to compare models. Deviance-based tests calculate the change in deviance between a simpler model and a more complex model and statistically tests the change using a χ^2 distribution, with degrees of freedom equal to the change in the number of parameters (Singer & Willett, 2003). Deviance-based tests are suitable for nested models only (i.e., when the model constraints are a subset of another model) (Singer & Willett, 2003).

Pseudo R^2 was calculated based on proportional change in residual variance (Singer & Willett, 2003).

The unadjusted associations of occupational complexity with MMSE change trajectories were then examined in a series of conditional growth models. Model 1 added occupational complexity to the best fitting unconditional growth model as a predictor of both initial status (intercept) and change (slope). The interaction terms for occupational complexity and time were of primary interest and a significant interaction would indicate that change in MMSE over the study interval varied as a function of occupational complexity, as hypothesised. To quantify the role of occupational complexity in explaining MMSE change trajectories along an “effect size-type metric” (Gerstorf, Ram, Lindenberger, & Smith, 2013, p. 1813), change in Pseudo R^2 was calculated based on proportional change in the level-2 (between-person) variance components (Singer & Willett, 2003).

The independent associations of occupational complexity with MMSE change trajectories were then examined in a series of covariate adjusted conditional growth models. The three complexity variables (people, data, and things) were assessed separately. Model 2 examined whether occupational complexity was a significant predictor of MMSE change trajectories controlling for age, gender, and education, by adding these covariates to Model 1 as predictors of both initial status and change. All subsequent models included these covariates (e.g., Wilson et al., 2009). To assess whether the associations between occupational complexity and MMSE change were independent of the additional covariates, age at retirement was added as a level-2 predictor in Model 2A, occupational status was added as a level-2 predictor in Model 2B, the NART was added as a level-2 predictor and medical conditions and depression were added as level-1 predictors in Model 2C, and contributing study was added as a level-2 predictor in Model 2D. In Model 3, all three occupational complexity variables were entered at the same time thereby taking into account their shared variance. Given the moderate to high associations between occupational complexity and occupational status (see Table 4.7), status was examined as a covariate in a separate model. Given the moderate correlation between age at retirement and age, age at retirement was examined in a separate model. The advantage of this approach is that it enables comparisons between the results in this thesis and the results from other studies (which include different covariate sets) to be drawn more easily. The downside to this approach however, is that a large number of models and estimates are reported.

To explore whether the associations between occupational complexity and MMSE change differ by education, gender, or age at retirement, deviance-based hypothesis tests were used to assess whether inclusion of cross-product interaction terms contributed significantly to model fit (e.g., Wilson et al., 2009). Interaction terms for occupational complexity and education or gender were added to Model 2 as a predictors of initial status and change. An interaction term for occupational complexity and age at retirement was added to Model 2A as a predictor of initial status and change. If an improvement in model fit was observed, analyses were carried out separately for the different strata (i.e., high / low education, male / female, early / late retirement) (e.g., Kleinbaum, Kupper, Nizam, & Rosenberg, 2008). This approach was recommended by Messing et al. (2003) in relation to gender in occupational health research.

All analyses were conducted using the mixed model procedure in SPSS 21.0 and the full information maximum likelihood (FIML) method (Singer & Willett, 2003). Random effects were calculated using an unstructured covariance matrix, which imposes no constraints on the covariance structure of the data (Heck, Thomas, & Tabata, 2010).

4.2.5 Data preparation

To aid in the interpretation of the model estimates, time-invariant, continuous measures were grand mean centred: occupational complexity with data was centred at 3.33; complexity with people was centred at 1.26; complexity with things was centred at 2.36; baseline age was centred at 78.71; age at retirement was centred at 61.75; and NART scores were centred at 27.89. Time-invariant binary variables were effectively 'centred' at the value, 0: gender was centred at male (0) versus female (1); education was centred at low (0 = age left school ≤ 14 years) versus high (1 = age left school ≥ 15 years); occupational status was centred at blue-collar (0) versus white-collar (1); and, contributing study was centred at ALSA (0) versus SOPS (1). Time-varying covariates were number of medical conditions and depression. Medical conditions were entered as raw scores. Depression was centred at 16, as scores greater than 16 are indicative of possible depression (Anstey, von Sanden, Sargent-Cox, et al., 2007). The time-varying predictors were not decomposed into their within-person and between-person parts as predictions about their effects on the associations between occupational complexity and MMSE change were not formulated (Hoffman & Stawski, 2009).

The distributional properties of the time-invariant predictor variables were considered to be adequate for MLM (i.e., skew and kurtosis less than or equal to ±2.00 and 3.00, respectively, as specified by Hofer et al., 2002). Using growth modelling techniques to estimate the associations between similarly distributed occupational complexity measures and cognitive ageing, Finkel et al. (2009) reported equivalent results for continuous (or log transformed in the case of complexity with people) and binary measures. Therefore, no transformations were performed for the current analyses and the occupational complexity variables were used as continuous measures. MLM using the maximum likelihood method assumes that residuals are normally distributed and this assumption was assessed during the modelling process (Singer & Willett, 2003).

4.3 Results

The results are presented in two major parts. First, the results from unconditional models describing change in MMSE scores are presented. Second, results from models examining whether and how occupational complexity with data, people, and things predict levels of, and change in, MMSE scores are presented.

First, the bivariate relationships among the predictor variables and with the cognitive measures are explored. Correlations between the study variables are presented in Table 4.7. Significant inter-correlations for all three complexity measures were observed. Higher complexity with data was associated with higher complexity with people. Higher complexity with data and people were associated with lower complexity with things. Higher occupational complexity with data and people were also associated with higher performance on the NART and the MMSE, more years of schooling, and high occupational status. Conversely, higher complexity with things was associated with poorer performance on the NART and the MMSE, fewer years of schooling, and low occupational status. Higher complexity with data and things were associated with an older age at retirement. Also, males were more likely to have held occupations higher in complexity with data and things. Older age was associated with an older age at retirement.

Table 4.7

Bivariate Correlations for the Study Variables

	Data	**People**	**Things**	**Age**	**Gender**	**Edu**	**AgeRetire**	**OccStat**	**NART**	**MedCdns**	**CES-D**	**MMSE**	**Study**
Data	1.000												
People	.380***	1.000											
Things	-.130***	-.572***	1.000										
Age	.069***	.039***	.029**	1.000									
Gender	-.137***	.152***	-.287***	-.119***	1.000								
Edu	.228***	.135***	-.197***	-.029**	.087***	1.000							
AgeRetire	.085***	.016	.072***	.404***	-.317***	-.028**	1.000						
OccStat	.614***	.304***	-.519***	.007	.125***	.327***	-.025**	1.000					
NART	.266***	.221***	-.272***	-.046***	.027*	.279***	-.021	.373***	1.000				
MedCdns	-.012	.023	-.027	-.010	.028	-.014	-.012	.023	.033	1.000	.		
CES-D	-.053**	-.018	.004	.119***	.024	-.049**	-.004	-.038*	-.032	.141***	1.000		
MMSE	.128***	.057***	-.093***	-.256***	.044**	.161***	-.140***	.177***	.268***	-.014	-.147***	1.000	
Study	-.137***	.022*	-.047***	.132***	.051***	-.028**	.181***	-.117***	.035**	.124***	-.041*	-.221***	1.000

Notes. Data in long format as used for the multilevel modelling procedures (e.g., Wagner et al., 2013). Spearman correlation coefficients are reported as some measures are not normally distributed (Data, People, Things, MedCdns, CES-D, and MMSE). Data, People, Things: Occupational complexity with data, people, and things, higher scores indicate higher complexity. Gender: 0=Male, 1=Female. Edu: Education; 0=left school before age 14 or less, 1=left school age 15 or more. AgeRetire: Age at retirement. OccStat: Occupational status; 0=blue-collar, 1=white-collar. NART: National Adult Reading Test, higher scores indicate better performance. MedCdns: Number of medical conditions, higher scores indicate more medical conditions. CES-D: Centre for Epidemiological Studies – Depression scale, higher scores indicate more depression symptoms. MMSE: Mini Mental Status Examination, higher scores indicate better cognitive function. Study: Contributing Study; 0=ALSA, 1=SOPS. **p*<.05;***p*<.01; ****p*<.001.

4.3.1 MMSE change

Results from the unconditional means and growth models are reported in Table 4.8. The unconditional means model revealed that the intraclass correlation coefficient (ICC[10]) was .35, suggesting that 35% of the total variation in MMSE scores was between-person variation. With substantial within-person variation (65%), linear and non-linear (quadratic) change trajectories were modelled. Goodness-of-fit criteria and Pseudo R_{ε}^2 indicated that the inclusion of the quadratic slope[11] increased model fit ($\Delta\chi^2$ (1) = 123.74, p<.001) and explained additional variance.

Table 4.8

Unconditional Means and Growth Models for MMSE Scores Over Time

	Unconditional Means Model	**Unconditional Linear Growth Model**	**Unconditional Quadratic Growth Model**
	Est. (SE)	**Est. (SE)**	**Est. (SE)**
FE-Intercept, γ_{00}	48.23 (0.22)***	50.49 (0.22)***	49.63 (0.23)***
FE-Time, γ_{10}	–	-1.29 (0.05)***	0.11 (0.13)
FE-Time^2, γ_{20}	–	–	-0.16 (0.01)***
RE-Residual, σ_{ϵ}^2	79.62 (2.49)***	52.34 (2.16)***	45.98 (1.94)***
RE-Intercept, σ_0^2	43.08 (3.17)***	46.91 (3.33)***	47.41 (3.15)***
RE-Time, σ_1^2	–	0.69 (0.23)**	0.98 (0.22)***
RE-Covariance, σ_{01}	–	5.68 (0.67)***	6.80 (0.60)***
Goodness-of-fit:			
-2LL	28778.27	28241.51	28117.77
Δ-2LL		536.76***	123.74***
AIC	28784.27	28253.51	28131.77
BIC	28803.00	28290.98	28175.48
Explained variance:			
Within-person:			
Pseudo R_{ε}^2		0.343	0.423

Notes. Unstandardised estimates (Est.) and standard errors (SE) are presented. FE: Fixed Effect. RE: Random Effect. MMSE T scores standardised to the baseline ALSA/SOPS combined sample (*M*=50, *SD*=10). Time: years since baseline. -2LL = Deviance. Δ-2LL = [-2LL model 2] – [-2LL current model]. AIC: Akaike information criterion. BIC: Bayesian information criterion. Pseudo R_{ε}^2 = ($\sigma_{\epsilon\,\text{unconditional means model}}^2 - \sigma_{\epsilon\,\text{unconditional growth model}}^2$) / $\sigma_{\epsilon\,\text{unconditional means model}}^2$). Dashes indicate that effect was not estimated. *p<.05; **p<.01; ***p<.001.

[10] The ICC is given by the equation: $\sigma_0^2/(\sigma_0^2 + \sigma_\epsilon^2)$, where, σ_ϵ^2, is the variance of the level-1 residual and, σ_0^2, is the variance of the level-2 residual (Singer & Willett, 2003).

[11] Rabe-Hesketh and Skrondal (2012, p. 214) suggested: "random slopes be included only if… the data provide sufficient information" and, "it makes sense to allow for more flexibility in the fixed part of the model than the random part". Thus, a quadratic effect of time was included in the fixed part of the model but not in the random part.

It was concluded that cognitive ageing, as measured by the MMSE, followed a non-linear change trajectory. As illustrated in Figure 4.1, MMSE change was characterised by an accelerating rate of decline over increasing time (γ_{20} = -0.16, *p*<.001).

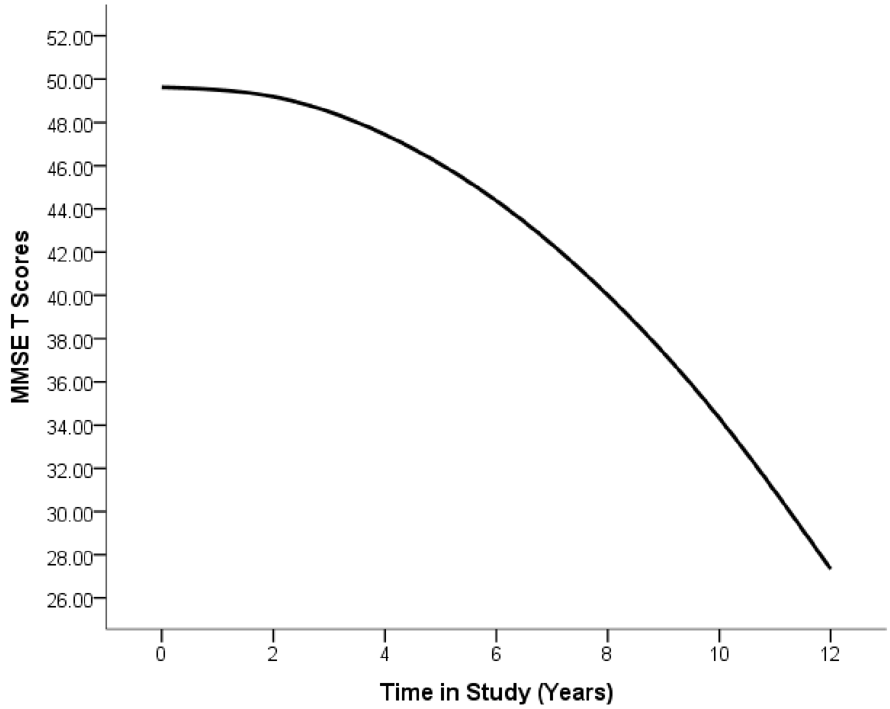

Figure 4.1. Predicted MMSE score change trajectory

The variance components in the unconditional quadratic growth model were significantly different from zero. With the indication that individual differences in MMSE score trajectories remained to be explained, occupational complexity was added to the unconditional growth model as a predictor of both initial level and change. Consistent with Gerstorf et al. (2013), models included the main effects of each predictor variable (covariates included) on the linear change trajectory and on the curvature of the average change trajectories (i.e., quadratic change).

4.3.2 Occupational complexity and MMSE

The unadjusted and adjusted associations of occupational complexity with level of, and change in, MMSE are presented next, followed by the modifying role of education, gender, and age at retirement, on the associations between occupational complexity and MMSE are presented.

Unadjusted associations of occupational complexity with MMSE

Model 1 examined the unadjusted associations of occupational complexity with levels of, and change in, MMSE. Parameter estimates produced by Model 1 are presented in Table 4.9. They show that higher complexity with data was associated with higher initial levels of MMSE performance (γ_{04} = 0.52), and a slower rate of MMSE decline (γ_{14} = 0.16). Higher complexity with people was associated with higher initial levels of MMSE performance (γ_{04} = 0.40), but not rates of MMSE decline. Higher complexity with things was associated with lower initial levels of MMSE performance (γ_{04} = 0.34), but not rates of MMSE decline. Pseudo R^2 revealed the occupational complexity variables explained only a small fraction of between-person variation in levels and rates of change. For example, occupational complexity with data explained 3.5% of variability in level and 5.1% of variability in change. Occupational complexity with people and things explained 1.5% and 1.3% of variability in level, respectively.

Table 4.9

Parameter Estimates from Multilevel Models Examining Occupational Complexity Predicting MMSE Performance and Change

	Model 1: OC		
	Data Est. (SE)	**People** Est. (SE)	**Things** Est. (SE)
Fixed Effects			
Intercept, γ_{00}	49.62 (0.23)***	49.62 (0.23)***	49.62 (0.23)*
Time, γ_{10}	0.10 (0.13)	0.11 (0.13)	0.11 (0.13)
Time^2, γ_{20}	-0.16 (0.01)***	-0.16 (0.01)***	-0.16 (0.01)***
OC, γ_{04}	0.52 (0.10)***	0.40 (0.10)***	-0.34 (0.09)***
Time×OC, γ_{14}	0.16 (0.05)**	-0.00 (0.06)	0.06 (0.05)
Time^2×OC, γ_{24}	-0.01 (0.01)	0.00 (0.01)	-0.00 (0.00)
Random Effects			
Residual, σ_ϵ^2	45.86 (1.93)***	45.93 (1.94)***	45.28 (1.89)***
Intercept, σ_0^2	45.77 (3.09)***	46.71 (3.12)***	46.78 (3.10)***
Time, σ_1^2	0.93 (0.22)***	0.98 (0.22)***	1.04 (0.22)***
Covariance, σ_{01}^2	6.53 (0.59)***	6.76 (0.60)***	6.98 (0.60)***
Goodness-of-fit			
-2LL	28068.02	28102.40	28100.03
AIC	28088.02	28122.40	28120.03
BIC	28150.46	28184.84	28182.48
Variance Explained: Between Person			
Level - Pseudo R_0^2	0.035	0.015	0.013
Slope - Pseudo R_1^2	0.051	0.000	-0.061[a]

Notes. Unstandardised estimates (Est.) and standard errors (SE) are presented. MMSE T scores standardised to the baseline sample (*M*=50, *SD*=10). Time: years since baseline. OC: Occupational complexity, higher scores indicate greater complexity. Data: Occupational complexity with data, grand mean centred (*M*=3.33). People: Occupational complexity with people, grand mean centred (*M*=1.26). Things: Occupational complexity with things, grand mean centred (*M*=2.36). -2LL = Deviance. AIC: Akaike information criterion. BIC: Bayesian information criterion. Pseudo R_0^2 = ($\sigma_{0\,\text{unconditional growth model}}^2 - \sigma_{0\,\text{conditional model}}^2$) / $\sigma_{0\,\text{unconditional growth model}}^2$). Pseudo R_1^2 = ($\sigma_{1\,\text{unconditional growth model}}^2 - \sigma_{1\,\text{conditional model}}^2$) / $\sigma_{1\,\text{unconditional growth model}}^2$). [a]Negative Pseudo R^2 values are due to a redistribution of variance between levels (Singer & Willett, 2003). *p<.05; p<.01; ***p<001.

Covariate adjusted associations of occupational complexity with MMSE

Model 2: Age, gender, and education

Model 2 examined the association of occupational complexity with levels of, and change in, MMSE adjusted for age, gender, and education. Parameter estimates produced by Model 2 are presented in Table 4.10. As expected, adjustment for covariates resulted in the main effects of occupational complexity on initial MMSE decreasing in magnitude by 11.5% for data, 17.5% for people, and 35.3% for things. However, each of the associations of occupational complexity with MMSE level remained significantly different from zero. The significant interaction between occupational complexity with data and linear time remained unchanged. Figure 4.2

shows the expected MMSE score trajectories for people who previously held occupations higher or lower in complexity with data, based on the parameter estimates from Model 2.

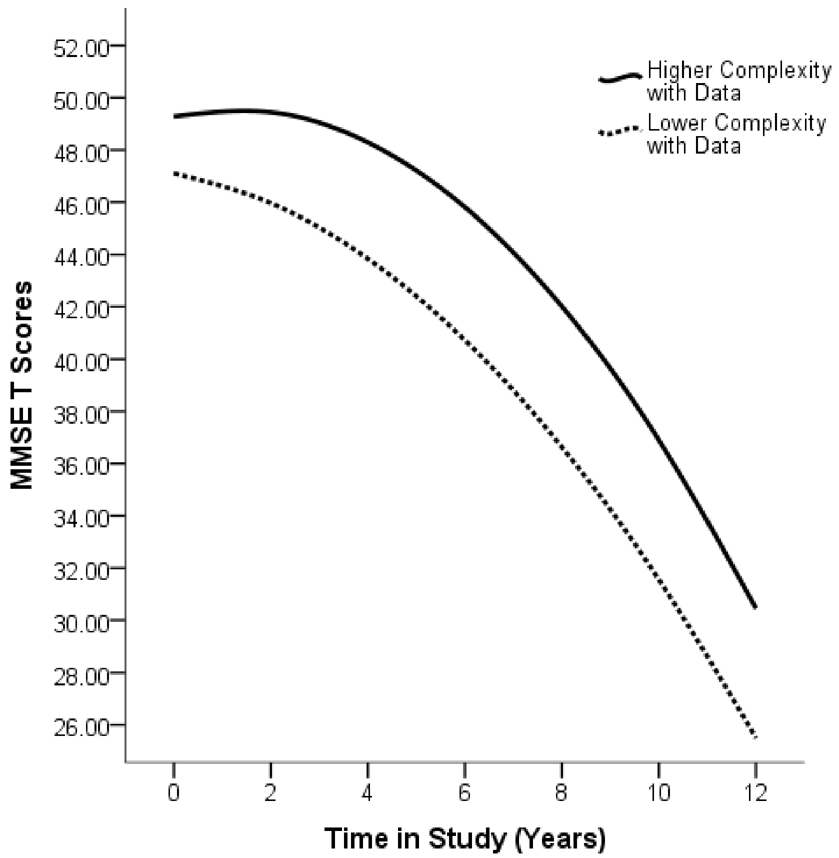

Figure 4.2. Predicted MMSE score trajectories by lower (-1SD) and higher (+1SD) occupational complexity with data

Parameter estimates for the other predictor variables show, as expected, that older age at baseline was associated with lower initial MMSE scores, a faster rate of decline over linear time, and a small deceleration in decline over increasing time. High levels of education were associated with higher initial MMSE scores, but not differential rates of decline. Gender was not associated with level of, or change in, MMSE. Inclusion of the covariates in Model 2 accounted for considerably more variance in levels (Pseudo R_0^2) and slopes (Pseudo R_1^2) than Model 1.

Table 4.10

Parameter Estimates from Multilevel Models Examining Occupational Complexity Predicting MMSE Performance and Change, and Adjusting for Age, Gender, and Education

Model 2: OC + Age + Gender + Education			
	Data **Est. (SE)**	**People** **Est. (SE)**	**Things** **Est. (SE)**
Fixed Effects			
Intercept, γ_{00}	48.20 (0.30)***	48.18 (0.31)***	48.22 (0.31)***
Time, γ_{10}	0.04 (0.19)	0.01 (0.19)	-0.05 (0.19)
Time^2, γ_{20}	-0.14 (0.02)***	-0.14 (0.02)***	-0.14 (0.02)***
Age, γ_{01}	-0.38 (0.03)***	-0.38 (0.03)***	-0.38 (0.03)***
Gender, γ_{02}	0.89 (0.46)	0.57 (0.46)	0.29 (0.47)
Edu, γ_{03}	2.72 (0.43)***	2.99 (0.43)**	3.08 (0.42)***
OC, γ_{04}	0.46 (0.09)***	0.33 (0.10)**	-0.22 (0.08)**
Time×Age, γ_{11}	-0.21 (0.02)***	-0.21 (0.02)***	-0.21 (0.02)***
Time×Gender, γ_{12}	-0.38 (0.26)	-0.49 (0.26)	-0.39 (0.27)
Time×Edu, γ_{13}	-0.13 (0.26)	0.02 (0.25)	0.10 (0.25)
Time×OC, γ_{14}	0.16 (0.05)**	0.03 (0.06)	0.07 (0.05)
Time^2×Age, γ_{21}	0.01 (0.00)***	0.01 (0.00)***	0.01 (0.00)***
Time^2×Gender, γ_{22}	0.03 (0.03)	0.04 (0.03)	0.03 (0.03)
Time^2×Edu, γ_{23}	-0.01 (0.03)	-0.02 (0.03)	-0.02 (0.03)
Time^2×OC, γ_{24}	-0.01 (0.01)	0.00 (0.01)	-0.00 (0.01)
Random Effects			
Residual, σ_{ϵ}^2	44.04 (1.79)***	43.96 (1.78)***	43.64 (1.76)***
Intercept, σ_0^2	32.20 (2.47)***	32.74 (2.48)***	32.91 (2.47)***
Time, σ_1^2	0.68 (0.19)**	0.72 (0.19)***	0.75 (0.19)***
Covariance, σ_{01}^2	4.68 (0.49)***	4.84 (0.49)***	4.96 (0.49)***
Goodness-of-fit			
-2LL	27728.77	27763.02	27771.53
AIC	27766.77	27801.02	27809.53
BIC	27885.41	27919.66	27928.17
Variance Explained: Between Person			
Level - Pseudo R_0^2	0.321	0.309	0.306
Slope - Pseudo R_1^2	0.306	0.265	0.235

Notes. Unstandardised estimates (Est.) and standard errors (SE) are presented. MMSE T scores standardised to the baseline sample (*M*=50, *SD*=10). Time: years since baseline. OC: Occupational complexity, higher scores indicate greater complexity. Data: Occupational complexity with data, grand mean centred (*M*=3.33). People: Occupational complexity with people, grand mean centred (*M*=1.26). Things: Occupational complexity with things, grand mean centred (*M*=2.36). Age: baseline age, grand mean centred at 78.71. Gender: 0=Male, 1=Female. Edu: Education, 0=Low, 1=High. Dashes indicate that effect was not estimated. -2LL = Deviance. AIC: Akaike information criterion. BIC: Bayesian information criterion. Pseudo R_0^2 = ($\sigma^2_{0\ \text{unconditional growth model}} - \sigma^2_{0\ \text{conditional model}}$) / $\sigma^2_{0\ \text{unconditional growth model}}$). Pseudo R_1^2 = ($\sigma^2_{1\ \text{unconditional growth model}} - \sigma^2_{1\ \text{conditional model}}$) / $\sigma^2_{1\ \text{unconditional growth model}}$). *$p$<.05; p<.01; ***p<001.

Occupational complexity is the key predictor variable and this thesis' main aim is to evaluate the full spectrum of its effects. So, despite the non-significant results for some terms, they were retained in all subsequent models. In this way, the controlled association of occupational complexity with cognitive ageing is interpreted based on relations with an index of the overall rate of change during the data collection period (Gerstorf et al., 2013; Piccinin et al., 2013). Also, retaining the terms ensured consistency across models and the two studies (Study 1 and Study 2)

Model 2A: Age at retirement

To control for the influence of retirement timing and retirement duration (i.e., time since age at retirement) on cognitive ageing, age at retirement was added to Model 2 as a predictor of both initial status and rates of change. The parameter estimates for Model 2A are presented in Table 4.11. The associations between occupational complexity with data, people, and things, and MMSE remained unchanged with the addition of age at retirement, suggesting that the associations of occupational complexity with MMSE are independent of retirement timing and retirement duration. Furthermore, age at retirement was not a significant predictor of levels of MMSE, or rates of MMSE change, suggesting that retirement timing and retirement duration did not impact on cognitive ageing at the global level.

Table 4.11

Parameter Estimates from Multilevel Models Examining Occupational Complexity Predicting MMSE Performance and Change, and Adjusting for Age at Retirement

Model 2 + Age at Retirement			
	Data **Est. (SE)**	**People** **Est. (SE)**	**Things** **Est. (SE)**
Fixed Effects			
Intercept, γ_{00}	48.27 (0.31)***	48.25 (0.31)***	48.29 (0.31)***
Time, γ_{10}	0.06 (0.19)	0.03 (0.19)	-0.04 (0.19)
Time^2, γ_{20}	-0.14 (0.02)***	-0.14 (0.01)***	-0.14 (0.02)***
Age, γ_{01}	-0.36 (0.04)***	-0.36 (0.04)***	-0.36 (0.04)***
Gender, γ_{02}	0.66 (0.48)	0.32 (0.48)	0.06 (0.50)
Edu, γ_{03}	2.71 (0.43)***	2.98 (0.43)***	3.08 (0.42)***
OC, γ_{04}	0.47 (0.09)***	0.34 (0.10)***	-0.22 (0.08)**
RA, γ_{05}	-0.06 (0.04)	-0.06 (0.04)	-0.06 (0.04)
Time×Age, γ_{11}	-0.21 (0.02)***	-0.21 (0.02)***	-0.21 (0.02)***
Time×Gender, γ_{12}	-0.42 (0.28)	-0.54 (0.28)	-0.42 (0.28)
Time×Edu, γ_{13}	-0.13 (0.26)	0.02 (0.25)	0.10 (0.25)
Time×OC, γ_{14}	0.16 (0.05)**	0.03 (0.06)	0.07 (0.05)
Time×RA, γ_{15}	-0.01 (0.02)	-0.01 (0.02)	-0.01 (0.02)
Time^2×Age, γ_{21}	0.01 (0.00)***	0.01 (0.00)***	0.01 (0.00)***
Time^2×Gender, γ_{22}	0.03 (0.03)	0.04 (0.03)	0.03 (0.03)
Time^2×Edu, γ_{23}	-0.01 (0.03)	-0.02 (0.03)	-0.02 (0.03)
Time^2×OC, γ_{24}	-0.01 (0.01)	0.00 (0.01)	-0.00 (0.01)
Time^2×RA, γ_{25}	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Random Effects			
Residual, σ_ϵ^2	44.02 (1.79)***	42.96 (1.79)***	43.63 (1.76)***
Intercept, σ_0^2	32.10 (2.46)***	32.64 (2.48)***	32.82 (2.46)***
Time, σ_1^2	0.68 (0.19)***	0.71 (0.19)***	0.75 (0.19)***
Covariance, σ_{01}^2	4.67 (0.49)***	4.83 (0.49)***	4.95 (0.49)***
Goodness-of-fit			
-2LL	27725.26	27759.33	27768.67
AIC	27769.26	27803.33	27812.67
BIC	27906.63	27940.70	27950.04

Notes. Unstandardised estimates (Est.) and standard errors (SE) are presented. MMSE T scores standardised to the baseline sample (*M*=50, *SD*=10). Time: years since baseline. OC: Occupational complexity, higher scores indicate greater complexity. Data: Occupational complexity with data, grand mean centred (*M*=3.33). People: Occupational complexity with people, grand mean centred (*M*=1.26). Things: Occupational complexity with things, grand mean centred (*M*=2.36). Age: baseline age, grand mean centred at 78.71. Gender: 0=Male, 1=Female. Edu: Education, 0=Low, 1=High. RA: Age at retirement, grand mean centred at 61.75. -2LL = Deviance. AIC: Akaike information criterion. BIC: Bayesian information criterion. *p<.05; p<.01; **p<001.

Model 2B: Occupational status

To control for the possible influences of the socio-economic aspects of occupations on cognitive ageing, occupational status was added to Model 2 as a predictor of both initial status and rates of change. The parameter estimates for Model 2B are presented in Table 4.12. The findings are interpreted with reference to the high correlations (refer to Table 4.7) observed between occupational status and occupational complexity with data (ρ = .614, p<.001) and things (ρ = -.519, p<.001).

Controlling for age, gender, education, and occupational status, the main effect of occupational complexity with data on MMSE scores remained significant, but the magnitude of the association was reduced by 46 per cent. Controlling for occupational status, the significant main effects of occupational complexity with people and things on MMSE scores were reduced to non-significance. After additional control for occupational status, higher occupational complexity with data was not a significant predictor of MMSE change, however complexity with things was associated with 0.15 *T score* units per year less decline in MMSE scores over linear time.

Occupational status was a significant predictor of level of MMSE, and rates of MMSE change. Controlling for complexity with data, higher occupational status was associated with higher initial MMSE scores (γ_{05} = 1.64), but not differential rates of MMSE change. Controlling for complexity with people or things, high occupational status was associated with slower MMSE decline over linear time and acceleration in decline over increasing time.

Table 4.12

Parameter Estimates from Multilevel Models Examining Occupational Complexity Predicting MMSE Performance and Change, and Adjusting for Occupational Status

	Model 2 + Occupational Status		
	Data Est. (SE)	**People** Est. (SE)	**Things** Est. (SE)
Fixed Effects			
Intercept, γ_{00}	47.72 (0.34)***	47.58 (0.33)*	47.48 (0.35)
Time, γ_{10}	-0.06 (0.21)	-0.18 (0.20)	-0.35 (0.21)
Time^2, γ_{20}	-0.13 (0.02)***	-0.13 (0.02)***	-0.12 (0.02)**
Age, γ_{01}	-0.38 (0.03)***	-0.39 (0.03)	-0.38 (0.03)
Gender, γ_{02}	0.60 (0.47)	0.37 (0.46)	0.33 (0.47)
Edu, γ_{03}	2.43 (0.44)***	2.44 (0.44)	2.48 (0.44)
OC, γ_{04}	0.26 (0.11)*	0.17 (0.10)	-0.04 (0.09)
OccStatus, γ_{05}	1.64 (0.55)**	2.14 (0.47)	2.33 (0.49)
Time×Age, γ_{11}	-0.21 (0.02)***	-0.21 (0.02)***	-0.21 (0.02)**
Time×Gender, γ_{12}	-0.43 (0.27)	-0.53 (0.26)	-0.36 (0.27)
Time×Edu, γ_{13}	-0.21 (0.26)	-0.19 (0.26)	-0.18 (0.26)
Time×OC, γ_{14}	0.11 (0.07)	-0.02 (0.06)	0.15 (0.05)*
Time×OccStatus, γ_{15}	0.37 (0.33)	0.71 (0.28)*	1.03 (0.29)*
Time^2×Age, γ_{21}	0.01 (0.00)***	0.01 (0.00)***	0.01 (0.00)**
Time^2×Gender, γ_{22}	0.03 (0.03)	0.04 (0.03)	0.03 (0.03)
Time^2×Edu, γ_{23}	0.00 (0.03)	0.00 (0.03)	0.00 (0.03)
Time^2×OC, γ_{24}	-0.00 (0.01)	0.01 (0.01)	-0.01 (0.01)
Time^2×OccStatus, γ_{25}	-0.04 (0.03)	-0.06 (0.03)*	-0.08 (0.03)*
Random Effects			
Residual, σ_{ϵ}^2	43.94 (1.78)***	43.97 (1.79)***	43.91 (1.78)***
Intercept, σ_0^2	31.77 (2.45)***	31.87 (2.46)***	32.04 (2.46)***
Time, σ_1^2	0.69 (0.19)***	0.70 (0.19)***	0.68 (0.18)***
Covariance, σ_{01}^2	4.67 (0.48)***	4.72 (0.48)***	4.68 (0.48)***
Goodness-of-fit			
-2LL	27716.20	27727.34	27720.99
AIC	27760.20	27771.34	27764.99
BIC	27897.57	27908.71	27902.36

Notes. Unstandardised estimates (Est.) and standard errors (SE) are presented. MMSE T scores standardised to the baseline sample (*M*=50, *SD*=10). Time: years since baseline. OC: Occupational complexity, higher scores indicate greater complexity. Data: Occupational complexity with data, grand mean centred (*M*=3.33). People: Occupational complexity with people, grand mean centred (*M*=1.26). Things: Occupational complexity with things, grand mean centred (*M*=2.36). Age: baseline age, grand mean centred at 78.71 years. Gender: 0=Male, 1=Female. Edu: Education, 0=Low, 1=High. OccStatus: Occupational Status, 0=bluecollar, 1=whitecollar. -2LL = Deviance. AIC: Akaike information criterion. BIC: Bayesian information criterion. *p<.05; **p<.01; ***p<.001.

Model 2C: Premorbid ability and current health

Model 2C added premorbid ability (as indicated by performance on the NART) as a level-2 predictor, and medical conditions and depression as level-1 predictors. The parameter estimates produced by Model 2C are presented in Table 4.13. After controlling for premorbid ability, and time varying measures of medical conditions and depression, occupational complexity with data was no longer a significant predictor of initial MMSE scores or rates of change in MMSE. Complexity with people and with things were no longer significant predictors of initial MMSE scores. However, higher complexity with things was associated with a marginally slower rate of cognitive decline over linear time (γ_{14} = 0.14, p = .041).

As expected, higher premorbid ability was associated with higher initial MMSE scores. However, given that premorbid ability and medical conditions did not predict change in MMSE, it appeared to be adjustment for depression that accounted for the prior association between occupational complexity with data and MMSE change.

Table 4.13

Parameter Estimates from Multilevel Models Examining Occupational Complexity Predicting MMSE Performance and Change, and Adjusting for Premorbid Ability, Medical Conditions, and Depression

Model 2 + NART + Medical Conditions + Depression			
	Data **Est. (SE)**	**People** **Est. (SE)**	**Things** **Est. (SE)**
Fixed Effects			
Intercept, γ_{00}	49.00 (0.45)***	49.01 (0.45)***	49.04 (0.45)***
Time, γ_{10}	-0.86 (0.27)***	-0.90 (0.27)**	-1.00 (0.27)***
Time^2, γ_{20}	0.04 (0.03)	0.04 (0.04)	0.05 (0.04)
Age, γ_{01}	-0.34 (0.04)***	-0.34 (0.04)***	-0.34 (0.04)***
Gender, γ_{02}	0.73 (0.50)	0.65 (0.49)	0.54 (0.51)
Edu, γ_{03}	1.57 (0.47)***	1.66 (0.47)***	1.63 (0.47)***
OC, γ_{04}	0.13 (0.10)	0.02 (0.10)	-0.07 (0.09)
NART, γ_{05}	0.30 (0.03)***	0.31 (0.03)***	0.31 (0.03)***
Time×Age, γ_{11}	-0.17 (0.03)***	-0.17 (0.03)***	-0.17 (0.03)***
Time×Gender, γ_{12}	-0.28 (0.38)	-0.38 (0.38)	-0.16 (0.39)
Time×Edu, γ_{13}	-0.68 (0.37)	-0.55 (0.37)	-0.46 (0.37)
Time×OC, γ_{14}	0.14 (0.08)	0.03 (0.08)	0.14 (0.07)*
Time×NART, γ_{15}	-0.03 (0.02)	-0.02 (0.02)	-0.01 (0.02)
Time^2×Age, γ_{21}	0.01 (0.00)**	0.01 (0.00)**	0.01 (0.00)**
Time^2×Gender, γ_{22}	0.02 (0.05)	0.02 (0.05)	0.00 (0.05)
Time^2×Edu, γ_{23}	0.05 (0.05)	0.04 (0.05)	0.04 (0.05)
Time^2×OC, γ_{24}	-0.01 (0.01)	-0.00 (0.01)	-0.01 (0.01)
Time^2×NART, γ_{25}	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
MedCdns	-0.15 (0.19)	-0.16 (0.19)	-0.16 (0.19)
CES-D	-0.14 (0.02)***	-0.14 (0.02)***	-0.14 (0.02)***
Random Effects			
Residual, σ_ϵ^2	37.62 (2.25)***	37.57 (2.26)***	37.40 (2.25)***
Intercept, σ_0^2	17.56 (2.70)***	17.68 (2.72)***	17.86 (2.72)***
Time, σ_1^2	0.56 (0.20)**	0.62 (0.21)**	0.62 (0.21)**
Covariance, σ_{01}^2	2.35 (0.57)***	2.39 (0.58)***	2.36 (0.58)***
Goodness-of-fit			
-2LL	16749.62	16767.42	16762.48
AIC	16797.62	16815.42	16810.48
BIC	16939.57	16954.37	16949.42

Notes. Data missing for the NART, medical conditions and depression, and this model is not nested in Model 2. Unstandardised estimates (Est.) and standard errors (SE) are presented. MMSE T scores standardised to the baseline sample (*M*=50, *SD*=10). Time: years since baseline. OC: Occupational complexity, higher scores indicate greater complexity. Data: Occupational complexity with data, grand mean centred (*M*=3.33). People: Occupational complexity with people, grand mean centred (*M*=1.26). Things: Occupational complexity with things, grand mean centred (*M*=2.36). Age: baseline age, grand mean centred at 78.71. Gender: 0=Male, 1=Female. Edu: Education, 0=Low, 1=High. NART: National Adult Reading Test, higher scores indicate better performance, grand mean centred at 27.89. MedCdns: Number of medical conditions, higher scores indicate more conditions. CES-D: Centre for Epidemiological Studies – Depression scale, centred at 16 (scores >16 correspond to the cutoff for depression). -2LL = Deviance. AIC: Akaike information criterion. BIC: Bayesian information criterion. *p<.05; **p<.01; ***p<.001.

Model 2D: Contributing Study

To assess whether the associations between occupational complexity and MMSE scores might be explained by systematic differences in sampling or the methods of the two contributing studies (i.e., the ALSA and the SOPS), contributing study was added to Model 2 as a predictor of initial status and rates of change. The estimates produced by Model 2D are presented in Table 4.14. They show that the SOPS was associated with lower initial MMSE scores, faster rates of decline over linear time, and a deceleration in decline over increasing time. After controlling for contributing study, occupational complexity with data remained a significant predictor of initial MMSE scores, but not differential rates of change in MMSE. Occupational complexity with people and things also remained significant predictors of initial MMSE scores.

Table 4.14

Parameter Estimates from Multilevel Models Examining Occupational Complexity Predicting MMSE Performance and Change, and Adjusting for Contributing Study

	Model 2 + Contributing Study		
	Data **Est. (SE)**	**People** **Est. (SE)**	**Things** **Est. (SE)**
Fixed Effects			
Intercept, γ_{00}	48.20 (0.34)***	48.26 (0.34)***	48.33 (0.35)***
Time, γ_{10}	0.97 (0.21)***	0.99 (0.21)***	0.95 (0.21)***
Time^2, γ_{20}	-0.21 (0.02)***	-0.21 (0.02)***	-0.21 (0.02)***
Age, γ_{01}	-0.39 (0.04)***	-0.39 (0.04)***	-0.38 (0.04)***
Gender, γ_{02}	0.93 (0.48)	0.64 (0.48)	0.36 (0.49)
Edu, γ_{03}	2.75 (0.45)***	3.00 (0.44)***	3.08 (0.44)***
OC, γ_{04}	0.44 (0.10)***	0.32 (0.10)**	-0.22 (0.09)**
Study, γ_{05}	-0.68 (0.53)	-1.05 (0.52)*	-1.13 (0.52)*
Time×Age, γ_{11}	-0.15 (0.02)***	-0.15 (0.02)***	-0.15 (0.02)***
Time×Gender, γ_{12}	-0.15 (0.26)	-0.20 (0.26)	-0.16 (0.27)
Time×Edu, γ_{13}	-0.19 (0.26)	-0.14 (0.25)	0.09 (0.25)
Time×OC, γ_{14}	0.08 (0.06)	0.04 (0.06)	0.03 (0.05)
Time×Study, γ_{15}	-2.89 (0.29)***	-2.95 (0.29)***	-2.94 (0.29)***
Time^2×Age, γ_{21}	0.01 (0.00)***	0.01 (0.00)***	0.01 (0.00)***
Time^2×Gender, γ_{22}	0.01 (0.03)	0.01 (0.03)	0.01 (0.03)
Time^2×Edu, γ_{23}	-0.00 (0.03)	-0.00 (0.03)	-0.00 (0.03)
Time^2×OC, γ_{24}	-0.00 (0.01)	-0.00 (0.01)	-0.00 (0.01)
Time^2×Study, γ_{25}	0.23 (0.03)***	0.23 (0.03)***	0.23 (0.03)***
Random Effects			
Residual, σ_ϵ^2	45.21 (1.89)***	45.28 (1.89)***	45.36 (1.91)***
Intercept, σ_0^2	36.87 (2.82)***	37.35 (2.84)***	37.47 (2.85)***
Time, σ_1^2	0.44 (0.18)*	0.44 (0.18)*	0.46 (0.18)*
Covariance, σ_{01}^2	4.02 (0.55)***	4.05 (0.56)***	4.13 (0.56)***
Goodness-of-fit			
-2LL	27571.17	27587.94	27597.22
AIC	27615.17	27631.94	27641.22
BIC	27752.53	27769.31	27778.59

Notes. Unstandardised estimates (Est.) and standard errors (SE) are presented. T scores standardised to the baseline sample (*M*=50, *SD*=10). Time: years since baseline. Data: Occupational complexity with data, grand mean centred (*M*=3.33). People: Occupational complexity with people, grand mean centred (*M*=1.26). Things: Occupational complexity with things, grand mean centred (*M*=2.36). OC: Occupational complexity, higher scores indicate greater complexity. Age: baseline age, grand mean centred at 78.71. Gender: 0=Male, 1=Female. Edu: Education, 0=Low, 1=High. Study: Contributing Study, 0=ALSA, 1=SOPS. -2LL = Deviance. AIC: Akaike information criterion. BIC: Bayesian information criterion. *p<.05; **p<.01; ***p<.001.

Model 3: Complexity with Data, People, and Things

Model 3 added all three occupational complexity variables into the same model and the parameter estimates produce by this model are presented in Table 4.15. After accounting for their shared variance, only occupational complexity with data remained a significant predictor of initial MMSE scores and rates of change in MMSE.

Table 4.15

Parameter Estimates from Multilevel Models Examining Occupational Complexity Involving Data, People, and Things Predicting MMSE Performance and Change

Model 3: Data + People + Things			
	Intercept Est. (SE)	**Linear Slope Est. (SE)**	**Quadratic Slope Est. (SE)**
Fixed Effects	48.34 (0.31)***	-0.01 (0.19)	-0.14 (0.02)***
Age	-0.39 (0.03)***	-0.21 (0.02)***	0.01 (0.00)***
Gender	0.60 (0.48)	-0.25 (0.27)	0.02 (0.03)
Edu	2.59 (0.43)***	-0.09 (0.26)	-0.01 (0.03)
Data	0.43 (0.10)***	0.16 (0.06)**	-0.01 (0.01)
People	0.06 (0.12)	-0.00 (0.07)	0.00 (0.01)
Things	-0.17 (0.09)	0.08 (0.06)	-0.00 (0.01)
Random Effects			
Residual variance	43.68 (1.77)***		
Variance	32.01 (2.45)***	0.70 (0.19)**	
Covariance	4.75 (0.49)***		
Goodness-of-fit			
-2LL	27720.77		
AIC	27770.77		
BIC	27926.87		

Notes. Unstandardised estimates (Est.) and standard errors (SE) are presented. MMSE T scores standardised to the baseline sample (*M*=50, *SD*=10). Time: years since baseline. Data: Occupational complexity with data, grand mean centred (*M*=3.33). People: Occupational complexity with people, grand mean centred (*M*=1.26). Things: Occupational complexity with things, grand mean centred (*M*=2.36). Age: baseline age, grand mean centred at 78.71. Gender: 0=Male, 1=Female. Edu: Education, 0=Low, 1=High. -2LL = Deviance. AIC: Akaike information criterion. BIC: Bayesian information criterion. *p<.05; **p<.01; ***p<.001.

Modifying role of education, gender, and age at retirement

As the relationships between occupational complexity and cognitive ageing may vary by education, gender, and age at retirement, Model 2 was repeated with terms to allow for interactions among occupational complexity (data, people, or things), the covariates (education or gender), and time (linear and quadratic). Model 2A was repeated with terms to allow for interactions among occupational complexity (data, people, or things), age at retirement, and time (linear and quadratic).

Relative model fit indices are provided in Table 4.16. Deviance-based tests (Δ-2LL = [-2LL $_{\text{Model 2}}$] – [-2LL $_{\text{Current model}}$]) revealed the associations of occupational complexity with MMSE change did not vary by education or gender. Deviance-based tests (Δ-2LL = [-2LL $_{\text{Model 2A}}$] – [-2LL $_{\text{Current model}}$]) also revealed the associations of occupational complexity with MMSE change did not vary by age at retirement. The data were also re-analysed using a gender mean-centred age at retirement variable. That is, age at retirement was centred at age 60 for females and age 65 for males. However, the results from those analyses did not differ from the presented results.

Table 4.16

Parameter Estimates from Multilevel Models Examining Occupational Complexity by Education, Gender, and Age at Retirement Predicting MMSE Performance and Change

	Model 2 + OC × Education			**Model 2 + OC × Gender**			**Model 2A + OC × Age at Retirement**		
	Data Est. (SE)	**People Est. (SE)**	**Things Est. (SE)**	**Data Est. (SE)**	**People Est. (SE)**	**Things Est. (SE)**	**Data Est. (SE)**	**People Est. (SE)**	**Things Est. (SE)**
Fixed Effects									
Intercept	48.16 (0.31)***	48.16 (0.31)***	48.19 (0.31)***	48.18 (0.31)*	48.18 (0.31)***	48.24 (0.31)***	48.27 (0.31)***	48.25 (0.31)***	48.29 (0.31)***
Time	0.05 (0.19)	0.01 (0.19)	-0.06 (0.19)	0.03 (0.19)	0.02 (0.19)	-0.05 (0.19)	0.06 (0.19)	0.03 (0.19)	-0.04 (0.19)
Time^2	-0.14 (0.02)***	-0.14 (0.02)***	-0.14 (0.02)***	-0.14 (0.02)***	-0.14 (0.02)***	-0.14 (0.02)***	-0.14 (0.02)***	-0.14 (0.02)***	-0.14 (0.02)***
Age	-0.38 (0.03)***	-0.38 (0.03)	-0.38 (0.03)***	-0.39 (0.03)***	-0.38 (0.03)***	-0.38 (0.03)***	-0.36 (0.04)***	-0.36 (0.04)***	-0.36 (0.04)***
Gender	0.90 (0.46)*	0.55 (0.46)	0.27 (0.47)	0.85 (0.46)	0.58 (0.46)	0.49 (0.50)	0.67 (0.48)	0.32 (0.48)	0.07 (0.49)
Edu	2.67 (0.43)***	3.00 (0.433)***	3.07 (0.42)***	2.73 (0.43)	3.00 (0.43)***	3.10 (0.42)***	2.71 (0.43)***	2.98 (0.43)***	3.08 (0.42)***
OC	0.38 (0.12)**	0.26 (0.16)	-0.13 (0.11)	0.51 (0.10)	0.36 (0.11)**	-0.27 (0.09)**	0.47 (0.09)***	0.34 (0.10)**	-0.22 (0.08)**
RA	–	–	–	–	–	–	-0.06 (0.04)	-0.07 (0.04)	-0.06 (0.04)
Covariate×OC	0.20 (0.19)	0.12 (0.20)	-0.20 (0.16)	-0.20 (0.21)	-0.10 (0.21)	0.25 (0.20)	-0.01 (0.01)	0.00 (0.02)	0.00 (0.01)
Time×Age	-0.21 (0.02)***	-0.21 (0.02)***	-0.21 (0.02)***	-0.21 (0.02)***	-0.21 (0.02)***	-0.21 (0.02)***	-0.21 (0.02)***	-0.21 (0.02)***	-0.21 (0.02)***
Time×Gender	-0.38 (0.26)	-0.49 (0.26)	-0.39 (0.27)	-0.37 (0.27)	-0.51 (0.26)	-0.49 (0.28)	-0.42 (0.28)	-0.53 (0.28)	-0.42 (0.28)
Time×Edu	-0.13 (0.26)	0.02 (0.25)	0.04 (0.25)	-0.113 (0.26)	-0.00 (0.25)	0.09 (0.25)	-0.13 (0.26)	0.02 (0.25)	0.10 (0.25)
Time×OC	0.16 (0.07)*	0.03 (0.10)	0.15 (0.07)*	0.16 (0.06)*	-0.03 (0.07)	0.10 (0.06)	0.16 (0.05)**	0.03 (0.06)	0.07 (0.05)
Time×RA	–	–	–	–	–	–	-0.01 (0.02)	-0.01 (0.02)	-0.01 (0.02)
Time×Covariate×OC	-0.02 (0.11)	-0.01 (0.12)	-0.18 (0.10)	0.00 (0.12)	0.19 (0.12)	-0.13 (0.11)	-0.00 (0.01)	-0.02 (0.01)	0.00 (0.01)
Time^2×Age	0.01 (0.00)***	0.01 (0.00)***	0.01 (0.00)***	0.01 (0.00)***	0.01 (0.00)***	0.01 (0.00)***	0.01 (0.00)***	0.01 (0.00)***	0.01 (0.00)***
Time^2×Gender	0.03 (0.03)	0.04 (0.03)	0.03 (0.03)	0.03 (0.03)	0.04 (0.03)	0.04 (0.03)	0.03 (0.03)	0.04 (0.03)	0.03 (0.03)
Time^2×Edu	-0.01 (0.03)	-0.02 (0.03)	-0.01 (0.03)	-0.01 (0.03)	-0.01 (0.03)	-0.02 (0.03)	-0.01 (0.03)	-0.02 (0.03)	-0.02 (0.03)
Time^2×OC	-0.01 (0.01)	-0.00 (0.01)	-0.01 (0.01)	-0.01 (0.01)	0.01 (0.01)	-0.01 (0.01)	-0.01 (0.01)	0.00 (0.01)	-0.01 (0.01)
Time^2×RA	–	–	–	–	–	–	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Time^2×Covariate×OC	-0.00 (0.00)	0.01 (0.01)	0.02 (0.01)	0.01 (0.01)	-0.01 (0.01)	0.01 (0.01)	0.00 (0.00)	0.00 (0.00)	-0.00 (0.00)
Random Effects									
Residual, σ_ϵ^2	44.00 (1.78)***	43.96 (1.78)***	43.64 (1.76)***	44.07 (1.79)***	43.95 (1.78)***	43.60 (1.76)***	44.06 (1.79)***	43.98 (1.79)***	43.65 (1.76)***
Intercept, σ_0^2	32.18 (2.46)***	32.75 (2.48)***	32.80 (2.46)***	32.23 (2.47)***	32.75 (2.48)***	32.84 (2.46)***	32.12 (2.47)***	32.73 (2.48)***	32.84 (2.47)***
Time, σ_1^2	0.68 (0.19)***	0.72 (0.19)***	0.74 (0.19)***	0.67 (0.19)***	0.71 (0.19)***	0.75 (0.19)***	0.67 (0.19)***	0.71 (0.19)***	0.74 (0.19)***
Covariance, σ_{01}^2	4.69 (0.48)***	4.84 (0.49)***	4.93 (0.49)***	4.66 (0.48)***	4.82 (0.49)***	4.96 (0.49)***	4.66 (0.49)***	4.81 (0.49)***	4.94 (0.49)***

Goodness-of-fit									
-2LL	27727.62	27762.40	27764.58	27725.81	27760.04	27769.54	27724.37	27755.48	27767.32
Δ-2LL (df=3)	1.15	0.62	6.95	2.96	2.98	1.99	0.89	3.85	1.35
AIC	27771.62	27806.40	27808.58	27769.81	27804.04	27813.54	27774.37	27805.48	27817.32
BIC	27908.99	27943.77	27945.95	27907.18	27941.41	27950.91	27930.48	27961.58	27973.42

Notes. Unstandardised estimates (Est.) and standard errors (SE) are presented. MMSE T scores standardised to the baseline sample (*M*=50, *SD*=10). Time: years since baseline. OC: Occupational complexity, higher scores indicate greater complexity. Data: Occupational complexity with data, grand mean centred (*M*=3.33). People: Occupational complexity with people, grand mean centred (*M*=1.26). Things: Occupational complexity with things, grand mean centred (*M*=2.36). Age: baseline age, grand mean centred at 78.71. Gender: 0=Male, 1=Female. Edu: Education, 0=Low, 1=High. RA: Age at retirement, grand mean centred (*M*=61.75). -2LL = Deviance. Δ-2LL = [-2LL simpler model] – [-2LL current model]. AIC: Akaike information criterion. BIC: Bayesian information criterion. Dashes indicate parameter was not estimated. $^*p<.05$; $^{**}p<.01$; $^{***}p<001$. .

4.4 Discussion

The present study contributes novel findings on the long-term associations between occupational complexity and general cognitive ability. To date, only two longitudinal studies (Gow, Avlund, et al., 2012; Potter et al., 2006) have examined whether and how cognitively stimulating occupational demands predict general cognitive ability in later life. Three cross-sectional studies (Andel et al., 2007; Correa Ribeiro et al., 2013; Potter et al., 2008) have examined the relations of occupational complexity with cognitive status as measured by the MMSE or the Telephone Interview for Cognitive Status (TICS). The results are presented by complexity type (i.e., data, people, and, things) and interpreted in the context of these prior studies. Given Study 1 and Study 2 have equivalent research aims, a theoretical interpretation of the main findings, and practical implications, are presented in the general discussion chapter (Chapter 6).

4.4.1 Occupational complexity with data

In a population-based sample of older retired Australians, people who previously held occupations involving higher levels of complexity with data had higher initial levels of general cognitive ability compared to people who previously held occupations lower in complexity, and the advantage was maintained over an 11 year period. The association was robust when considered in light of differences in age, gender, education (Model A), retirement timing and duration (Model 2A), occupational status (Model 2B), and complexity with people and things (Model 3).

The finding that higher occupational complexity with data was associated with higher levels of MMSE independent of occupational status is consistent with previous studies. For example, in a cross-sectional study Andel et al. (2007) reported only complexity of work with data was associated with MMSE performance above and beyond age, gender, childhood socioeconomic status, education, and adult socioeconomic status. Gow, Avlund, et al. (2012) also reported intellectually challenging jobs were associated with higher levels of, but not rates of change in a cognitive ability composite in analyses adjusting for age, gender, education, and social class. Thus, cognitive stimulation afforded by complex occupational activity appears to be uniquely associated with cognitive functioning in later life.

The association between occupational complexity and MMSE performance was attenuated by the NART, an index of premorbid ability. In the present study, premorbid ability was assessed when the sample was aged 79 years, on average, and was used in analyses to limit any possible bias from including data from people with dementia. The NART requires people to pronounce irregular words, for example *superfluous*, and presumably, to be able to pronounce this word correctly, people must have encountered it previously. Thus, the NART is a test of crystallized ability and performances on the NART are determined predominantly by exposures to a varied and enriched lifestyle. Indeed, Richards and Sacker (2003) showed that the NART was associated with a number of contextual factors across the life course. If the NART can be taken as a valid indicator of prior ability, then the results in the current study suggest that people with higher cognitive ability are more likely to engage in occupations with higher levels of complexity. However, it would be hazardous to draw inferences about the relative associations of prior ability and occupational complexity with age-related cognitive decline when prior ability is measured by the NART and in late old age.

Early results were suggestive of differential preservation by showing that higher complexity with data was associated with slower rates of cognitive decline, independent of age, gender, and education. However, later models showed that this finding could be explained by current symptoms of depression and systematic differences between the ALSA and the SOPS. The present study sample included data from WWII veterans and widows, indeed the SOPS sample was drawn, in part, from lists of WWII veterans and widows. War veterans may be more likely to experience mental or physical health problems as a consequence of their war time experiences and some evidence suggests that depression is a risk factor for cognitive decline in old age. For example, using bivariate dual change score models and data from the ALSA, Bielak et al. (2011) showed that depressive symptoms predicted subsequent change in perceptual speed, whereas perceptual speed did not reliably predict change in depressive symptoms. The relationships also held when Bielak et al. excluded data from people who scored less than 24 on the MMSE at any assessment occasion, suggesting that their findings were not biased by the inclusion of data from people with dementia. Also, the employment opportunities for war veterans may have differed between Sydney and Adelaide. Consequently, the interrelationships between war experiences, employment opportunities, and health, may have resulted in a spurious association between occupational complexity with data and cognitive change.

Previously, in a sample of WWII male-twin veterans, Potter et al. (2006) showed general intellectual demands to be associated with stability in general cognitive ability over a 7-year period in models adjusted for depression. However, they measured change aggregated over two time intervals and also included baseline cognition scores as a covariate and these approaches to modelling change have been shown to generate biased estimates (e.g., Glymour, Weuve, Berkman, Kawachi, & Robins, 2005). Thus, the inconsistent findings between the current study and the study by Potter and colleagues might be attributed to methodological differences.

Although premorbid ability was examined as a covariate and the results showed that premorbid ability was not associated with rates of cognitive decline, it is plausible that the findings were biased by the inclusion of data from people with pre-clinical dementia. As elucidated by Sliwinski et al. (1996), the presence of people with pre-clinical dementia in normal samples can increase variability in cognitive outcomes and lead to overestimates of the associations between a predictor variable and cognition. For example, in six parallel studies on the associations between education and MMSE change, (Piccinin et al., 2013) found a significant education by time interaction in only one study. When they excluded data from “demented and dementing individuals” (p. 385) from that study in additional analyses, the interaction was reduced to non-significance. If the present study included data from people with pre-clinical dementia then greater MMSE score variability may have resulted, leading to an increased chance of observing an association between occupational complexity and cognitive change.

In sum, occupational complexity with data was associated with higher levels of cognition and slower rates of cognitive decline, in models adjusted for age, gender, education, and age at retirement. However, the associations were accounted for by premorbid ability, current symptoms depression, and differences between the two contributing studies. It appears that when occupational activity occurs sometime in the past, and when other intervening or more proximal factors may impinge on cognitive performance or change, the associations of occupational complexity on cognitive functioning may be washed out.

4.4.2 Occupational complexity with people

Initial findings showing a positive association between occupational complexity with people and MMSE performance were accounted for by differences in occupational status (Model 2B), current symptoms of depression and premorbid ability (Model 2C), and complexity with data (Model 3).

The finding that complexity with people was not robustly associated with MMSE performance is consistent with cross-sectional studies of normal ageing (e.g., Andel et al., 2007; Correa Ribeiro et al., 2013). The results in this study suggest that the association between occupational complexity with people and general cognitive ability might stem from its relations to complexity with data, and to other socio-economic or lifestyle factors.

The present study is the only study to have examined the associations of occupational complexity involving data, people, and things with MMSE change. One other longitudinal study (Finkel et al., 2009) found robust, positive associations only between complexity with people and levels of cognitive function. However, that study measured cognition in multiple domains. Therefore, the null findings in the current study in relation to complexity with people might be due to the choice of cognitive outcome measure. This idea is addressed in the next study.

4.4.3 Occupational complexity with things

The findings in relation to complexity with things were mixed. Higher occupational complexity with things was associated with lower levels of MMSE, but not with differential rates of MMSE change when controlling for age, gender, and education (Model 2). However, after additionally controlling for occupational status (Model 2B), and premorbid ability and current symptoms of depression (Model 2C), higher occupational complexity with things with associated with a slower rate of MMSE decline (but not with initial MMSE scores).

Occupations in the Australian CCLO that are rated at higher levels of complexity with things (e.g., engineers, architects, farm managers, radio communication operators) also tend to be rated at the highest levels of complexity with data. Thus, it may be that that when that component of complexity with things that operates negatively on cognition, perhaps the physical hazards of working with machines, is statistically removed by the inclusion of occupational status, that complexity with things reveals a positive relationship with cognition. Thus, some of the equivocal nature of the extant results in relation to complexity with things may stem from differences in the actual work profiles of the samples studied. This might also imply a possible non-linear relationship for complexity involving things and cognition. The highest levels of complexity with things may be related to better cognition, but at the lower levels (as captured to a greater degree in this study) the relationship may be negative. However, this interpretation breaks down somewhat when it is considered that no participant in the present study held an occupation at the highest levels of complexity with things (i.e., precision working [7] and setting-up [8]: refer to Table 4.3). Furthermore, Correa Ribeiro et al. (2013) found a positive association between *intermediate* levels of complexity with things and cognition, but no association between high levels of complexity with things and cognition. Another alternative and parsimonious explanation for the equivocal results in this and previous studies, is that the cognitive challenge involved in working with machines, tool, and work aids, is not measured reliably in the US DOT (refer to Chapter 3).

4.4.4 Education, gender, and age at retirement

The associations between occupational complexity and MMSE change trajectories did not differ by education. This is consistent with Potter et al. (2008). Although, Potter and colleagues also reported that the cross-sectional association of higher general intellectual demands with general cognitive ability was greater for men who had lower levels of intellectual aptitude in early adulthood. This might suggest that among older cohorts, education is less adequate as a proxy measure for cognitive ability in early life. It may be that educational achievements in the first half of last century were not sufficiently determined by intellectual aptitudes, perhaps because they played a lesser role in determining future career prospects then, they do in current times (Australian Human Rights Commission, 2012; Broom et al., 1976). A more direct measure of cognitive ability in earlier life may have produced different results in this thesis. Nevertheless, the current study's findings add further support to the notion that the associations between occupational complexity and cognition function in late life reflect the persistence of long-term individual differences in cognitive ability.

Occupations and labour markets tend to be gender segregated, and the degree of the segregation was considerable during the period when the participants in the DYNOPTA were economically active. This is evidenced to a certain extent in the current study by the finding that men held occupations higher in complexity with data whilst women held occupations higher in complexity with people (refer to Section 4.2) and that men retired at later ages than did women. Thus, it might have been assumed that males would have an advantage over females in accruing cognitive reserve from work-related activity. However, consistent with the findings from previous studies, the present study found similar associations between occupational complexity and cognitive function for males and females (Gow, Avlund, et al., 2012; Karp et al., 2009).

Motivated largely by the findings of Gow, Avlund, et al. (2012) the role of retirement timing in modifying associations between occupational activity and general cognitive ability were also explored. Gow, Avlund, et al. reported a positive association between intellectually challenging jobs and cognitive ability at baseline was reversed when they controlled for ability assessed 10 years earlier. They suggested their finding might be explained by the earlier retirement of people in more complex occupations. The present study found no evidence to support this proposition. However, in the present study, the sample had been retired on average 17 years at baseline, and previous evidence (e.g., Bonsang et al., 2012) suggests that the detrimental effect of retirement on cognitive function, whilst not instantaneous, tends to occur in the early stages of retirement. So, perhaps too much time had elapsed to capture potentially more proximal losses in ability that could accompany the immediate post-retirement years.

4.4.5 Strengths and limitations

This study has a number of strengths. Firstly, non-linear cognitive change was able to be examined because four waves of data were used. Secondly, the larger sample of the DYNOPTA afforded statistical power for examining the vast number of cross-product interactions terms in this study (Aguinis et al., 2005; Anstey, Byles, et al., 2010). Taken together, these methodological attributes have provided a comprehensive initial look at occupational complexity as a possible explanation for individual differences in cognitive performance and change.

The results should be interpreted in the context of a number of limitations. The main limitation in Study 1, which is addressed in Study 2, relates to the choice of cognitive outcome measure. The MMSE was developed as a screening tool for dementia. Consequently, the MMSE is not a very sensitive measure of age-associated cognitive decline, and the decline that is evidence by the MMSE may represent underestimates of true declines. Also, performances on the MMSE might be biased by the environment in which the test is taken, or by the mood of the individual at the time the test is taken. Additionally, small mistakes on the MMSE, such as forgetting the date, may not be indicative of true cognitive decline. Finally, the MMSE does not assess specific cognitive domains in detail, so it cannot be used to measure domain specific cognitive decline. Thus, subtle associations between occupational complexity and cognition may not have been detected in this study. Study 2 addresses this limitation by assessing cognition across domains and using more sensitive measures of age-associated cognitive decline.

Other limitations in this study concern a lack of effective control for prior ability, selective longitudinal attrition, and possible measurement error in relation to the complexity ratings. Also a more sensitive measure of cognitive effort over an individual's career might have provided richer insights. As these issues apply to both Study 1 and Study 2 they are discussed in detail in the general discussion chapter (Chapter 6).

4.4.6 Conclusion

In conclusion, the associations between occupational complexity and cognitive ageing showed the pattern predicted by preserved differentiation. The results suggest that people with higher levels of cognitive ability select, or are placed by employers, into occupations with higher levels of complexity and the higher average level of cognitive ability is maintained over time. Study 2 further examines the associations between previous occupational complexity and normal cognitive ageing using more sensitive tests of age-related cognitive decline and controlling for additional correlates of normal cognitive ageing.

CHAPTER 5: OCCUPATIONAL COMPLEXITY, PHYSICAL JOB DEMANDS AND COGNITIVE AGEING: 11-YEAR EVIDENCE FROM THE ALSA

5.1 Overview of Study 2

The aim in Study 2 is to examine whether and how complex occupational demands and physical job demands are associated with performances and changes in processing speed, episodic memory, and crystallized ability, using longitudinal data from the ALSA. Whether the associations between the occupational activity demands and cognitive ageing (a) differ by education, gender, and age at the time of retirement, and (b) hold when the influence of age, gender, education, age at time of retirement, occupational status, medical conditions, smoking status, alcohol consumption, as well as time-varying measures of depression and activity engagement (cognitive, social, and physical) are statistically controlled, are also explored.

As per Study 1, the expectation is that higher occupational complexity will be related to slower rates of cognitive decline. As the literature on occupational physical activity is equivocal, no specific expectations are held about whether and how physical job demands might be associated with cognitive change.

5.2 Method

In this section the methodology is presented. The ALSA is described first, then the sample and measures selected from the ALSA are defined. The statistical procedure and the preparation of the data are also outlined.

5.2.1 Procedure

The ALSA is an ongoing population based study of ageing (Luszcz et al., 2007). The ALSA commenced in 1992 and is conducted by the Flinders Centre for Ageing Studies in South Australia. Ethical approval for the ALSA was obtained from the Clinical Investigation Committee of Flinders Medical Centre in South Australia and informed consent was given by each participant in the study.

The primary ALSA sample was randomly drawn from the South Australian electoral roll (Hugo, Healy, & Luszcz, 1987). Potential participants included those aged 70 years or older who lived in either the community or residential care, in metropolitan South Australia (Luszcz et al., 2007). To compensate for the expected higher mortality rates among males and the very old (i.e., people aged 85 plus), individuals in these groups were over-sampled (Luszcz et al., 2007). Of the 2,703 South Australians who were eligible for inclusion in the sample, 1,477 (55%) volunteered to be interviewed. In addition, individuals aged over 65 who were residing with the primary participants were invited to participate. From this source, an additional 610 individuals (including 565 spouses of primary participants) were added to the sample (Luszcz et al., 2007). In sum, the Wave 1 (Baseline) ALSA sample comprised 2,087 individuals, aged between 65 and 103 years (M = 78.16, SD = 6.69). Approximately half of the sample was female (49.4%).

Study 2 uses four waves of ALSA data, collected at Wave 1 (Baseline), Wave 3, Wave 6, and Wave 7. These waves provided the necessary cognitive data and they also contributed data to the DYNOPTA dataset. A brief summary of the ALSA timeline, mean age of participants, and response rates at the relevant waves is presented in Table 5.1. Baseline assessment took place in between September 1992 and March 1993. The Wave 3, 6, and 7 assessments took place approximately 2, 8 and 11 years, respectively, after baseline. Comprising an extensive face-to-face interview conducted in the participants' place of residence, the baseline assessment collected information on occupation and retirement (Luszcz et al., 2007). Cognitive data were collected during the clinical assessments, which were conducted approximately two weeks after the home interview by graduates who received special training in the standard administration of all instruments (Anstey et al., 2003; Luszcz et al., 2007). By Wave 7, 58% of the baseline participants were deceased.

Table 5.1

Summary of the ALSA Waves 1, 3, 6, 7

Wave	Year	Mean Age (SD)	Interview Response Rate for Eligible %	Response (n)	Clinical Response Rate for Eligible %	Response (n)	Confirmed Deceased since Baseline
1	1992	78.2 (6.7)		2087	77.19	1611	
3	1994	79.6 (6.5)	93.07	1679	84.75	1423	210
6	2000	83.6 (5.6)	74.13	791	66.62	527	926
7	2003	84.9 (4.9)	74.35	486	81.11	395	1218

Notes. Eligible means survivors. Source: Luszcz et al. (2007)

5.2.2 Sample

Participants were included in the sample if they provided valid data on all five occupational activity demand measures (complexity with data, people, things, and movement- and strength-related job demands) and self-reported at baseline they were completely retired from the labour force. Also, to maintain consistency across analyses, participants were included if they contributed data for at least one cognitive measure for at least one time point (Bielak, Gerstorf, et al., 2014). At baseline, 1,422 (980 males, 442 females) participants provided data on all the occupational measures. Of those, 1,341 (980 males, 442 females) participants contributed data for at least one cognitive measure and 1,381 (964 males, 417 females) participants indicated they were retired. Self-reported age at retirement ranged from 40 years to 85 years for males (M = 63.61; SD = 5.02) and from 20 to 85 years for females (M = 56.65; SD = 10.99). Some 31 female participants were excluded from the sample because they had retired before age 40; consistent with Study 1. Overall, 1,276 (912 males, 364 females) participants met the requirements for inclusion in this study.

With an interest in normal cognitive ageing, data from people who scored less than 24 on the MMSE at any occasion were excluded (e.g., Anstey et al., 2003; Bielak, Gerstorf, et al., 2014; Folstein et al., 1985; Luszcz et al., 1997). The MMSE is a screening tool for cognitive impairment and "the cutoff of 23/24 for probable dementia is widely recommended and has been validated in studies of the sensitivity and specificity of the MMSE" (Anstey, Burns, et al., 2010, p. 3). Screening eliminated data from 217 (158 males, 59 females) participants. The final sample (n = 1,059), representing 50.7% of the total baseline sample, had a mean follow-up length of 7.06 years (SD = 3.62; range 0 - 13 years) and 71.2% are male (n = 754). The final sample also provided complete baseline data for the covariates.

Sample selectivity analysis

To address questions of selectivity, the study sample was compared with the residual (n = 1,028) participants from the total ALSA sample on some of the covariate measures and the cognitive outcome measures at baseline. Independent samples t tests were used for group comparisons on continuous variables and chi-square (χ^2) tests were used for categorical variables. Descriptive statistics are presented in Table 5.2. In relation to the study covariates, included participants were younger (d = 0.19), more likely to be male (d = 0.92), and to have more years of schooling (d = 0.16). Additionally, included participants were more likely to have remained in the ALSA for longer (d = 0.09). In relation to the cognitive outcome measures, selectivity analyses showed that included participants were more likely to have performed better on perceptual speed (d = 0.23) and verbal reasoning (d = 0.17). Differences were not found in memory scores.

Gender differences between the study sample and the residual ALSA participants are large. The maleness of the sample is consistent with the gender composition of the labour market prior to the 1960s. For example, females made up just 18% and 19% of the total workforce in 1933 and 1947, respectively. By 1966 they made up 25% of the workforce (Broom et al., 1976).

Table 5.2

Baseline Descriptive Statistics for Sample Selectivity Analyses

	Included (*n* = 1059)	**Excluded[a]**	**Test statistic, *p* value**
Age, M (SD)	78.09 (6.18)	79.34 (7.11)	*t*(2027.03) = -4.28, *p*=.000
Male, n (%)	754 (71.2)	302 (29.4)	χ^2(1, 2087) = 363.33, *p*= .000
Left school ≤ age 14 years, n (%)	554 (52.3)	602 (60.0)	χ^2(1, 2061) = 12.11, *p*=.001
Medical Conditions, M (SD)	1.58 (1.18)	1.49 (1.23)	*t*(2085) = 1.59, *p*=.113
CES-D ≥ 16	97 (9.2)	183 (18.2)	χ^2(1, 2064) = 35.68, *p*=.000
Smoking Status, n (%)			
Never	414 (39.1)	604 (59.9)	χ^2(2, 2068) = 93.86, *p*=.000
Former	550 (51.9)	324 (32.1)	
Current	95 (9.0)	81 (8.0)	
Alcohol Consumption, n (%)			
Abstain.	323 (30.5)	451 (44.8)	χ^2(2, 2066) = 47.97, *p*=.000
≤ 2 standard drinks	576 (54.4)	457 (45.4)	
>2 standard drinks	160 (15.1)	99 (9.8)	
Cognitive activity, M (SD)	5.21 (2.46)	4.66 (2.61)	*t*(2035.38) = 4.99, *p*=.000
Social activity, M (SD)	4.20 (2.42)	4.30 (2.52)	*t*(2045.83) = -0.98, *p*=.326
Physical activity, M (SD)	5.37 (8.43)	4.22 (6.90)	*t*(2027.39) = 3.43, *p*=.001
Years in Study, M (SD)	7.06 (3.62)	6.74 (3.85)	*t*(2085) = 2.04, *p*=.042
[a]Perceptual Speed, M (SD)	50.98 (9.20)	48.71 (10.84)	*t*(1045.21) = 3.89, *p*=.000
[a]Immediate Memory, M (SD)	50.35 (9.00)	49.53 (11.13)	*t*(1096.29) = 1.44, *p*=.150
[a]Delayed Memory, M (SD)	50.09 (9.17)	49.87 (10.97)	*t*(1114.40) = 0.38, *p*=.705
[a]Verbal Reasoning, M (SD)	50.74 (9.56)	49.02 (10.49)	*t*(1377.00) = 3.34, *p*=.001

Notes. [a]For some variables, data are missing. All χ^2 tests that were based on a 2 × 2 contingency table applied the Yates' continuity correction. Scores of 16 or more on the CES-D are indicative of depression. Cognitive and social activity engagement is measured in hours per week. Physical activity engagement is measured in number of sessions every 2 weeks. Higher cognitive test scores indicate better performance. Cognitive scores were standardised to the T metric (*M* = 50, *SD* = 10) using the baseline ALSA sample.

Table 5.3 summarises the number of participants at each wave of data collection and the number of observations contributed by participants on each cognitive measure. Data on verbal reasoning were collected during the home interview rather than the clinical assessment hence the relatively larger number of cases for that measure (Anstey et al., 2003). Table 5.3 shows that the number of participants at each wave decreased, due primarily to mortality (Wagner et al., 2013). To address of mortality-related selection bias, background variables that have previously been found to be informative about causes of incomplete data and mortality-related drop out in the ALSA, are included in the analyses (Anstey & Luszcz, 2002a, 2002b; Anstey et al., 2001).

Table 5.3

Number of Participants at Each Wave and Number of Observations Contributed by Participants, by Cognitive Measure and Gender

	Cognitive Measure											
	Perceptual Speed			Immediate Memory			Delayed Memory			Verbal Reasoning		
Wave	**T**	**M**	**F**	**T**	**M**	**F**	**T**	**M**	**F**	**T**	**M**	**F**
1	706	509	197	733	519	214	729	516	213	901	630	271
3	679	479	200	719	509	210	717	507	210	-[a]	-	-
6	256	163	93	286	178	108	286	178	108	339	208	131
7	178	103	75	193	109	84	191	108	83	194	114	80
No.Obs.												
1	297	226	71	286	218	68	284	216	68	597	450	147
2	345	252	93	359	266	93	357	265	92	178	113	65
3	144	92	52	153	99	54	155	101	54	167	97	70
4	100	62	38	117	67	50	115	65	50	-	-	-
Total	1819	1254	565	1931	1315	616	1923	1309	614	1454	967	596

Notes. Number of observations (No.Obs). Total sample (T), n = 1,059. Males (M), n = 754. Females (F), n = 305.
[a] Wave 3 verbal reasoning scores were not used due to an inconsistency in the coding of those data.

5.2.3 Measures

Occupational Complexity

Occupational complexity was indicated by three variables: complexity involving work with (a) data, (b) people, and (c) things. Occupational information was collected at baseline. Participants were asked "What kind of work have you done most of your life?" Answers were coded using the CCLO (Australian Bureau of Statistics, 1971) and complexity scores for data, people, and things were applied to each occupation code (Australian Data Archive; Broom et al., 1973). *Complexity scores were reversed so that higher scores indicate higher levels of complexity.*

Table 5.4 provides descriptive statistics for the three occupational complexity variables. Mean complexity was 3.67 for data (SD = 2.25; Mdn = 4; range 0 - 7), 1.32 for people (SD = 2.26; Mdn = 1; range = 0 - 8), and 2.35 for things (SD = 2.69; Mdn = 2; range = 0 - 6). Males were more likely to have held occupations higher in complexity with data (d = 0.17) and with things (d = 0.26), but less likely to have a held occupations higher in complexity with people (d = 0.14).

Table 5.4

Baseline Descriptive Statistics for Occupational Complexity with Data, People, and Things by Gender

Complexity with Data

Function (Level)	**Total %**	**Male %**	**Female %**
No sig. relationship (0)	22.8	24.1	19.3
Comparing (1)	0.1	0.1	0.0
Copying (2)	2.8	0.3	9.2
Computing (3)	5.5	3.6	10.2
Compiling (4)	28.4	25.1	39.7
Analysing (5)	14.7	14.9	14.4
Coordinating (6)	22.8	28.4	8.9
Synthesising (7)	2.9	3.6	1.3
M (SD)	3.67 (2.24)	3.81 (2.35)	3.30 (1.93)
Median)	4	4	4
Skew	-0.625	-0.706	-0.557
Kurtosis	-.933	-.955	-.668
Test Statistic, *p*-value	U(df) = 90,813, Z = -5.50, *p*=.000		

Complexity with People

Function (Level)	**Total %**	**Male %**	**Female %**
No sig. relationship (0)	64.7	70.8	49.5
Serving (1)	8.4	1.6	25.2
Speaking/signalling (2)	4.8	5.4	3.3
Persuading (3)	7.6	8.6	5.2
Diverting (4)	0.3	0.3	0.3
Supervising (5)	2.6	3.4	0.7
Instructing (6)	5.4	2.3	13.1
Negotiating (7)	4.6	5.7	2.0
Mentoring (8)	1.5	1.9	0.7
M (SD)	1.32 (2.26)	1.25 (2.27)	1.50 (2.22)
Median	0	0	1
Skew	1.63	1.712	1.455
Kurtosis	1.304	1.621	.627
Test Statistic, p-value	U(df) = 132,806, Z = 4.63, *p*=.000		

Complexity with Things

Function (Level)	**Total %**	**Male %**	**Female %**
No sig. relationship (0)	49.8	41.2	70.8
Handling (1)	8.2	8.9	6.6
Feeding/offbearing (2)	0.2	0.1	0.3
Tending (3)	3.5	3.1	4.6
Manipulating (4)	5.7	7.0	2.3
Driving/operating (5)	2.7	3.8	0.0
Operating/controlling (6)	29.9	35.8	15.4
Precision working (7)	0	0	0.0
Setting up (8)	0	0	0.0
M (SD)	2.35 (2.69)	2.81 (2.74)	1.23 (2.22)
Median	1	1	0
Skew	0.445	0.126	1.500
Kurtosis	-1.663	-1.845	.499
Test Statistic, *p*-value	U(df) = 78,416, Z = -8.81, *p*=.000		

Notes. Higher complexity levels/scores indicate higher complexity. Mann Whitney U tests were used to assess group differences in complexity as the variables were not distributed normally.

Physical job demands

Movement-related job demand was indexed by the question: "In your job, were you mainly sitting, standing still, or moving around a lot?" Responses were coded: 1 = Sitting, 2 = Standing or 3 = Moving around a lot. Given a low response frequency in the standing category (*n* = 78), this response category was combined with moving around a lot (Brown et al., 2012)[12]. The resultant movement-related variable was coded: 0 = Sitting; 1 = Standing or Moving around at lot. At baseline, 75.6% (*n* = 801) of the sample had previously held a job that required them to be standing or moving around a lot.

Strength-related job demand was indexed by a question that asked participants if their job required them to perform heavy physical work. Responses were coded: 0 = No; 1 = Yes. At baseline, 40.6% (*n* = 430) of the sample had previously held a job with strength-related physical demands.

Table 5.5 provides descriptive statistics for the physical job demand variables by gender. Only 1.7% of the sample had a job that required strength-related (i.e., heavy) work and no-movement-related demand (i.e. sitting). Almost half of the male participants (45.5%) held a job with both strength- and movement-related demands, whereas 43.3% of females held a job with movement-related demand, but no strength-related demand. The gender differences are largely consistent with historical, gender-based occupational segregation. For example, females were less likely to be found in labouring, mining, and construction-related occupations that are typically associated with heavy physical workloads, and were more likely to be found in clerical or service occupations (Broom et al., 1976).

[12] The Australian physical activity and sedentary behaviour guidelines (Department of Health, 2014) distinguish between light activities that require standing up and moving around in the workplace from sedentary activities including sitting at work.

Table 5.5

Descriptive Statistics for Physical Job Demands by Gender

		Males		Females		Total	
		Strength-related demand					
		No, n (%)	**Yes, n (%)**	**No, n (%)**	**Yes, n (%)**	**No, n (%)**	**Yes, n (%)**
Movement-related demand	**No, n (%)**	141 (18.7)	13 (1.7)	99 (32.5)	5 (0.02)	240 (22.7)	18 (1.7)
	Yes, n (%)	257 (34.1)	343 (45.5)	132 (43.3)	69 (22.6)	389 (36.7)	412 (38.9)
Test statistic, *p*-value		$\chi^2(1, 754) = 114.79$, p=.000		$\chi^2(1, 305) = 30.92$, p=.000		$\chi^2(1, 1059) = 158.10$, p=.000	

Notes. Chi square tests applied the Yates' continuity correction for a 2×2 contingency table.

Cognitive ability

Perceptual speed was assessed by the Digit Symbol Substitution Test (DSST; Wechsler, 1981). This task required subjects to transcribe symbols corresponding to the digits 1 - 9 into a randomly ordered array of 93 digits. Standard instructions to work as rapidly as possible were given. The symbols were available for reference throughout the substitution task. To permit an economical assessment of nonverbal, incidental memory, administration was modified according to the procedures of Hart et al. (1987; see also Luszcz, 1992). The number of substitutions completed correctly at 90 seconds was used to index perceptual speed. Scores ranged from 0 to 90.

Immediate and delayed episodic memory was measured by one of four 15-item versions of the Boston Naming Test (Mack, Freed, Williams, & Henderson, 1992). Participants were shown a series of 15 pictures and asked to name the object pictured. Afterward they were asked to recall the names of as many pictures as they could. The number of correctly recalled picture names represented their immediate episodic memory score. Participants then completed two other cognitive tasks lasting approximately 10 minutes. Afterwards they were again asked to recall the names of as many pictures as possible, providing a measure of delayed recall. Scores ranged from 0 to 15.

Verbal reasoning was indexed by performance on the WAIS-R similarities subtest (Weschler, 1981). Participants were asked to explain the similarities between three items: Apple-Banana, Boat-Car, and, Egg-Seed, using standard guidelines. Items were scored 0 for an incorrect response, 1 for a partially correct answer, or 2 for a correct response, to give a score out of six.

Table 5.6 presents descriptive statistics for the four cognitive measures across Waves 1 (Baseline), 3, 6, and 7 of the ALSA. Due in part to selective longitudinal attrition the means for some cognitive measures increased over time (Anstey & Luszcz, 2002b; Gerstorf et al., 2009). Cognition scores were standardized to a *T* metric (*M* = 50; *SD* = 10) using the mean scores of the ALSA baseline sample (Gerstorf et al., 2009; Hoppmann, Gerstorf, & Luszcz, 2008).

Table 5.6

Descriptive Statistics for the Cognitive Measures by Wave

		Wave 1	Wave 3	Wave 6	Wave 7
Perceptual Speed	**n**	706	679	256	178
	M (SD)	50.98 (9.20)	51.24 (9.58)	50.93(9.05)	49.70 (8.94)
Immediate Memory	**n**	733	719	286	193
	M (SD)	50.35 (9.00)	48.81 (8.99)	48.74 (10.30)	48.28 (10.45)
Delayed Memory	**n**	729	717	286	191
	M (SD)	50.09 (9.17)	48.37 (8.99)	48.05 (10.08)	50.29 (10.54)
Verbal Reasoning	**n**	901	-[a]	339	194
	M (SD)	50.74 (9.56)	-[a]	48.58 (10.23)	51.46 (8.59)

Notes. Higher test scores indicate better cognitive performance. Cognitive scores were standardised to the T metric (*M* = 50, *SD* = 10) using the ALSA baseline sample. [a]Wave 3 verbal reasoning scores were not used due to an inconsistency in the coding of those data.

Time-invariant covariates

Age was a continuous variable. Mean age at baseline was 78.09 years (*SD* = 6.18; range = 65.07-97.71; skew = .352, kurtosis = -.541).

Gender was a binary variable coded as: 0 = male; 1 = female. At baseline, 71.1% (*n* = 754) of the sample was male and 28.9% (*n* = 305) female.

Education was defined by the age at which the participant left school. The response options were: 1 = never went to school; 2 = under 14 years; 3 = 14 years; 4 = 15 years; 5 = 16 years; 6 = 17 years; and, 7 = 18 years or more. At baseline, 52.3%

(*n* = 554) of the sample had left school at age 14 or less and 47.7% (*n* = 505) had left school at age 15 or more (*M* = 3.84, *SD* = 1.43, skew = .661, kurtosis = -.361).

Age at retirement was calculated as the difference between the participants' self-reported year of retirement and their birth year. At baseline, the mean age at retirement was 61.89 (*SD* = 6.20; range = 40-85; skew = -.544, kurtosis = 1.803), the mean year of retirement was 1976 (range = 1942-1992), and the sample had been retired on average 16.76 years (*SD* = 6.93; range = 1-51). Approximately half of the total sample (53.2%; *n* = 566) had retired at the pension eligibility age (60 for females and 65 for males), whereas 21.7% (*n* = 230) had retired earlier, and 24.8% (*n* = 263) had retired later than the pension age.

Occupational status was indexed by the binary variable: 0 = blue-collar; 1= white-collar, using the 16 ANU1 social-status group scale (IPUMS-International). At baseline, 51% (*n* = 540) of the sample was classified as blue-collar.

Smoking status was indicated by self-report. Participants were classed as never smoked, current smoker, or former smokers, based on their responses to questions concerning smoking. At baseline, about 52% (*n* = 550) of the sample reported they were former smokers.

Alcohol consumption was coded according to the current Australian National Health and Medical Research Council guidelines (National Health and Medical Research Council, 2009). The 2009 guidelines advise both men and women to drink no more than two standard drinks per day to reduce their health risks over a lifetime. Accordingly, alcohol consumption was defined by the average number of standard drinks consumed per day, where: 0 = abstain; 1 = two or fewer standard drinks; and, 2 = more than two standard drinks. At baseline, 54.4% (*n* = 54.4) of the sample reported that the consumed two or fewer standard drinks per day.

Medical conditions were self-reports of eight current chronic medical conditions that have been found to influence cognitive functioning: arthritis, cancer, diabetes, heart attack, heart condition, hypertension, small stroke/TIA, and stroke (Deary et al., 2009). At baseline, the number of conditions reported ranged from 0 to 6 with a mean of 1.58 (*SD* = 1.18; skew = .718, kurtosis = .418).

Time-varying covariates

Depression was assessed using the Centre for Epidemiological Studies – Depression scale (CES-D: Radloff, 1977; Radloff & Teri, 1986). The CES-D scale comprises 20 items to which participants are required to respond with reference to the way the individual felt in the last week on a 4-point Likert scale. The scale ranged from 0 = rarely or none of the time to 3 = most of the time. Items are summed to give a total score, ranging from 0 to 60. A score of 16 or more reflects possible depression (Anstey, Butterworth, et al., 2007). Observed scores at baseline ranged from 0 to 43, with a mean of 7.13 (*SD* = 6.44). Internal reliability at baseline was high (α = 0.84).

Cognitive activity engagement was assessed by the only two (of 21) 'cognitive' items from the Adelaide Activity Profile (AAP: Bond & Clark, 1998; Clark & Bond, 1995). The two AAP items were (i) time spent doing an activity that involved some active participation and thought, and (ii) time spent reading. The AAP asks people about how frequently they performed activities in a typical three month period. In order to combine the responses from the two items, the frequency for each activity was transformed into days per week engaged in the activity (Bielak, Gerstorf, et al., 2014). For example, participation in a hobby once a month was converted to 0.25 days per week, once a fortnight was converted to 0.50 days per week, and once a week or more was converted to 1 day per week . The item frequencies were then summed to create total hours per week engaged in cognitive activity (Bielak, Gerstorf, et al., 2014). Observed scores ranged from 0 to 8 hours per week, with a mean of 5.21 (*SD* = 2.46).

Social activity engagement was assessed by four items from the AAP. The items were (i) participation in social activities at a centre (e.g., a club, church, a community centre), (ii) participation in an outdoor social activity, (iii) frequency in making telephone calls to friends or family, and (iv) frequency in inviting people to one's own home (Hoppmann et al., 2008). As per the cognitive activity items the reported frequency for each activity was transformed into days per week engaged in the activity. For example, participation in a social activity at a centre less than once a month was converted to 0.125 days per week, about once a month was converted to 0.25 days per week, about once a fortnight was converted to 0.50 days per week, and once a week or more was converted to 1 day per week (Bielak, Gerstorf, et al., 2014). The item frequencies were summed to create total hours per week engaged in social activity (Bielak, Gerstorf, et al., 2014). Observed scores ranged from 0 to 12 hours per week, with a mean of 4.20 (*SD* = 2.42).

Physical activity was assessed via two questions that asked participants to report the number of sessions they walked, and the number of sessions they engaged in vigorous exercise over the past two weeks (Bielak, Gerstorf, et al., 2014). As walking expends less energy than vigorous exercise, the item metrics were converted using metabolic equivalent values (MET[13]), with light (< 3 METs) and vigorous (≥ 6 METs) activities as reference (Brown et al., 2012; Department of Health, 2014). Physical activity was calculated as the sum of the number of walking sessions plus three times the number of sessions engaged in vigorous exercise, and higher scores reflect more sessions in the past two weeks (Bielak, Gerstorf, et al., 2014). Observed

[13] "Metabolic equivalent (MET) is the unit used to define levels of activity, in multiples of resting metabolic rate. One MET is defined as energy expenditure at rest, usually equivalent to 3.5mL of oxygen uptake per kg per minute" (Brown et al., 2012, p. v).

scores ranged from 0 to 70 session every two weeks, with a mean engagement of 5.37 (*SD* = 8.43).

Baseline descriptive statistics for the covariates are presented in Table 5.7. Gender differences at baseline were examined using independent samples *t* tests for continuous variables and chi-square (χ^2) tests for categorical variables. As expected mean age at retirement was younger for females compared to males (*d* = 0.81). This result is consistent with the historical differences in pension eligibility ages for males and females. Also, females were more likely to be engaged in white-collar occupations (*d* = 0.32).

Table 5.7

Baseline Descriptive Statistics for the Covariates by Total Sample and by Gender

	Total (*n* = 1059)	**Males (*n* = 754)**	**Females (*n* = 305)**	**Test statistic, *p*-value**
Age, M (SD)	78.09 (6.18)	78.87 (5.90)	76.18 (6.45)	$t(1057) = 6.54$, p=.000
[a]Education, n (%)				
Age left school ≤ 14 years	554 (52.3)	420 (55.7)	134 (43.9)	$\chi^2(1, 1059) = 11.59$, p=.001
Age left school ≥ 15 years	505 (47.7)	334 (44.3)	171 (56.1)	
Age at Retirement, M (SD)	61.89 (6.20)	63.35 (4.96)	58.28 (7.39)	$t(419.24) = 11.04$, p=.000
Occupational Status, n (%)				
Blue-collar	540 (51.0)	419 (55.6)	121 (39.7)	$\chi^2(1, 1059) = 21.33$, p=.000
White-collar	519 (49.0)	335 (44.4)	184 (60.3)	
Medical Conditions, M (SD)	1.58 (1.18)	1.62 (1.20)	1.47 (1.14)	$t(1057) = 1.80$, p=.072
Smoking status, n (%)				
Never	414 (39.1)	233 (30.9)	181 (59.3)	$\chi^2(2, 1059) = 90.64$, p=.000
Former	550 (51.9)	461 (61.1)	89 (26.2)	
Current	95 (9.0)	60 (8.0)	35 (11.5)	
Alcohol Consumption, n (%)				
Abstain	323 (30.5)	211 (28.0)	112 (36.7)	$\chi^2(2, 1059) = 21.82$, p=.000
≤ 2 standard drinks	576 (54.4)	406 (53.8)	170 (55.7)	
> 2 Standard drinks	160 (15.1)	137 (18.2)	23 (7.5)	
CES-D, M (SD)	7.13 (6.44)	7.30 (6.76)	6.72 (5.56)	$t(678.2) = 1.44$, p=.151
Cognitive activity, M (SD)	5.21 (2.46)	5.03 (2.46)	5.65 (2.39)	$t(1057) = -3.78$, p=.000
Social activity, M (SD)	4.20 (2.42)	3.78 (2.23)	5.23 (2.56)	$t(501.19) = -8.70$, p=.000
Physical activity, M (SD)	5.37 (8.43)	5.85 (9.07)	4.20 (6.45)	$t(783.13) = 3.33$, p=.001

Notes. All χ^2 tests that were based on a 2 × 2 contingency table applied the Yates' continuity correction. [a] In the statistical analyses education (as determined by age left school) is treated as a continuous variable. Medical conditions: higher values indicate a greater number of conditions. CES-D, higher scores indicate more depression symptoms. Cognitive activity, higher scores indicates more hours per week engaged in activity. Social activity, higher scores indicates more hours per week engaged in activity. Physical activity, higher scores indicates more sessions engaged in activity every 2 weeks.

5.2.4 Statistical approach

The study questions were addressed using a standard MLM approach (Raudenbush & Bryk, 2002; Singer & Willett, 2003). To assist in comparing results across the studies, the modelling process in Study 2 was consistent with that used in Study 1 (Piccinin et al., 2013). Time was specified as years since baseline and was individual specific. Levels of, and change in, each cognitive measure were assessed separately. In a first step, an unconditional means model was estimated to assess the amount of variation in each cognitive measure at the between-person and within-person levels, and to determine whether there was sufficient variation at each level to warrant further analysis. In a second step, unconditional growth models were fit to the four cognitive measures. In order to select a suitable level-1 change trajectory for each cognitive measure, linear and non-linear (quadratic) change were estimated and models were compared using relative model fit indices (Singer & Willett, 2003). The fixed effect of linear time, the random effect of linear time, and the fixed effect of quadratic time were added sequentially. Differences in deviance (-2 Log Likelihood [-2LL]) and change in Pseudo R^2 were used to compare models. Pseudo R^2 was calculated based on proportional change in variance components (Singer & Willett, 2003).

The unadjusted associations of the occupational variables (i.e., the occupational complexity and physical job demand measures) with each cognitive change trajectory were then examined in a series of conditional growth models. Model 1 added the occupational variables to the best fitting unconditional growth model as a predictor of both level (intercept) and change (slope). Change in Pseudo R^2, calculated based on proportional change in the level-2 (between-person) variance components (Singer & Willett, 2003), was used to quantify the role of the occupational variables in explaining cognitive change trajectories (Gerstorf et al., 2013).

The covariate adjusted associations of the occupational variables with the cognitive trajectories were then examined in a series of conditional growth models.

The occupational variables were assessed separately. Model 2 examined whether the occupational variables were significant predictors of cognitive change trajectories controlling for age, gender, and education, by adding these covariates to Model 1 as predictors of both initial status and rates of cognitive change. All subsequent models included terms to control the potentially confounding effects of age, gender, and education on initial level and rate of change (e.g., Wilson et al., 2009). To assess whether the associations between the occupational variables and cognitive change were independent of the additional covariates, age at retirement was added as a level-2 predictor in Model 2A, occupational status was added as a level-2 predictor in Model 2B, depression and the activity engagement variables were added as level-1 predictors and medical conditions[14], smoking status, alcohol consumption were added as level-2 predictors in Model 2C. In Model 3 the occupational complexity variables were entered into a model via simultaneous entry, and the physical job demand variables were entered into another model via simultaneous entry.

To explore whether the associations between the occupational variables and cognitive change differed by education, gender, or age at retirement, deviance-based hypothesis tests were used to assess whether inclusion of cross-product interaction terms contributed significantly to model fit (e.g., Wilson et al. 2009). Interaction terms for the occupational variables and education or gender were added to Model 2 as a predictor of level and change. Interaction terms for the occupational variables and age at retirement were added to Model 2A as a predictor of initial status and rates of cognitive change.

All analyses were conducted using the mixed model procedure in SPSS 21.0 statistical software. As the research questions focused on fixed and random effects, the full information maximum likelihood (FIML) method was used (Singer &

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[14] Given a time varying measure of medical conditions was not a significant predictor of change in Study 1, this Study used a time-invariant measure.

Willett, 2003). Random effects were calculated using an unstructured covariance matrix.

5.2.5 Data preparation

The time-invariant, continuous measures were grand mean centred. Occupational complexity with data was centred at 3.67, complexity with people was centred at 1.32, complexity with things was centred at 2.35, baseline age was centred at 78.09, and number of medical conditions was centred at 1.58. In order to provide the models with greater information with which to estimate interactions between education and occupational complexity, this study treated education (as determined by age left school) as a continuous variable, centred at 15 years (e.g., Kiely, Anstey, & Luszcz, 2013). Age at retirement was centred at 61.89 years. This also represents the midpoint between the female and male pension eligibility ages. The centring points were largely equivalent to those in Study 1.

Time-invariant binary variables were centred at the value 0. Gender was centred at male (0) versus female (1), movement-related job demand was centred at sitting (0) versus standing or moving (1), strength-related job demand was centred at non-heavy (0) versus heavy (1), and occupational status was centred at blue-collar (0) versus white-collar (1). Smoking status was dummy coded and current smoker (0) was the reference category. Alcohol consumption was dummy coded and more than 2 drinks per day (0) was the reference category.

Depression was treated as time-varying and scores were centred at 16, the cut-off score for possible depression on the CES-D. The cognitive, social and physical activity engagement variables were also treated as time-varying and their raw scores were used in the models (Singer & Willett, 2003). The time-varying predictors were not decomposed into their within-person and between-person parts as no substantive predictions about their effects on the associations between the occupational demands and cognitive ageing were posed (Hoffman & Stawski, 2009).

Consistent with Study 1, the distributional properties of the time-invariant predictors and the outcome variables[15] were considered to be adequate for MLM (e.g., Hofer et al., 2002). Therefore, no transformations were performed. Assumptions of normality were assessed during the modelling process (Singer & Willett, 2003).

5.3 Results

The results are presented in three major parts. First, the results from unconditional models describing average patterns of change in perceptual speed, immediate memory, delayed memory, and verbal reasoning, are presented. Second, results from models examining whether and how occupational complexity with data, people, and things predict levels of, and change in, the cognitive abilities are presented. Third, results from models examining whether and how the physical job demand variables predict levels of, and change in, the cognitive abilities are presented.

Before estimating multilevel models, the bivariate relationships among the predictor variables, and with the cognitive measures, are explored. Correlations are presented in Table 5.8. Significant inter-correlations for all three complexity measures were observed. Higher complexity with data was associated with higher complexity with people. Higher complexity with data and people were associated with lower complexity with things. This pattern of associations was consistent with Study 1. Higher complexity with data was associated with sedentary job demands but not with strength-related job demand. Higher complexity with people was associated with movement-related job demand, but not strength-related job demand.

[15] Perceptual speed (skew = -1.362, kurtosis = .163), immediate memory (skew = -.017, kurtosis = -.044), delayed memory (skew = .195, kurtosis = .012), verbal reasoning (skew = .143, kurtosis = .089). Analyses conducted in long format.

Higher complexity with things was associated with movement- and strength-related job demands. High occupational status was associated with higher complexity with data and lower complexity with things. Older age was associated with an older age at retirement. Higher complexity with things, movement-related job demand, and strength-related job demand were associated with lower performances on all cognitive measures. Higher complexity with data and people were associated with better cognitive performances. Complexity with data was not associated with immediate or delayed memory performance.

Table 5.8

Bivariate Correlations for the Study Variables

	Data	People	Things	MJD	SJD	Age	Gender	Edu	RA	OccStat	MedCdns	CES-D	CogAct	SocAct	PhysAct	PS	IM	DM	VR
Data	1.000																		
People	.358***	1.000																	
Things	-.109***	-.571***	1.000																
MJD	-.034*	.046**	.274***	1.000															
SJD	-.110***	-.257***	.405***	.389***	1.000														
Age	.132***	.050**	.066***	.083***	.027	1.000													
Gender	-.169***	.142***	-.271***	-.144***	-.212***	-.197***	1.000												
Edu	.203***	.139***	-.212***	-.195***	-.252***	-.003	.116***	1.000											
RA	.126***	.006	.109***	.119***	.125***	.433***	-.382***	-.029	1.000										
OccStat	.578***	.271***	-.511***	-.354***	-.303***	.035*	.144***	.337***	-.016	1.000									
MedCdns	-.014	-.009	-.022	-.065***	-.009	-.030	-.054***	.011	-.040**	.037*	1.000								
CES-D	-.045*	-.012	-.007	-.021	.022	.117***	.029	-.010	-.003	-.025	.146***	1.000							
CogAct	.079***	.055**	-.100***	-.045*	-.093***	-.083***	.112***	.162***	-.059**	.138***	.007	-.083***	1.000						
SocAct	.017	.134***	-.133***	-.081***	-.143***	-.209***	.290***	.122***	-.144***	.097***	-.021	-.057**	.125***	1.000					
PhysAct	.016	-.008	.002	.033	-.005	-.082***	-.039	-.004	.033	.004	-.066**	-.077***	.041*	.087***	1.000				
PS	.104***	.111***	-.225***	-.133***	-.186***	-.379***	.142***	.161***	-.141***	.189***	-.091***	-.176***	.197***	.204***	.065**	1.000			
IM	.032	.062**	-.122***	-.092***	-.102***	-.271***	.149***	.077**	-.135***	.119***	-.054*	-.133***	.147***	.151***	.038	.458***	1.000		
DM	.030	.046*	-.121***	-.096***	-.089***	-.276***	.159***	.075**	-.111***	.115***	-.072**	-.127***	.130***	.131***	.035	.402***	.768***	1.000	
VR	.165***	.113***	-.114***	-.117***	-.073**	-.117***	.030	.215***	0.21	.196***	-.011	-.107***	.184***	.122***	.054*	.224***	.191***	.186***	1.000

Notes. Data in long format (e.g., Wagner et al., 2013). Spearman correlation coefficients are reported as some measures are not normally distributed (Data, People, Things, MedCdns, CES-D, PhysAct). Data: Occupational complexity with data; higher scores indicate greater complexity. People: Occupational complexity with people; higher scores indicate greater complexity. Things: Occupational complexity with things; higher scores indicate greater complexity. MJD: Movement-related job demand: 0=No (sitting), 1=Yes (standing or moving). SJD: Strength-related job demand: 0=No (non-heavy), 1=Yes (heavy). Age: age in years at baseline. Gender: Male (0), Female (1). Edu: Education reflected by age left school. RA: Age at retirement. OccStat: Occupational status, blue-collar (0), white-collar (1). MedCdns: Number of medical conditions. CES-D: Centre for Epidemiological Studies Depression Scale, higher scores indicate more depression symptoms. CogAct: Cognitive activity, higher scores indicates more hours per week engaged in activity. SocAct: Social activity, higher scores indicates more hours per week engaged in activity. PhysAct: Physical activity, higher scores indicates more sessions engaged in activity every 2 weeks. PS: Perceptual Speed; IM: Immediate Memory; DM: Delayed Memory; VR: Verbal Reasoning. *p<.05; **p<.01; ***p<.001

5.3.1 Cognitive ageing

Separate models were estimated for each of the four cognitive measures: perceptual speed (PS), immediate memory (IM), delayed memory (DM), and verbal reasoning (VR), over time (years) in study. Unconditional means (or intercept only) models revealed substantial within-person and between-person variation in each cognitive measure. As indicated by the intraclass correlation coefficient (ICC[16]): 67% of the total variance in perceptual speed, 43% of the total variance in immediate memory, 47% of the total variance in delayed memory, and 50% of the total variance in verbal reasoning, was the result of between-person differences. With substantial within-person variation in each cognitive measure to be modelled, linear and non-linear (quadratic) trajectories were estimated and compared. A quadratic model (with one intercept and two slope parameters) requires a minimum of four waves of data (Singer & Willett, 2003). As there were three waves of data available for verbal reasoning, only linear change was estimated for this measure.

The relative model fit indices for the alternative growth models are presented in Table 5.9. Adding the fixed effect of quadratic time improved model fit, as indicted by differences in deviance (Δ-2LL) and Pseudo R^2_ε, for perceptual speed and delayed memory but not for immediate memory. It was concluded that perceptual speed and delayed memory followed non-linear change trajectories, whilst immediate memory and verbal reasoning followed a linear change trajectory.

[16] The ICC is given by the equation: $\sigma_0^2/(\sigma_0^2 + \sigma_\epsilon^2)$, where, σ_ϵ^2, is the variance of the level-1 residual and, σ_0^2, is the variance of the level-2 intercept (Singer & Willett, 2003).

Table 5.9

Relative Model Fit Indices for Alternative Unconditional Cognitive Growth Models

Model	**-2LL**	**df**	**AIC**	**BIC**	**Δ-2LL**	**Δdf**	***p***	$\boldsymbol{\sigma_\varepsilon^2}$	**Pseudo** $\boldsymbol{R_\varepsilon^2}$
				Perceptual Speed (PS)					
IO Model	12754.75	3	12760.75	12777.27				32.25	
+ FE-Time	12599.97	4	12607.97	12629.99	154.78	1	<.001	26.37	0.182
+ RE-Time	12575.40	6	12587.70	12620.42	24.57	2	<.001	22.45	0.304
+ FE-Time^2	**12570.44**	**7**	**12584.44**	**12622.97**	**4.96**	**1**	**<.05**	**22.25**	**0.310**
+ RE-Time^2	Model was not estimated								
				Immediate Memory (IM)					
IO model	13873.17	3	13879.17	13777.65				50.07	
+ FE-Time	13791.17	4	13799.17	13821.42	82.00	1	<.001	46.09	0.079
+ RE-Time	**13758.64**	**6**	**13770.64**	**13804.02**	**32.53**	**2**	**<.001**	**42.39**	**0.153**
+ FE-Time^2	13757.24	7	13771.24	13810.18	1.40	1	>.05	42.45	0.152
+ RE-Time^2	Model was not estimated								
				Delayed Memory (DM)					
IO model	13777.65	3	13783.65	13800.34				47.05	
+ FE-Time	13720.05	4	13728.05	13750.29	57.06	1	<.001	44.70	0.050
+ RE-Time	13691.87	6	13703.87	13737.23	28.18	2	<.001	39.62	0.158
+ FE-Time^2	**13674.60**	**7**	**13688.60**	**13727.52**	**17.27**	**1**	**<.001**	**39.30**	**0.165**
+ RE-Time^2	13673.31	10	13693.31	13748.91	1.29	3	>.05	37.98	0.193
				Verbal Reasoning (VR)					
IO model	10650.20	3	10656.20	10672.06				48.10	
+ FE-Time	**10637.62**	**4**	**10645.62**	**10666.77**	**12.58**	**1**	**<.001**	**46.25**	**0.038**
+ RE-Time	[b]Variance components could not be estimated								
+ FE-Time^2	[c]Model was not estimated								

Notes. The best fitting model is highlighted in bold. IO Model: Intercept only model. -2LL = Deviance. Δ-2LL = [-2LL$_{\text{simpler model}}$] – [-2LL$_{\text{more complex model}}$]. AIC: Akaike information criterion. BIC: Bayesian information criterion. σ_ε^2: Residual within-person (level-1) variance. Pseudo R_ε^2 = ($\sigma^2_{\epsilon\,\text{unconditional means model}} - \sigma^2_{\epsilon\,\text{unconditional growth model}}$) / $\sigma^2_{\epsilon\,\text{unconditional means model}}$). [b] A convergence warning was encountered when the random effect of linear time was added in verbal reasoning: the variance of the random slope and the covariance for the randomly varying intercept and slope could not be estimated. In response, a number of the estimation default options in SPSS were altered, for example, the maximum iterations and scoring steps were increased (Singer & Willett, 2003). However, model convergence was still not achieved. [c]Only three waves of verbal reasoning data were available, thus non-linear change was not examined.

The fixed effects (sample mean estimates) and random effects (representing individual variations from the sample means) for the best fitting, unconditional growth models are summarised in Table 5.10. Predicted change trajectories for the four cognitive outcome measures over time in study are illustrated in Figure 5.1.

Table 5.10

Parameter Estimates for the Best Fitting Unconditional Cognitive Growth Models

	Perceptual Speed (PS)	**Immediate Memory (IM)**	**Delayed Memory (DM)**	**Verbal Reasoning (VR)**
	Est. (SE)	**Est. (SE)**	**Est. (SE)**	**Est. (SE)**
Fixed effects				
Intercept, γ_{00}	50.97 (0.33)***	49.93 (0.28)***	49.93 (0.32)***	50.40 (0.32)***
Time, γ_{10}	-0.21 (0.13)	-0.45 (0.05)***	-0.99 (0.17)***	-0.17 (0.05)***
Time^2, γ_{20}	-0.03 (0.01)*	–	0.07 (0.02)***	–
Random effects				
Residual, σ_ϵ^2	22.25 (1.24)***	42.39 (2.24)***	39.30 (2.08)***	46.25 (2.96)***
Intercept, σ_0^2	67.11 (4.27)***	36.76 (3.78)***	43.82 (3.89)***	50.41 (4.61)***
Time, σ_1^2	0.23 (0.06)***	0.21 (0.08)*	0.27 (0.08)**	–[a]
Covariance, σ_{01}	-0.71 (0.46)	1.06 (0.52)*	-0.01 (0.51)	–[a]

Notes. Unstandardised estimates (Est.) and standard errors (SE) are presented. T scores for cognitive measures are standardised to the baseline sample (*M*=50, *SD*=10). -2LL = Deviance. AIC: Akaike information criterion. BIC: Bayesian information criterion. Dashes indicate that effect was not estimated. [a]For model convergence, the variance component could not be estimated. *p<.05; **p<.01; ***p<.001.

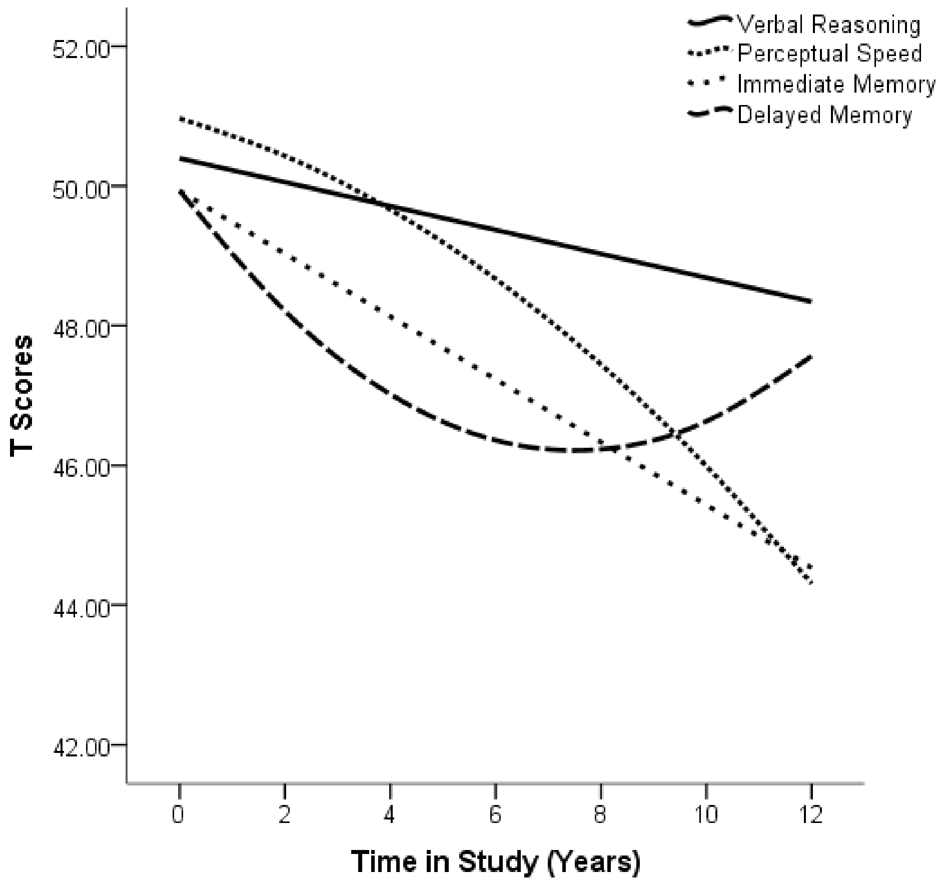

Figure 5.1. Predicted cognitive change trajectories

In relation to perceptual speed, and immediate and delayed memory, the random effects for both the intercept and slope were significantly different from zero, indicating that individual differences in initial levels and rates of change remained to be explained. In relation to verbal reasoning, between-person variations in level only, remained to be explained. Thus, the occupational activity demand variables were added to the best fitting unconditional growth models as a predictor of both initial status and rates of cognitive change. For perceptual speed and delayed memory, models also included main effects of each predictor on the curvature of the average change trajectory (i.e., quadratic time). The average change trajectory for verbal reasoning over time in study demonstrated decline, yet non-convergence indicated individual change rates did not sufficiently deviate from the average. Therefore, the main effects of the predictor variables on the linear change trajectory for verbal reasoning were tested in the absence of the random effects (e.g., Gerstorf et al., 2013).

5.3.2 Occupational complexity and cognitive ageing

In this section, results from models examining whether and how occupational complexity with data, people, and things predict levels of, and change in, the cognitive abilities are presented. The unadjusted followed by the adjusted associations of occupational complexity with cognition are presented first. Then, the modifying roles of education, gender, and age at the time of retirement are presented.

Unadjusted associations of occupational complexity with cognition

Model 1 added occupational complexity to the unconditional cognitive growth models as a predictor of both initial levels of cognitive function and rates of cognitive change. The three occupational complexity variables (i.e., data, people, and things) were examined in separate models. Table 5.11 presents the estimates generated from Model 1. Significant main effects of occupational complexity on initial cognitive performance were observed. Higher complexity with data was associated with 0.63 *T score* units higher on perceptual speed and 0.81 *T score* units higher on verbal reasoning. Higher complexity with people was associated with 0.55

T score units higher on perceptual speed and 0.59 *T score* units higher on verbal reasoning. Conversely, higher complexity with things was associated with 0.67 *T score* units lower on perceptual speed, 0.34 *T score* units lower on immediate memory, and 0.47 *T score* units lower on delayed memory. None of the interaction terms (Occupational Complexity × Time and, Occupational Complexity × Time^2) were significantly different from zero for any of the cognitive measures, suggesting occupational complexity did not moderate cognitive change.

Pseudo R^2 revealed that the occupational complexity variables explained only a small fraction of between-person variation in cognitive ageing. For example, occupational complexity with data accounted for 2.4% of variability in initial perceptual speed and 6.2% of variability initial verbal reasoning. Occupational complexity with people accounted for 1.9% of variability in initial perceptual speed and 3.4% of variability initial verbal reasoning. Occupational complexity with things accounted for 6.0% of variability in initial perceptual speed, 2.8% of variability in initial immediate memory, and 3.9% variability in initial delayed memory.

Table 5.11

Parameter Estimates from Multilevel Models Examining Occupational Complexity Predicting Cognitive Performance and Change

	Model 1: Data				Model 1: People				Model 1: Things			
	PS Est. (SE)	**IM Est. (SE)**	**DM Est. (SE)**	**VR Est. (SE)**	**PS Est. (SE)**	**IM Est. (SE)**	**DM Est. (SE)**	**VR Est. (SE)**	**PS Est. (SE)**	**IM Est. (SE)**	**DM Est. (SE)**	**VR Est. (SE)**
Fixed Effects												
Intercept, γ_{00}	50.95 (0.33)***	49.93 (0.28)***	49.93 (0.32)***	50.34 (0.32)***	50.95 (0.33)***	49.93 (0.28)***	49.93 (0.32)***	50.37 (0.32)***	50.97 (0.32)***	49.94 (0.28)***	49.94 (0.31)***	50.40 (0.32)***
Time, γ_{10}	-0.20 (0.13)	-0.45 (0.05)***	-0.99 (0.17)***	-0.17 (0.05)***	-0.20 (0.13)	-0.45 (0.05)***	-0.99 (0.17)***	-0.17 (0.05)***	-0.21 (0.13)	-0.45 (0.05)***	-1.00 (0.17)***	-0.18 (0.05)***
Time^2, γ_{20}	-0.03 (0.01)*	–	0.07 (0.02)***	–	-0.03 (0.01)*	–	0.07 (0.02)***	–	-0.03 (0.01)*	–	0.07 (0.02)***	–
OC, γ_{01}	0.63 (0.15)***	0.10 (0.13)	0.09 (0.14)	0.81 (0.14)***	0.55 (0.14)***	0.11 (0.12)	0.11 (0.14)	0.59 (0.14)***	-0.67 (0.12)***	-0.34 (0.10)**	-0.47 (0.12)***	-0.23 (0.12)
Time×OC, γ_{11}	-0.06 (0.06)	0.04 (0.03)	0.01 (0.08)	0.00 (0.02)	-0.03 (0.06)	0.02 (0.03)	-0.03 (0.07)	-0.01 (0.02)	-0.07 (0.05)	0.01 (0.02)	0.07 (0.06)	-0.01 (0.02)
Time^2×OC, γ_{21}	0.01 (0.01)	–	0.00 (0.01)	–	–	–	0.00 (0.01)	–	0.01 (0.00)	–	-0.00 (0.01)	–
Random Effects												
Residual, σ_{ϵ}^2	22.29 (1.24)***	42.44 (2.24)***	39.30 (2.08)***	45.90 (2.94)***	22.32 (1.24)***	42.45 (2.28)***	39.27 (2.08)***	46.00 (2.97)***	22.22 (1.24)***	42.47 (2.25)***	39.27 (2.08)***	45.92 (2.96)***
Intercept, σ_0^2	65.47 (4.19)***	36.73 (3.78)***	43.90 (3.89)***	47.65 (4.46)***	65.81 (4.20)***	36.72 (3.78)***	43.86 (3.89)***	49.10 (4.55)***	63.09 (4.08)***	35.73 (3.75)***	42.11 (3.82)***	50.41 (4.60)***
Time, σ_1^2	0.22 (0.06)***	0.21 (0.08)*	0.27 (0.08)**	–[a]	0.22 (0.06)***	0.21 (0.08)*	0.28 (0.09)**	–[a]	0.23 (0.06)***	0.21 (0.08)*	0.26 (0.08)**	–[a]
Covariance, σ_{01}^2	-0.71 (0.46)	0.99 (0.52)	-0.08 (0.51)	–[a]	-0.75 (0.46)	1.00 (0.52)	-0.03 (0.52)	–[a]	-0.67 (0.46)	1.09 (0.52)*	0.22 (0.51)	–[a]
Goodness-of-fit												
-2LL	12549.39	13753.70	13671.79	10551.15	12553.17	13756.82	13673.93	10569.89	12524.94	13747.27	13655.87	10582.99
AIC	12569.39	13769.70	13691.79	10563.15	12573.17	13772.82	13693.93	10581.89	12544.94	13763.27	13675.87	10594.99
BIC	12624.23	13814.21	13747.38	10594.84	12628.20	13817.33	13749.52	10613.58	12599.98	13807.78	13731.46	10626.68
Explained variance: Between-person												
Level Pseudo R_0^2	0.024	–	–	0.062	0.019	–	–	0.034	0.060	0.028	0.039	–
Slope Pseudo R_1^2	0.043	–	–	–[a]	0.043	–	–	–[a]	0.000	0.000	0.037	–[a]

Notes. Unstandardised estimates (Est.) and standard errors (SE) are presented. PS: Perceptual Speed. IM: Immediate Memory. DM: Delayed Memory. VR: Verbal Reasoning. T scores for cognitive measures standardised to the baseline sample (*M*=50, *SD*=10). Time: years in study. Data: Occupational complexity with data, grand mean centred (*M*=3.67). People: Occupational complexity with people, grand mean centred (*M*=1.32). Things: Occupational complexity with things, grand mean centred (*M*=2.35). OC: Occupational complexity, higher scores indicate greater complexity. -2LL = Deviance. AIC: Akaike information criterion. BIC: Bayesian information criterion. Pseudo R_0^2 = (σ_0^2unconditional growth model – σ_0^2conditional model) / σ_0^2unconditional growth model). Pseudo R_1^2 = (σ_1^2unconditional growth model – σ_1^2conditional model) / σ_1^2unconditional growth model). Dashes indicate that effect was not estimated. [a]For model convergence, variance component could not be estimated. *p<.05; **p<.01; ***p<.001.

Covariate adjusted associations of occupational complexity with cognition

Model 2: Age, gender, and education

Model 2 added baseline age, gender, and education to Model 1 as predictors of both initial status and rates of cognitive change. Parameter estimates generated by Model 2 are presented in Table 5.12. They showed the associations between occupational complexity with data and levels of perceptual speed and verbal reasoning were independent of age, gender, and education. Similarly, the associations between occupational complexity with people and levels of perceptual speed and verbal reasoning were also independent of age, gender, and education. The magnitudes of the associations between occupational complexity with data and people and verbal reasoning were marginally reduced by 8% and 17%, respectively. The associations between occupational complexity with things and levels of perceptual speed and delayed memory were independent of age, gender, and education, although the magnitudes of the associations were reduced by 31% and 45%, respectively. The association between complexity with things and immediate memory was completely accounted for by age, gender, and education. To ensure consistency in the models used to examine the associations of occupational complexity with the cognitive outcome measures within Study 1, and between Study 1 and Study 2, non-significant results for some terms were retained in future models.

Table 5.12

Parameter Estimates from Multilevel Models Examining Occupational Complexity Predicting Cognitive Performance and Change, and Adjusting for Age, Gender, and Education

	Model 2: Data				**Model 2: People**				**Model 2: Things**			
	PS Est. (SE)	**IM Est. (SE)**	**DM Est. (SE)**	**VR Est. (SE)**	**PS Est. (SE)**	**IM Est. (SE)**	**DM Est. (SE)**	**VR Est. (SE)**	**PS Est. (SE)**	**IM Est. (SE)**	**DM Est. (SE)**	**VR Est. (SE)**
Fixed Effects												
Intercept, γ_{00}	50.60 (0.34)***	49.39 (0.32)***	49.15 (0.36)***	50.41 (0.38)***	50.74 (0.34)***	49.43 (0.32)***	49.19 (0.36)***	50.62 (0.38)***	50.92 (0.35)***	49.51 (0.32)***	49.31 (0.36)***	50.68 (0.38)***
Time, γ_{10}	-0.50 (0.17)**	-0.57 (0.07)***	-1.05 (0.21)***	-0.28 (0.06)***	-0.51 (0.16)**	-0.55 (0.07)***	-1.05 (0.21)***	-0.28 (0.06)***	-0.49 (0.17)**	-0.56 (0.07)***	-1.08 (0.21)***	-0.28 (0.06)**
Time^2, γ_{20}	-0.01 (0.02)	–	0.06 (0.02)**	–	-0.01 (0.02)	–	0.06 (0.02)**	–	-0.01 (0.02)	–	0.07 (0.02)**	–
Age, γ_{01}	-0.64 (0.05)***	-0.43 (0.05)***	-0.39 (0.05)***	-0.23 (0.05)***	-0.64 (0.05)***	-0.43 (0.05)***	-0.40 (0.05)***	-0.22 (0.05)***	-0.62 (0.05)***	-0.42 (0.04)***	-0.38 (0.05)***	-0.21 (0.05)***
Gender, γ_{02}	1.12 (0.66)	1.79 (0.60)**	2.60 (0.68)***	0.23 (0.70)	0.63 (0.66)	1.62 (0.60)**	2.46 (0.68)***	-0.32 (0.70)	0.10 (0.68)	1.39 (0.62)*	2.10 (0.70)**	-0.35 (0.72)
Edu, γ_{03}	1.08 (0.21)***	0.25 (0.19)	0.45 (0.22)*	1.14 (0.22)***	1.15 (0.21)***	0.28 (0.19)	0.49 (0.22)*	1.24 (0.22)***	1.17 (0.21)***	0.28 (0.19)	0.45 (0.21)*	1.38 (0.22)***
OC, γ_{04}	0.66 (0.13)***	0.22 (0.12)	0.19 (0.14)	0.74 (0.15)***	0.52 (0.13)***	0.15 (0.12)	0.10 (0.13)	0.49 (0.14)***	-0.46 (0.11)***	-0.18 (0.10)	-0.26 (0.12)*	-0.09 (0.12)
Time×Age, γ_{11}	-0.09 (0.03)***	-0.02 (0.01)	-0.04 (0.03)	-0.03 (0.01)**	-0.09 (0.03)***	-0.02 (0.01)	-0.04 (0.03)	-0.03 (0.01)**	-0.09 (0.03)***	-0.02 (0.01)	-0.04 (0.03)	-0.03 (0.01)**
Time×Gender, γ_{12}	0.22 (0.29)	0.03 (0.11)	-0.14 (0.37)	-0.05 (0.10)	0.23 (0.29)	0.01 (0.11)	-0.15 (0.37)	0.04 (0.10)	0.16 (0.30)	0.03 (0.12)	-0.06 (0.37)	-0.05 (0.10)
Time×Edu, γ_{13}	-0.14 (0.10)	0.04 (0.04)	-0.13 (0.12)	0.03 (0.04)	-0.14 (0.10)	0.06 (0.04)	-0.12 (0.12)	0.04 (0.03)	-0.16 (0.10)	0.06 (0.04)	0.11 (0.12)	0.03 (0.03)
Time×OC, γ_{14}	-0.01 (0.06)	0.04 (0.03)	0.03 (0.08)	0.01 (0.02)	0.02 (0.06)	0.02 (0.03)	-0.00 (0.07)	-0.01 (0.02)	-0.08 (0.05)	0.01 (0.02)	0.05 (0.06)	-0.01 (0.02)
Time^2×Age, γ_{21}	0.01 (0.00)*	–	0.00 (0.00)	–	0.01 (0.00)*	–	0.00 (0.00)	–	0.01 (0.00)*	–	0.00 (0.00)	–
Time^2×Gender, γ_{22}	-0.02 (0.03)	–	0.00 (0.03)	–	-0.02 (0.03)	–	0.00 (0.03)	–	-0.02 (0.03)	–	-0.00 (0.03)	–
Time^2×Edu, γ_{23}	0.01 (0.01)	–	0.02 (0.01)	–	0.01 (0.01)	–	0.02 (0.01)	–	0.01 (0.01)	–	0.02 (0.01)	–
Time^2×OC, γ_{24}	0.00 (0.01)	–	0.00 (0.01)	–	0.00 (0.01)	–	0.00 (0.01)	–	0.01 (0.00)	–	-0.00 (0.01)	–
Random Effects												
Residual, σ_ϵ^2	21.53 (1.19)***	42.08 (2.21)***	38.89 (2.04)***	45.05 (2.90)***	21.56 (1.19)***	42.13 (2.22)***	38.90 (2.04)***	45.34 (2.95)***	21.48 (1.19)***	42.11 (2.22)***	38.87 (2.04)***	45.20 (2.93)***

Intercept, σ_0^2	45.54 (3.18)***	28.25 (3.37)***	34.92 (3.45)***	42.84 (4.23)***	46.22 (3.21)***	28.36 (3.38)***	35.00 (3.46)***	43.87 (4.34)***	45.61 (3.19)***	28.15 (3.37)***	34.37 (3.43)***	45.08 (4.37)***
Time, σ_1^2	0.20 (0.05)***	0.20 (0.08)*	0.26 (0.08)**	–[a]	0.20 (0.05)***	0.21 (0.08)*	0.26 (0.08)**	–[a]	0.21 (0.05)***	0.21 (0.08)*	0.24 (0.08)**	–[a]
Covariance, σ_{01}^2	-0.72 (0.35)*	0.83 (0.47)	-0.08 (0.47)	–[a]	-0.76 (0.36)*	0.85 (0.48)	-0.03 (0.47)	–[a]	-0.72 (0.36)*	0.93 (0.48)	0.16 (0.46)	–[a]
Goodness-of-fit												
-2LL	12236.64	13606.26	13523.84	10476.75	12246.56	13612.74	13529.15	10495.26	12240.06	13612.56	13521.89	10507.01
AIC	12274.64	13634.26	13561.84	10500.75	12284.56	13640.74	13567.15	10519.26	12278.06	13640.56	13559.89	10531.01
BIC	12379.21	13712.15	13667.47	10564.14	12389.13	13718.63	13672.78	10582.65	12382.63	13718.46	13665.52	10594.40

Notes. Unstandardised estimates (Est.) and standard errors (SE) are presented. PS: Perceptual Speed. IM: Immediate Memory. DM: Delayed Memory. VR: Verbal Reasoning. T scores for cognitive measures are standardised to the baseline sample (*M*=50, *SD*=10). Time: years in study. Data: Occupational complexity with data, grand mean centred (*M*=3.67). People: Occupational complexity with people, grand mean centred (*M*=1.32). Things: Occupational complexity with things, grand mean centred (*M*=2.35). OC: Occupational complexity, higher scores indicate greater complexity. Age: baseline age, grand mean centred at 78.09 years. Gender: 0=Male, 1=Female. Edu: Education, grand mean centred at 15 years. Dashes indicate that effect was not estimated. [a]For model convergence, variance component could not be estimated. -2LL = Deviance. AIC: Akaike information criterion. BIC: Bayesian information criterion. *p<.05; **p<.01; ***p<.001

Model 2B: Age at Retirement

Age at time of retirement was added to Model 2 as a predictor of initial status and rates of change. The parameter estimates produced by Model 2B are presented in Table 5.13. The associations between the occupational complexity variables and cognition remained unchanged with the addition of age at retirement, suggesting that the relationships were independent of retirement timing and retirement duration. Age at retirement was a significant predictor of initial perceptual speed and verbal reasoning. The parameter estimates from Model 2B suggest that, controlling for age, gender, education, and occupational complexity (data, people or things), each additional year of age at retirement was associated with approximately 0.11 *T score* units higher in perceptual speed and 0.18 *T score* units higher in verbal reasoning. Age at retirement did not moderate cognitive change.

Table 5.13

Parameter Estimates from Multilevel Models Examining Occupational Complexity Predicting Cognitive Performance and Change, and Adjusting for Age at Retirement

	Model 2B: Data				**Model 2B: People**				**Model 2B: Things**			
	PS Est. (SE)	**IM Est. (SE)**	**DM Est. (SE)**	**VR Est. (SE)**	**PS Est. (SE)**	**IM Est. (SE)**	**DM Est. (SE)**	**VR Est. (SE)**	**PS Est. (SE)**	**IM Est. (SE)**	**DM Est. (SE)**	**VR Est. (SE)**
Fixed Effects												
Intercept, γ_{00}	50.48 (0.35)***	49.32 (0.32)***	49.04 (0.37)***	50.24 (0.38)***	50.61 (0.35)***	49.36 (0.32)***	49.08 (0.37)***	50.44 (0.38)***	50.79 (0.35)***	49.43 (0.33)***	49.19 (0.37)***	50.49 (0.38)***
Time, γ_{10}	-0.52 (0.17)**	-0.56 (0.08)***	-1.04 (0.21)***	-0.28 (0.07)***	-0.52 (0.17)**	-0.54 (0.08)***	-1.03 (0.21)***	-0.27 (0.07)***	-0.50 (0.17)**	-0.55 (0.08)***	-1.07 (0.21)***	-0.28 (0.07)***
Time^2, γ_{20}	-0.01 (0.02)	–	0.06 (0.02)**		-0.01 (0.02)	–	0.06 (0.02)**		-0.01 (0.02)	–	0.07 (0.02)***	
Age, γ_{01}	-0.67 (0.05)***	-0.45 (0.05)***	-0.42 (0.05)***	-0.28 (0.05)***	-0.68 (0.05)***	-0.45 (0.05)***	-0.42 (0.05)***	-0.28 (0.06)***	-0.66 (0.05)***	-0.44 (0.05)***	-0.42 (0.05)***	-0.26 (0.06)***
Gender, γ_{02}	1.61 (0.70)*	2.07 (0.65)***	3.06 (0.73)***	0.91 (0.73)	1.17 (0.70)	1.91 (0.64)**	2.93 (0.73)***	0.42 (0.73)	0.63 (0.72)	1.69 (0.66)**	2.56 (0.75)***	0.41 (0.75)
Edu, γ_{03}	1.06 (0.21)***	0.24 (0.19)	0.43 (0.22)*	1.13 (0.22)***	1.12 (0.21)***	0.27 (0.19)	0.46 (0.22)*	1.22 (0.22)***	1.15 (0.21)***	0.26 (0.19)	0.42 (0.21)*	1.35 (0.22)***
OC, γ_{04}	0.65 (0.13)***	0.22 (0.12)	0.18 (0.14)	0.72 (0.14)***	0.52 (0.13)***	0.15 (0.12)	0.10 (0.13)	0.48 (0.14)***	-0.45 (0.11)***	-0.18 (0.10)	-0.26 (0.12)*	-0.09 (0.12)
RA, γ_{05}	0.11 (0.05)*	0.06 (0.05)	0.10 (0.06)	0.18 (0.06)**	0.11 (0.05)*	0.06 (0.05)	0.10 (0.06)	0.18 (0.06)**	0.11 (0.05)*	0.06 (0.05)	0.10 (0.06)	0.18 (0.06)**
Time×Age, γ_{11}	-0.10 (0.03)***	-0.02 (0.01)	-0.04 (0.03)	-0.03 (0.01)**	-0.10 (0.03)***	-0.02 (0.01)	-0.04 (0.03)	-0.02 (0.01)*	-0.09 (0.03)***	-0.02 (0.01)	-0.03 (0.03)	-0.03 (0.01)*
Time×Gender, γ_{12}	0.26 (0.31)	0.01 (0.12)	-0.19 (0.40)	-0.07 (0.11)	0.25 (0.31)	-0.02 (0.12)	-0.20 (0.39)	-0.07 (0.11)	0.18 (0.32)	-0.00 (0.13)	-0.10 (0.40)	-0.08 (0.11)
Time×Edu, γ_{13}	-0.14 (0.10)	0.05 (0.04)	-0.13 (0.12)	0.03 (0.04)	-0.14 (0.10)	0.06 (0.04)	-0.12 (0.12)	0.04 (0.03)	-0.16 (0.10)	0.06 (0.04)	-0.11 (0.12)	0.03 (0.03)
Time×OC, γ_{14}	-0.00 (0.06)	0.04 (0.03)	0.03 (0.08)	0.01 (0.02)	0.01 (0.06)	0.02 (0.03)	-0.00 (0.07)	-0.01 (0.02)	-0.08 (0.05)	0.01 (0.02)	0.05 (0.06)	-0.01 (0.02)
Time×RA, γ_{15}	0.01 (0.03)	-0.00 (0.01)	-0.01 (0.03)	-0.01 (0.01)	0.01 (0.03)	-0.01 (0.01)	-0.01 (0.03)	-0.01 (0.01)	0.01 (0.03)	-0.01 (0.01)	-0.01 (0.03)	-0.01 (0.01)
Time^2×Age, γ_{21}	0.01 (0.00)*	–	0.00 (0.00)	–	0.01 (0.00)*	–	0.00 (0.00)	–	0.01 (0.00)*	–	0.00 (0.00)	–
Time^2×Gender, γ_{22}	-0.03 (0.03)	–	0.00 (0.04)	–	-0.03 (0.03)	–	0.00 (0.04)	–	-0.03 (0.03)	–	-0.00 (0.04)	–
Time^2×Edu, γ_{23}	0.01 (0.01)	–	0.02 (0.01)	–	0.01 (0.01)	–	0.02 (0.01)	–	0.01 (0.01)	–	0.02 (0.01)	–
Time^2×OC, γ_{24}	0.00 (0.01)	–	-0.00 (0.01)	–	0.00 (0.01)	–	0.00 (0.01)	–	0.01 (0.00)	–	-0.00 (0.01)	–

Time^2×RA, γ_{25}	-0.00 (0.00)	–	-0.00 (0.00)	–	-0.00 (0.00)	–	-0.00 (0.00)	–	-0.00 (0.00)	–	-0.00 (0.00)	–
Random Effects												
Residual, σ_ϵ^2	21.52 (1.19)***	42.06 (2.07)***	38.84 (2.04)***	45.04 (2.90)***	21.56 (1.19)***	42.11 (2.21)***	38.85 (2.04)***	45.28 (2.94)***	21.48 (1.19)***	42.09 (2.21)***	38.82 (2.04)***	45.14 (2.92)***
Intercept, σ_0^2	45.07 (3.16)***	28.17 (3.36)***	34.68 (3.44)***	42.15 (4.20)***	45.69 (3.19)***	28.26 (3.37)***	34.75 (3.44)***	43.15 (4.29)***	45.10 (3.17)***	28.05 (3.37)***	34.12 (3.42)***	44.32 (4.33)***
Time, σ_1^2	0.20 (0.05)***	0.20 (0.08)*	0.26 (0.08)**	–[a]	0.20 (0.05)***	0.21 (0.08)*	0.26 (0.08)**	–[a]	0.21 (0.05)***	0.21 (0.08)*	0.24 (0.08)**	–[a]
Covariance, σ_{01}^2	-0.67 (0.35)	0.84 (0.47)	-0.05 (0.46)	–[a]	-0.70 (0.36)*	0.87 (0.48)	0.00 (0.47)	–[a]	-0.66 (0.36)	0.95 (0.48)*	0.19 (0.46)	–[a]
Goodness-of-fit												
-2LL	12229.94	13604.83	13519.86	10467.77	12239.04	13611.03	13524.73	10485.12	12232.65	13610.89	13517.62	10496.66
AIC	12273.94	13636.83	13563.86	10495.77	12283.04	13643.03	13568.73	10513.12	12276.65	13642.89	13561.62	10524.66
BIC	12395.02	13725.82	13686.17	10569.72	12404.12	13732.05	13691.04	10587.07	12397.74	13731.90	13683.93	10598.61

Notes. Unstandardised estimates (Est.) and standard errors (SE) are presented. PS: Perceptual Speed. IM: Immediate Memory. DM: Delayed Memory. VR: Verbal Reasoning. T scores for cognitive measures standardised to the baseline sample (*M*=50, *SD*=10). Time: years in study. Data: Occupational complexity with data, grand mean centred (*M*=3.67). People: Occupational complexity with people, grand mean centred (*M*=1.32). Things: Occupational complexity with things, grand mean centred (*M*=2.35). OC: Occupational complexity, higher scores indicate greater complexity. Age: baseline age, grand mean centred at 78.09 years. Gender: 0=Male, 1=Female. Edu: Education, grand mean centred at 15 years. RA: Age at retirement, grand mean centred at 61.89. -2LL = Deviance. AIC: Akaike information criterion. BIC: Bayesian information criterion. Dashes indicate that effect was not estimated. [a]For model convergence, variance component could not be estimated. *p<.05; **p<.01; ***p<.001.

Model 2C: Occupational status

Model 2C added occupational status as a predictor of both initial status and rates of change. The estimates produced by Model 2C are presented in Table 5.14. The associations between occupational complexity with data and levels of perceptual speed and verbal reasoning were independent of occupational status, although the magnitude of the associations were reduced by approximately 39% and 35%, respectively. The associations between occupational complexity with people and levels of perceptual speed and verbal reasoning were also independent of occupational status, although the magnitudes of the associations were reduced by approximately 31% and 33%, respectively. Similarly, the relationship between occupational complexity with things and levels of perceptual speed were independent of occupational status, but the magnitude of the association was reduced by 43%. Occupational status accounted for the prior association between complexity with things and delayed memory performance. High occupational status appeared to be associated with a higher initial level of perceptual speed, a slower rate of decline over linear time, and an accelerating rate of decline over increasing time.

Table 5.14

Parameter Estimates from Multilevel Models Examining Occupational Complexity Predicting Cognitive Performance and Change, and Adjusting for Occupational Status

	Model 2C: Data				Model 2C: People				Model 2C: Things			
	PS Est. (SE)	**IM Est. (SE)**	**DM Est. (SE)**	**VR Est. (SE)**	**PS Est. (SE)**	**IM Est. (SE)**	**DM Est. (SE)**	**VR Est. (SE)**	**PS Est. (SE)**	**IM Est. (SE)**	**DM Est. (SE)**	**VR Est. (SE)**
Fixed Effects												
Intercept, γ_{00}	49.66 (0.47)***	48.70 (0.44)***	48.47 (0.49)***	49.46 (0.52)***	49.50 (0.45)***	48.70 (0.42)***	48.48 (0.47)***	49.19 (0.50)***	49.67 (0.48)***	48.77 (0.45)***	48.73 (0.50)***	48.73 (0.53)***
Time, γ_{10}	-0.85 (0.22)***	-0.61 (0.07)***	-1.04 (0.28)***	-0.28 (0.09)**	-0.79 (0.21)***	-0.63 (0.09)***	-1.08 (0.27)***	-0.29 (0.08)**	-0.71 (0.23)**	-0.68 (0.10)***	-1.17 (0.28)***	-0.27 (0.09)**
Time^2, γ_{20}	0.03 (0.02)	–	0.06 (0.03)*	–	0.02 (0.02)	–	0.07 (0.03)*	–	0.01 (0.02)	–	0.07 (0.03)*	–
Age, γ_{01}	-0.65 (0.05)***	-0.43 (0.05)***	-0.39 (0.05)***	-0.23 (0.05)***	-0.65 (0.05)***	-0.43 (0.05)***	-0.39 (0.05)***	-0.23 (0.05)***	-0.64 (0.05)***	-0.43 (0.05)***	-0.39 (0.05)***	-0.23 (0.05)***
Gender, γ_{02}	0.67 (0.67)	1.47 (0.62)*	2.27 (0.70)***	-0.15 (0.71)	0.29 (0.66)	1.44 (0.60)*	2.27 (0.69)***	-0.61 (0.69)	0.01 (0.67)	1.36 (0.61)*	2.08 (0.70)**	-0.37 (0.71)
Edu, γ_{03}	0.93 (0.21)***	0.14 (0.20)	0.34 (0.22)	0.99 (0.23)***	0.89 (0.21)***	0.13 (0.20)	0.34 (0.22)	0.96 (0.23)***	0.94 (0.21)***	0.14 (0.20)	0.34 (0.22)	1.02 (0.23)***
OC, γ_{04}	0.40 (0.16)*	0.04 (0.15)	-0.00 (0.17)	0.48 (0.18)**	0.36 (0.13)**	0.06 (0.12)	0.01 (0.14)	0.33 (0.14)*	-0.26 (0.12)*	-0.07 (0.11)	-0.17 (0.13)	0.19 (0.13)
OccStat, γ_{05}	2.13 (0.74)**	1.54 (0.68)*	1.55 (0.78)*	2.09 (0.80)**	2.67 (0.64)***	1.57 (0.59)**	1.53 (0.67)*	2.92 (0.68)***	2.53 (0.67)***	1.48 (0.62)*	1.15 (0.70)	3.77 (0.73)***
Time×Age, γ_{11}	-0.10 (0.03)***	-0.02 (0.01)	-0.04 (0.03)	-0.03 (0.01)**	-0.10 (0.03)***	-0.02 (0.01)†	-0.04 (0.03)*	-0.03 (0.01)**	-0.10 (0.03)***	-0.02 (0.01)	-0.04 (0.03)	-0.03 (0.01)**
Time×Gender, γ_{12}	0.08 (0.30)	0.02 (0.12)	-0.12 (0.38)	-0.05 (0.10)	0.17 (0.29)	-0.00 (0.11)	-0.15 (0.37)	-0.05 (0.10)	0.15 (0.30)	0.04 (0.12)	-0.07 (0.37)	-0.06 (0.10)
Time×Edu, γ_{13}	-0.20 (0.01)*	0.04 (0.04)	-0.13 (0.13)	0.03 (0.04)	-0.20 (0.10)*	0.04 (0.04)	-0.13(0.13)	0.04 (0.04)	-0.20 (0.10)*	0.04 (0.04)	-0.13 (0.13)	0.03 (0.04)
Time×OC, γ_{14}	-0.10 (0.07)	0.03 (0.03)	0.03 (0.09)	0.01 (0.03)	-0.02 (0.06)	0.01 (0.03)	-0.01 (0.08)	-0.01 (0.02)	-0.04 (0.06)	0.03 (0.02)	0.06 (0.07)	-0.01 (0.02)
Time×OccStat, γ_{15}	0.81 (0.33)*	0.10 (0.14)	-0.03 (0.42)	-0.01 (0.12)	0.59 (0.29)*	0.17 (0.12)	0.08 (0.37)	0.02 (0.11)	0.16 (0.31)	0.24 (0.13)	0.18 (0.39)	-0.02 (0.11)
Time^2×Age, γ_{21}	0.01 (0.00)*	–	0.00 (0.00)	–	0.01 (0.00)*	–	0.00 (0.00)	–	0.01 (0.00)*	–	0.00 (0.00)	–
Time^2×Gender, γ_{22}	-0.01 (0.03)	–	0.00 (0.04)	–	-0.02 (0.03)	–	0.00 (0.03)	–	-0.02 (0.03)	–	-0.00 (0.03)	–
Time^2×Edu, γ_{23}	0.02 (0.01)	–	0.02 (0.01)	–	0.02 (0.01)	–	0.02 (0.01)	–	0.02 (0.01)	–	0.02 (0.01)	–

Time^2×OC, γ_{24}	0.01 (0.01)	–	0.00 (0.01)	–	0.00 (0.01)	–	0.00 (0.01)	–	0.00 (0.01)	–	-0.00 (0.01)	–
Time^2×OccStat, γ_{25}	-0.09 (0.03)**	–	-0.00 (0.04)	–	-0.06 (0.03)*	–	-0.00 (0.03)	–	-0.05 (0.03)	–	0.00 (0.04)	–
Random Effects												
Residual, σ_ϵ^2	21.43 (1.19)***	42.05 (2.21)***	38.93 (2.05)***	45.08 (2.90)***	21.45 (1.19)***	42.05 (2.21)***	38.91 (2.05)***	45.23 (2.93)***	21.39 (1.19)***	42.03 (2.21)***	38.79 (2.04)***	45.09 (2.91)***
Intercept, σ_0^2	44.31 (3.12)***	27.92 (3.35)***	34.50 (3.44)***	42.16 (4.20)***	44.29 (3.12)***	27.93 (3.36)***	34.50 (3.44)***	42.24 (4.24)***	44.24 (3.13)***	27.80 (3.35)***	34.21 (3.43)***	42.74 (4.24)***
Time, σ_1^2	0.20 (0.05)***	0.21 (0.08)*	0.26 (0.08)**	–[a]	0.20 (0.05)***	0.21 (0.08)*	0.26 (0.08)***	–[a]	0.21 (0.05)***	0.20 (0.08)*	0.25 (0.08)**	–[a]
Covariance, σ_{01}^2	-0.67 (0.35)	0.78 (0.47)	-0.07 (0.47)	–[a]	-0.76 (0.36)*	0.76 (0.48)	-0.06 (0.47)	–[a]	-0.74 (0.36)*	0.85 (0.48)	0.08 (0.47)	–[a]
Goodness-of-fit												
-2LL	12211.96	13598.53	13518.71	10468.78	12211.48	13599.40	13520.33	10472.87	12214.22	13598.50	13512.83	10476.31
AIC	12255.96	13630.53	13562.71	10496.78	12255.48	13631.40	13564.33	10500.87	12258.22	13630.50	13556.83	10578.26
BIC	12377.04	13719.55	13685.02	10570.73	12376.56	13720.42	13686.64	10574.82	12379.30	13719.52	13679.14	10578.26

Notes. Unstandardised estimates (Est.) and standard errors (SE) are presented. PS: Perceptual Speed. IM: Immediate Memory. DM: Delayed Memory. VR: Verbal Reasoning. T scores for cognitive measures standardised to the baseline sample (*M*=50, *SD*=10). Time: years in study. Data: Occupational complexity with data, grand mean centred (*M*=3.67). People: Occupational complexity with people, grand mean centred (*M*=1.32). Things: Occupational complexity with things, grand mean centred (*M*=2.35). OC: Occupational complexity, higher scores indicate greater complexity. Age: baseline age, grand mean centred at 78.09 years. Gender: 0=Male, 1=Female. Edu: Education, grand mean centred at 15 years. OccStat: Occupational status, 0=blue-Collar, 1=white-collar. Dashes indicate that effect was not estimated. [a]For model convergence, variance component could not be estimated. -2LL = Deviance. AIC: Akaike information criterion. BIC: Bayesian information criterion. *p<.05; **p<.01; ***p<.001.

Model 2D: Health and lifestyle factors

Baseline measures of medical conditions, smoking status, and alcohol consumption were added as level-2 predictors of initial status and rate of change in Model 2D, and depression and the three activity engagement variables were added as level-1 predictors. The estimates from this model are presented in Table 5.15. The associations between occupational complexity with data and levels of perceptual speed and verbal reasoning were independent of age, gender, education, medical conditions, depression, smoking status, alcohol consumption, and late life activity engagement. However, the magnitudes of the associations declined marginally by 8% for perceptual speed and by 19% for verbal reasoning. After controlling for the additional covariates, occupational complexity with data moderated change in immediate memory. Higher complexity with data was associated with slower decline (0.06 *T score* units per year) over linear time.

The associations between occupational complexity with people and levels of perceptual speed and verbal reasoning were also independent of age, gender, education, medical conditions, depression, smoking status, alcohol consumption, and late life activity engagement, although magnitudes of the associations declined by approximately 19%. The associations between occupational complexity with things and levels of perceptual speed and delayed memory were independent of age, gender, education, medical conditions, depression, smoking status, alcohol consumption, and late life activity engagement, and the magnitude of the associations were reduced marginally by about 9%.

Regarding the covariates, medical conditions were associated with lower initial levels of perceptual speed, but not rates of change. Being a former smoker was associated with slower rates of decline in perceptual speed over linear time, and accelerating decline with increasing time. As expected, possible depression was negatively associated with the four cognitive trajectories. Current cognitive activity was a positive predictor of each cognitive change trajectory and social activities were positively associated with perceptual speed, immediate memory and verbal reasoning trajectories. Physical activities were not associated with cognitive change.

Table 5.15

Parameter Estimates from Multilevel Models Examining Occupational Complexity Predicting Cognitive Performance and Change, and Adjusting for Medical Conditions, Alcohol Consumption, Smoking Status, Depression, and Late Life Activity Engagement

	Model 2D: Data				Model 2D: People				Model 2D: Things			
	PS Est. (SE)	**IM Est. (SE)**	**DM Est. (SE)**	**VR Est. (SE)**	**PS Est. (SE)**	**IM Est. (SE)**	**DM Est. (SE)**	**VR Est. (SE)**	**PS Est. (SE)**	**IM Est. (SE)**	**DM Est. (SE)**	**VR Est. (SE)**
Fixed Effects												
Intercept	46.61 (0.96)***	45.44 (0.98)***	45.91 (1.44)***	46.31 (1.14)***	46.71 (0.97)***	45.43 (0.98)***	45.90 (1.07)***	46.42 (1.15)***	46.77 (0.96)***	45.46 (0.98)***	45.99 (1.06)***	46.25 (1.15)***
Time	-0.68 (0.38)	-0.19 (0.15)	-1.13 (0.48)*	-0.50 (0.15)**	-0.67 (0.38)	-0.18 (0.16)	-1.13 (0.48)*	-0.49 (0.15)**	-0.64 (0.38)	-0.18 (0.16)	-1.16 (0.48)*	-0.48 (0.15)**
Time^2	0.03 (0.04)	–	0.11 (0.05)*	–	0.03 (0.04)	–	0.11 (0.05)*	–	0.02 (0.04)	–	0.11 (0.05)*	–
Age	-0.62 (0.05)***	-0.41 (0.05)***	-0.36 (0.05)***	-0.21 (0.05)***	-0.61 (0.05)***	-0.41 (0.05)***	-0.35 (0.05)***	-0.20 (0.05)***	-0.60 (0.05)***	-0.40 (0.05)***	-0.35 (0.05)***	-0.19 (0.05)***
Gender	0.45 (0.69)	1.19 (0.65)	2.08 (0.74)**	-0.52 (0.75)	0.01 (0.69)	1.07 (0.65)	1.95 (0.73)**	-1.00 (0.75)	-0.46 (0.70)	0.87 (0.66)	1.61 (0.75)*	-1.11 (0.77)
Edu	0.90 (0.20)***	0.17 (0.19)	0.39 (0.22)	0.99 (0.22)***	0.98 (0.20)***	0.20 (0.19)	0.43 (0.22)*	1.08 (0.22)***	0.98 (0.20)***	0.18 (0.19)	0.39 (0.22)	1.17 (0.22)***
OC	0.61 (0.13)***	0.18 (0.12)	0.19 (0.14)	0.64 (0.14)***	0.42 (0.13)**	0.11 (0.12)	0.06 (0.13)	0.40 (0.14)**	-0.42 (0.11)***	-0.16 (0.10)	-0.24 (0.12)*	-0.10 (0.12)
MedCdns	-0.66 (0.24)**	-0.38 (0.23)	-0.25 (0.26)	-0.29 (0.26)	-0.63 (0.24)*	-0.38 (0.23)	-0.23 (0.26)	-0.27 (0.26)	-0.68 (0.24)**	-0.38 (0.23)	-0.24 (0.26)	-0.27 (0.27)
Abstain	-1.26 (0.92)	0.59 (0.87)	-0.42 (1.00)	-0.53 (1.00)	-1.32 (0.93)	0.59 (0.87)	-0.47 (0.99)	-0.68 (1.00)	-0.19 (0.93)	0.66 (0.87)	-0.33 (0.99)	-0.72 (1.01)
≤ 2 drinks/day	-0.65 (0.84)	1.05 (0.78)	0.52 (0.91)	0.69 (0.90)	-0.62 (0.84)	1.06 (0.78)	0.52 (0.91)	0.65 (0.91)	-0.49 (0.84)	1.11 (0.78)	0.61 (0.90)	0.65 (0.92)
Never smoked	0.94 (0.62)	0.22 (0.59)	0.83 (0.67)	1.04 (0.70)	0.99 (0.63)	0.20 (0.59)	0.87 (0.67)	1.11 (0.70)	0.88 (0.63)	0.13 (0.59)	0.77 (0.67)	1.17 (0.70)
Former Smoker	-1.75 (1.07)	0.59 (1.00)	1.45 (1.12)	-1.62 (1.12)	-1.68 (1.08)	0.58 (1.00)	1.47 (1.12)	-1.47 (1.13)	-1.99 (1.07)	0.47 (1.00)	1.37 (0.12)	-1.50 (1.14)
Time×Age	-0.10 (0.03)***	-0.02 (0.01)	-0.06 (0.03)	-0.03 (0.01)*	-0.10 (0.03)***	-0.02 (0.01)	-0.06 (0.03)†	-0.02 (0.01)*	-0.10 (0.03)***	-0.01 (0.01)	-0.06 (0.03)	-0.02 (0.01)*
Time×Gender	0.20 (0.33)	0.12 (0.12)	-0.26 (0.41)	-0.08 (0.12)	0.24 (0.32)	0.09 (0.13)	-0.23 (0.41)	-0.09 (0.12)	0.16 (0.33)	0.11 (0.13)	-0.09 (0.42)	-0.08 (0.12)
Time×Educ	-0.09 (0.10)	0.03 (0.04)	-0.13 (0.13)	0.02 (0.04)	-0.10 (0.10)	0.04 (0.04)	-0.14 (0.13)	0.03 (0.04)	-0.10 (0.10)	0.05 (0.04)	-0.13 (0.13)	0.03 (0.04)
Time×OC	-0.04 (0.07)	0.06 (0.03)*	-0.04 (0.08)	0.02 (0.02)	0.03 (0.06)	0.01 (0.03)	0.01 (0.08)	0.00 (0.02)	-0.09 (0.05)	0.02 (0.02)	0.08 (0.07)	-0.00 (0.02)
Time×MedCdns	-0.09 (0.12)	0.01 (0.05)	0.03 (0.15)	0.05 (0.05)	-0.10 (0.12)	0.02 (0.05)	0.02 (0.15)	0.05 (0.05)	-0.09 (0.12)	0.01 (0.05)	0.02 (0.15)	0.05 (0.05)
Time×Abstain	0.04 (0.46)	-0.29 (0.19)	-0.46 (0.58)	0.21 (0.17)	0.07 (0.46)	-0.33 (0.19)	-0.42 (0.58)	0.21 (0.17)	0.13 (0.46)	-0.34 (0.19)	-0.49 (0.58)	0.21 (0.17)
Time×≤ 2 drinks/day	0.33 (0.42)	-0.23 (0.17)	-0.05 (0.53)	0.41 (0.16)	0.32 (0.42)	-0.23 (0.17)	-0.04 (0.53)	0.41 (0.16)	0.33 (0.42)	-0.24 (0.17)	-0.07 (0.52)	0.41 (0.16)*
Time×Never Smoked	-0.16 (0.30)	0.10 (0.12)	0.48 (0.39)	-0.09 (0.11)	-0.24 (0.310)	-0.07 (0.12)	0.42 (0.38)	-0.09 (0.11)	-0.27 (0.30)	-0.05 (0.12)	0.46 (0.39)	-0.10 (0.11)
Time×Former Smoker	1.18 (0.56)*	-0.15 (0.22)	1.18 (0.70)	-0.08 (0.21)	1.18 (0.56)*	-0.13 (0.23)	1.13 (0.70)	-0.07 (0.21)	1.05 (0.56)	-0.12 (0.23)	1.14 (0.70)	-0.08 (0.21)

Time^2×Age	0.01 (0.00)**	–	0.01 (0.00)	–	0.01 (0.00)**	–	0.01 (0.00)	–	0.01 (0.00)**	–	0.01 (0.00)	–
Time^2×Gender	-0.03 (0.03)	–	0.02 (0.04)	–	-0.03 (0.03)	–	0.01 (0.04)	–	-0.02 (0.03)	–	0.00 (0.04)	–
Time^2×Edu	0.00 (0.01)	–	0.01 (0.01)	–	0.01 (0.01)	–	0.02 (0.01)	–	0.01 (0.01)		0.02 (0.01)	–
Time^2×OC	0.01 (0.01)	–	0.01 (0.01)	–	-0.00 (0.01)	–	-0.00 (0.01)	–	0.01 (0.01)	–	-0.00 (0.01)	–
Time^2×MedCdns	0.00 (0.01)	–	-0.01 (0.02)	–	0.00 (0.01)	–	-0.01 (0.02)	–	0.00 (0.01)	–	-0.01 (0.02)	–
Time^2×Abstain	-0.00 (0.05)	–	0.03 (0.06)	–	-0.01 (0.05)	–	0.02 (0.06)	–	-0.02 (0.04)	–	0.02 (0.06)	–
Time^2× ≤ 2 drinks/day	-0.03 (0.04)	–	-0.02 (0.05)	–	-0.03 (0.04)	–	-0.02 (0.05)	–	-0.04 (0.04)	–	-0.02 (0.05)	–
Time^2×Never Smoked	0.01 (0.03)	–	-0.06 (0.04)	–	0.02 (0.03)	–	-0.05 (0.04)	–	0.02 (0.03)	–	-0.05 (0.04)	–
Time^2×Former Smoker	-0.11 (0.05)*	–	-0.13 (0.07)	–	-0.11 (0.05)*	–	-0.12 (0.07)	–	-0.09 (0.05)	–	-0.12 (0.07)	–
CES-D	-0.13 (0.03)***	-0.07 (0.03)*	-0.10 (0.03)**	-0.11 (0.04)**	-0.13 (0.03)***	-0.07 (0.03)*	-0.11 (0.03)**	-0.11 (0.04)**	-0.13 (0.03)***	-0.07 (0.03)*	-0.10 (0.03)**	-0.12 (0.04)**
CogAct	0.45 (0.07)***	0.30 (0.09)***	0.28 (0.09)**	0.36 (0.10)**	0.46 (0.07)***	0.31 (0.09)***	0.29 (0.09**)	0.37 (0.10)***	0.46 (0.07)***	0.31 (0.09)***	0.28 (0.09)**	0.38 (0.11)***
SocAct	0.23 (0.08)**	0.18 (0.09)*	0.06 (0.09)	0.22 (0.11)*	0.22 (0.08)**	0.18 (0.09)*	0.01 (0.09)	0.21 (0.11)*	0.24 (0.08)**	0.18 (0.09)*	0.06 (0.09)	0.24 (0.11)*
PhysAct	-0.00 (0.02)	0.02 (0.02)	0.01 (0.02)	0.02 (0.03)	-0.00 (0.02)	0.02 (0.02)	0.01 (0.02)	0.02 (0.03)	-0.00 (0.02)	0.02 (0.02)	0.01 (0.02)	0.02 (0.03)
Random Effects												
Residual, σ_ϵ^2	21.63 (1.25)***	43.51 (2.38)***	38.58 (2.13)***	44.87 (3.27)***	21.54 (1.25)***	43.48 (2.38)***	38.40 (2.11)***	45.30 (3.33)***	21.54 (1.25)***	43.49 (2.38)***	38.23 (2.10)***	45.26 (3.32)***
Intercept, σ_0^2	40.37 (2.97)***	25.48 (3.37)***	33.02 (3.42)***	40.03 (4.49)***	41.03 (3.00)***	25.56 (3.38)***	33.10 (3.42)***	40.73 (4.59)***	40.36 (2.98)***	25.31 (3.37)***	32.75 (3.40)***	41.52 (4.62)***
Time, σ_1^2	0.10 (0.05)*	0.04 (0.08)	0.16 (0.08)	–[a]	0.11 (0.05)*	0.05 (0.08)	0.17 (0.08)*	–[a]	0.11 (0.05)*	0.05 (0.08)	0.16 (0.08)	–[a]
Covariance, σ_{01}^2	-0.56 (0.33)	0.92 (0.47)*	-0.00 (0.47)	–[a]	-0.58 (0.34)	0.97 (0.48)*	0.01 (0.47)	–[a]	-0.57 (0.34)	1.06 (0.48)*	0.22 (0.47)	–[a]
Goodness-of-fit												
-2LL	11532.17	12757.58	12678.64	9787.59	11545.75	12766.55	12685.54	9804.53	11534.55	12765.59	12678.59	9813.55
AIC	11608.17	12813.58	12754.64	9839.59	11621.75	12822.55	12761.54	9856.53	11610.58	12821.59	12754.59	9865.55
BIC	11815.41	12967.69	12963.66	9975.21	11828.98	12976.66	12970.56	9992.14	11817.82	12975.70	12963.61	10001.17

Notes. Unstandardised estimates (Est.) and standard errors (SE) are presented. PS: Perceptual Speed. IM: Immediate Memory. DM: Delayed Memory. VR: Verbal Reasoning. T scores for cognitive measures standardised to the baseline sample (*M*=50, *SD*=10). Time: years in study. Data: Occupational complexity with data, grand mean centred (*M*=3.67). People: Occupational complexity with people, grand mean centred (*M*=1.32). Things: Occupational complexity with things, grand mean centred (*M*=2.35). OC: Occupational complexity, higher scores indicate greater complexity. Age: baseline age, grand mean centred at 78.09 years. Gender: 0=Male, 1=Female. Edu: Education, grand mean centred at 15 years. Smoking status: reference group is smoker. Alcohol consumption: reference group is Risky (more than 2 drinks daily). MedCdns: Number of medical conditions, grand mean centred (*M*=1.58). CES-D, centred at 16 (scores >16 correspond to the cutoff for depression). CogAct: cognitive activity. SocAct: social activity. PhysAct: physical activity. -2LL = Deviance. AIC: Akaike information criterion. BIC: Bayesian information criterion. *p<.05; **p<.01; ***p<.001.

Model 3: Complexity with Data, People, and Things

Model 3 added all three occupational complexity variables simultaneously. The parameter estimates generated are presented in Table 5.16. After accounting for their shared variance, complexity with data remained a significant predictor of initial perceptual speed and verbal reasoning, whereas complexity with people was no longer a significant predictor of cognition. Complexity with things also remained a significant predictor of cognition.

Table 5.16

Parameter Estimates from Multilevel Models Examining Occupational Complexity Involving Data, People, and Things Predicting Cognitive Performance and Change

	Data + People + Things			
	Perceptual Speed Est. (SE)	**Immediate Memory Est. (SE)**	**Delayed Memory Est. (SE)**	**Verbal Reasoning Est. (SE)**
Fixed Effects				
Intercept	50.75 (0.34)***	49.45 (0.32)***	49.27 (0.36)***	50.41 (0.38)***
Time	-0.47 (0.17)**	-0.57 (0.07)***	-1.08 (0.21)***	-0.28 (0.06)***
Time^2	-0.02 (0.02)	–	0.07 (0.02)***	–
Age	-0.64 (0.05)***	-0.43 (0.05)***	-0.38 (0.05)***	-0.24 (0.05)***
Gender	0.54 (0.67)	1.55 (0.62)*	2.22 (0.70)**	0.20 (0.72)
Education	0.96 (0.21)***	0.21 (0.19)	0.40 (0.22)	1.11 (0.23)***
Data	0.58 (0.14)***	0.22 (0.13)	0.22 (0.15)	0.63 (0.16)***
People	0.11 (0.15)	-0.02 (0.14)	-0.14 (0.16)	0.31 (0.16)
Things	-0.38 (0.12)**	-0.18 (0.12)	-0.30 (0.13)*	0.07 (0.13)
Time×Age	-0.09 (0.03)***	-0.02 (0.01)	-0.04 (0.03)	-0.03 (0.01)**
Time×Gender	0.13 (0.30)	0.05 (0.12)	-0.05 (0.38)	-0.06 (0.10)
Time×Education	-0.15 (0.10)	0.05 (0.04)	-0.13 (0.12)	0.03 (0.04)
Time×Data	-0.01 (0.07)	0.04 (0.03)	0.03 (0.08)	0.01 (0.02)
Time×People	-0.03 (0.07)	0.01 (0.03)	0.02 (0.09)	-0.02 (0.02)
Time×Things	-0.09 (0.06)	0.02 (0.02)	0.06 (0.07)	-0.02 (0.02)
Time^2×Age	0.01 (0.00)*	–	0.00 (0.00)	–
Time^2×Gender	-0.02 (0.03)	–	-0.00 (0.04)	–
Time^2×Education	0.01 (0.01)	–	0.02 (0.01)	–
Time^2×Data	0.00 (0.01)	–	0.02 (0.01)	–
Time^2×People	0.01 (0.01)	–	0.00 (0.01)	–
Time^2×Things	0.01 (0.01)	–	0.00 (0.01)	–
Random Effects				
Residual, σ_{ϵ}^2	21.57 (1.19)***	42.17 (2.22)***	38.87 (2.04)***	44.97 (2.91)***
Intercept, σ_0^2	43.86 (3.11)***	27.94 (3.37)***	34.29 (3.43)***	42.65 (4.23)***
Time, σ_1^2	0.20 (0.05)***	0.20 (0.08)*	0.24 (0.08)**	–[a]
-Covariance, σ_{01}	-0.73 (0.35)*	0.86 (0.48)	0.07 (0.47)	–[a]
Goodness of fit				
-2LL	12207.77	13603.33	13514.39	10472.63
AIC	12257.77	13639.33	13564.39	10504.63
BIC	12395.36	13739.48	13703.38	10589.15

Notes. Unstandardised estimates (Est.) and standard errors (SE) are presented. T scores for cognitive measures standardised to the baseline sample (*M*=50, *SD*=10). Time: years in study. Data: Occupational complexity with data, grand mean centred (*M*=3.67). People: Occupational complexity with people, grand mean centred (*M*=1.32). Things: Occupational complexity with things, grand mean centred (*M*=2.35). OC: Occupational complexity, higher scores indicate greater complexity. Age: baseline age, grand mean centred at 78.09 years. Gender: 0=Male, 1=Female. Edu: Education, grand mean centred at 15 years. Dashes indicate that effect was not estimated. [a]For model convergence, variance component could not be estimated . -2LL = Deviance. AIC: Akaike information criterion. BIC: Bayesian information criterion. *p<.05; **p<.01; ***p<.001.

Modifying role of education, gender, and age at retirement

Model 2 was repeated with terms to allow for interactions among occupational complexity (data, people, and things), the covariates (education and gender), and time (linear and quadratic, as appropriate). Model 2A was repeated with terms to allow for interactions among occupational complexity (data, people, and things), age at retirement, and time (linear and quadratic, as appropriate). Relative model fit indices are provided in Table 5.17 (parameter estimates are provided in Appendix B).

Deviance-based tests indicated that associations of occupational complexity involving data and people with the cognitive change trajectories did not vary by education, gender, or age at retirement. The association between occupational complexity with things and the cognitive change trajectories did not vary by gender or age at retirement. However, deviance-based tests revealed that association between occupational complexity with things and decline in delayed memory varied by education (Δ-2LL (3) = 9.52, p<.05). A post hoc analysis performed for higher and lower education groups revealed that complexity with things moderated rates of cognitive change in the lower education group (see Appendix B, Table B.2). Specifically, in the lower education group, higher complexity with things was associated with a slower rate of decline over linear time.

Table 5.17

Relative Model Fit Indices: Occupational Complexity by Education, Gender, and Age at Retirement Predicting Cognitive Performance and Change

	Model 2 + Data × Education					**Model 2 + People × Education**					**Model 2 + Things × Education**			
	PS	**IM**	**DM**	**VR**		**PS**	**IM**	**DM**	**VR**		**PS**	**IM**	**DM**	**VR**
-2LL	12232.81	13605.69	13521.46	10476.31		12241.93	13612.48	13528.36	10493.25		12238.79	13610.85	13512.37	10504.08
[a]Δ-2LL	3.83	0.57	2.38	0.44		4.63	0.26	0.79	2.01		1.27	1.71	9.52*	2.93
Δdf	3	2	3	2		3	2	3	2		3	2	3	2
AIC	12276.81	13637.69	13565.46	10504.31		12285.93	13644.48	13572.36	10521.25		12282.79	13642.85	13556.37	10532.08
BIC	12397.89	13726.71	13687.77	10578.26		12407.02	13733.50	13694.67	10595.20		12403.88	13731.87	13678.68	10606.03
	Model 2 + Data × Gender					**Model 2 + People × Gender**					**Model 2 + Things × Gender**			
	PS	**IM**	**DM**	**VR**		**PS**	**IM**	**DM**	**VR**		**PS**	**IM**	**DM**	**VR**
-2LL	12233.23	13605.33	13518.59	10473.82		12245.93	13610.32	13525.52	10494.08		12233.32	13611.32	13521.67	10505.47
[a]Δ-2LL	3.41	0.93	5.25	2.93		0.63	2.42	3.63	1.18		6.74	1.24	0.22	1.54
Δdf	3	2	3	2		3	2	3	2		3	2	3	2
AIC	12277.23	13637.33	13562.59	10501.82		12289.93	13642.32	13569.52	10522.08		12277.32	13643.32	13565.67	10533.47
BIC	12398.32	13726.35	13684.90	10575.77		12411.01	13731.34	13691.83	10596.03		12398.41	13732.34	13687.98	10607.42
	Model 2A + Data × Age at Retirement					**Model 2A + People × Age at Retirement**					**Model 2A + Things × Age at Retirement**			
	PS	**IM**	**DM**	**VR**		**PS**	**IM**	**DM**	**VR**		**PS**	**IM**	**DM**	**VR**
-2LL	12227.80	13601.82	13518.88	10467.52	12237.15	13610.77	13523.37	10484.08	12232.27	13608.40	13511.35	10495.91	12227.80	13601.82
[b]Δ-2LL	2.14	3.01	0.98	0.25	1.89	0.26	1.36	1.04	0.38	2.49	6.27	0.75	2.14	3.01
Δdf	3	2	3	2		3	2	3	2		3	2	3	2
AIC	12277.80	13637.82	13568.88	10499.52	12287.15	13646.77	13573.37	10516.08	12282.37	13644.40	13561.35	10527.91	12277.80	13637.82
BIC	12415.40	13737.96	13707.87	10584.03	12424.74	13746.92	13712.36	10600.59	12419.97	13744.55	13700.34	10612.43	12415.40	13737.96

Notes. PS: Perceptual Speed. IM: Immediate Memory. DM: Delayed Memory. VR: Verbal Reasoning. -2LL = Deviance. [a]Δ -2LL = [-2LL model 2] – [-2LL current model]. [b]Δ -2LL = [-2LL model 2A] – [-2LL current model]. AIC: Akaike information criterion. BIC: Bayesian information criterion. *p<.05; **p<.01; ***p<.001.

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5.3.3 Physical job demands and cognitive ageing

In this section, results from models examining whether and how the physical job demand variables predict levels of, and change in, the cognitive abilities are presented. The models are presented in the same order as above. The unadjusted, followed by the adjusted associations, of physical job demands with cognition are presented first. Then, the modifying roles of education, gender, and age at the time of retirement are presented.

Unadjusted associations of physical job demands with cognition

Model 1 added physical job demands to the unconditional cognitive growth models as predictors of initial levels cognitive function and rates of cognitive change. The two types of physical job demands (movement-related and strength-related) were examined in separate models. Table 5.18 presents the estimates generated from Model 1.

Significant main effects of movement- and strength-related job demands on cognitive functioning were found. Movement-related job demand was associated with 3.40 *T score* units lower on perceptual speed, 1.91 *T score* units lower on immediate memory, 1.62 *T score* units lower on delayed memory, and 2.69 *T score* units lower on verbal reasoning. Strength-related job demand was associated with 3.37 *T score* units lower on perceptual speed, 2.22 *T score* units lower on immediate memory, 2.24 *T score* units lower on delayed memory, and 1.37 *T score* units lower on verbal reasoning. None of the interaction terms (Physical Job Demands × Time and, Physical Job Demands × Time^2) were significantly different from zero for any of the cognitive measures, suggesting the physical job demands do not moderate rates of cognitive change.

Change in Pseudo R_0^2 indicated that the physical job demands accounted for only a small fraction of between-person differences in levels of cognitive function.

Specifically, movement- and strength-related job demands accounted for 3.9% and 5% of variability in level for perceptual speed, 1.7% and 3.1% of variability in level for immediate memory, 1.0% and 1.9% of variability in level for delayed memory and, 2.5% and 0.6 % of variability in level for verbal reasoning, respectively.

Table 5.18

Parameter Estimates from Multilevel Models Examining Physical Job Demands Predicting Cognitive Performance and Change

	Model 1: Movement-Related Job Demand				**Model 1: Strength-Related Job Demand**			
	PS Est. (SE)	**IM Est. (SE)**	**DM Est. (SE)**	**VR Est. (SE)**	**PS Est. (SE)**	**IM Est. (SE)**	**DM Est. (SE)**	**VR Est. (SE)**
Fixed Effects								
Intercept, γ_{00}	53.51 (0.64)***	51.36 (0.56)***	51.15 (0.62)***	52.41 (0.64)***	52.31 (0.41)***	50.82 (0.36)***	50.82 (0.40)***	50.95 (0.42)***
Time, γ_{10}	-0.11 (0.26)	-0.43 (0.10)***	-0.92 (0.32)**	-0.17 (0.09)	-0.06 (0.17)	-0.48 (0.07)***	-1.19 (0.21)***	-0.18 (0.05)**
Time^2, γ_{20}	-0.05 (0.01)*	–	0.07 (0.03)*	–	-0.04 (0.02)**	–	0.08 (0.02)***	–
PJD, γ_{01}	-3.40 (0.74)***	-1.91 (0.65)**	-1.62 (0.72)*	-2.69 (0.74)***	-3.37 (0.66)***	-2.22 (0.57)***	-2.24 (0.65)**	-1.37 (0.66)*
Time×PJD, γ_{11}	-0.13 (0.30)	-0.02 (0.12)	-0.10 (0.38)	-0.01 (0.11)	-0.38 (0.28)	0.08 (0.11)	0.51 (0.34)	0.00 (0.09)
Time^2×PJD, γ_{21}	0.03 (0.03)	–	-0.00 (0.04)	–	0.04 (0.03)	–	0.05 (0.03)	–
Random Effects								
Residual, σ_{ϵ}^2	22.26 (1.24)***	42.36 (2.24)***	39.29 (2.08)***	45.90 (2.95)***	22.22 (1.24)***	42.35 (2.24)***	39.25 (2.07)***	45.90 (2.95)***
Intercept, σ_0^2	64.47 (4.15)***	36.15 (3.75)***	43.39 (3.87)***	49.54 (4.55)***	63.77 (4.12)***	35.61 (3.72)***	42.97 (3.84)***	50.49 (4.60)***
Time, σ_1^2	0.22 (0.06)***	0.22 (0.08)*	0.27 (0.08)**	–[a]	0.23 (0.06)***	0.21 (0.08)*	0.27 (0.08)**	–[a]
Covariance, σ_{01}^2	-0.56 (0.46)	1.02 (0.52)	-0.08 (0.51)	–[a]	-0.69 (0.46)	1.09 (0.52)*	-0.00 (0.51)	–[a]
Goodness-of-fit								
-2LL	12544.10	13748.60	13664.49	10572.91	12532.05	13743.46	13661.56	10583.54
AIC	12564.10	13764.60	13684.49	10584.91	12552.05	13759.46	13681.56	10595.54
BIC	12619.14	13809.11	13740.09	10616.60	12607.09	13803.97	13731.16	10627.24
Explained variance:								
Between-person								
Level - Pseudo R_0^2	0.039	0.017	0.010	0.025	0.050	0.031	0.019	0.006
Slope - Pseudo R_1^2	0.043	-0.048[b]	0.000	–[a]	0.000	0.000	0.000	–[a]

Notes. Unstandardised estimates (Est.) and standard errors (SE) are presented. PS: Perceptual Speed. IM: Immediate Memory. DM: Delayed Memory. VR: Verbal Reasoning. T scores for cognitive measures standardised to the baseline sample (*M*=50, *SD*=10). Time: years in study. PJD: Physical Job Demands. Movement-related job demand: 0= No (sitting), 1=Yes (standing or moving). Strength-related job demand: 0=No (non-heavy), 1=Yes (heavy). Dashes indicate that effect was not estimated. [a]For model convergence, variance component could not be estimated -2LL = Deviance. AIC: Akaike information criterion. BIC: Bayesian information criterion. Pseudo R_0^2 = (σ_0^2 unconditional growth model − σ_0^2 conditional model) / σ_0^2 unconditional growth model). Pseudo R_1^2 = (σ_1^2 unconditional growth model − σ_1^2 conditional model) / σ_1^2 unconditional growth model). [b]Negative pseudo R^2 is due to a repartitioning of the variance between level and slope (Singer & Willett, 2003). *p<.05; **p<.01; ***p<.001.

Covariate adjusted associations of physical job demands with cognition

Model 2: Age, gender, and education

Model 2 added baseline age, gender, and education to Model 1 as predictors of initial levels of cognitive function and rates of cognitive change. Parameter estimates from Model 2 are presented in Table 5.19. The associations of movement-related job demand with levels of perceptual speed and verbal reasoning were independent of age, gender and education, although the magnitudes of the associations were reduced by 38% and 33%, respectively. Movement-related job demand was not independently associated with initial levels of immediate or delayed memory. The associations of strength-related job demand with levels of perceptual speed, and immediate and delayed memory, were independent of age, gender, and education. The magnitudes of the associations between strength-related job demand and perceptual speed and immediate memory were reduced by 26%. Strength-related job demand was not independently associated with initial levels of verbal reasoning.

Table 5.19

Parameter Estimates from Multilevel Models Examining Physical Job Demands Predicting Cognitive Performance and Change, and Adjusting for Age, Gender, and Education

	Model 2: Movement-Related Job Demand				Model 2: Strength Related Job Demand			
	PS Est. (SE)	**IM** Est. (SE)	**DM** Est. (SE)	**VR** Est. (SE)	**PS** Est. (SE)	**IM** Est. (SE)	**DM** Est. (SE)	**VR** Est. (SE)
Fixed Effects								
Intercept, γ_{00}	52.39 (0.63)***	50.28 (0.58)***	49.62 (0.65)***	52.01 (0.68)***	51.88 (0.44)***	50.20 (0.41)***	49.81 (0.46)***	50.82 (0.48)***
Time, γ_{10}	-0.36 (0.29)	-0.55 (0.12)***	-0.86 (0.36)*	-0.28 (0.11)**	-0.30 (0.21)	-0.61 (0.09)***	-1.24 (0.26)***	-0.28 (0.08)***
Time^2, γ_{20}	-0.04 (0.03)	–	0.06 (0.03)	–	-0.03 (0.02)	–	0.08 (0.03)**	–
Age, γ_{01}	-0.62 (0.05)***	-0.42 (0.05)***	-0.38 (0.05)***	-0.20 (0.05)***	-0.63 (0.05)***	-0.43 (0.04)***	-0.39 (0.05)***	-0.21 (0.05)***
Gender, γ_{02}	0.48 (0.67)	1.52 (0.60)*	2.42 (0.69)***	-0.38 (0.70)	0.17 (0.67)	1.27 (0.61)*	2.16 (0.70)**	-0.30 (0.71)
Edu, γ_{03}	1.19 (0.21)***	0.28 (0.19)	0.49 (0.22)*	1.31 (0.22)***	1.15 (0.21)***	0.22 (0.19)	0.43 (0.22)*	1.37 (0.23)***
PJD, γ_{04}	-2.11 (0.68)**	-1.08 (0.62)	-0.54 (0.70)	-1.79 (0.73)*	-2.49 (0.62)***	-1.66 (0.56)**	-1.35 (0.64)*	-0.40 (0.67)
Time×Age, γ_{11}	-0.09 (0.03)***	-0.02 (0.01)	-0.04 (0.03)	-0.03 (0.01)**	-0.09 (0.03)***	-0.02 (0.01)	-0.04 (0.03)	-0.03 (0.01)**
Time×Gender, γ_{12}	0.21 (0.29)	0.02 (0.11)	-0.18 (0.37)	-0.04 (0.10)	0.14 (0.30)	0.05 (0.12)	-0.05 (0.37)	-0.04 (0.10)
Time×Edu, γ_{13}	-0.16 (0.10)	0.06 (0.04)	-0.14 (0.12)	0.03 (0.04)	-0.18 (0.10)	0.07 (0.04)	-0.09 (0.12)	0.03 (0.04)
Time×PJD, γ_{14}	-0.19 (0.30)	-0.00 (0.12)	-0.25 (0.38)	-0.00 (0.11)	-0.46 (0.28)	0.13 (0.12)	0.43 (0.36)	-0.00 (0.10)
Time^2×Age, γ_{21}	0.01 (0.00)*	–	0.00 (0.00)	–	0.01 (0.00)*	–	0.00 (0.00)	–
Time^2×Gender, γ_{22}	-0.02 (0.03)	–	0.00 (0.03)	–	-0.02 (0.03)	–	-0.01 (0.03)	–
Time^2×Edu, γ_{23}	0.01 (0.01)	–	0.02 (0.01)	–	0.01 (0.01)	–	0.01 (0.01)	–
Time^2×PJD, γ_{24}	0.03 (0.03)	–	0.01 (0.04)	–	0.05 (0.03)	–	-0.04 (0.03)	–
Random Effects								
Residual, σ_ϵ^2	21.50 (1.19)***	42.02 (2.09)***	38.86 (2.04)***	45.18 (2.92)***	21.44 (1.19)***	42.01 (2.21)***	38.84 (2.04)***	45.20 (2.93)***
Intercept, σ_0^2	46.48 (3.23)***	28.34 (3.37)***	35.00 (3.45)***	44.47 (3.34)***	45.71 (3.19)***	27.92 (3.35)***	34.77 (3.44)***	45.19 (4.37)***
Time, σ_1^2	0.20 (0.05)***	0.21 (0.08)*	0.26 (0.08)**	–[a]	0.21 (0.05)***	0.21 (0.08)*	0.26 (0.08)**	–[a]
Covariance, σ_{01}^2	-0.62 (0.36)	0.89 (0.48)	-0.05 (0.46)	–[a]	-0.71 (0.36)	0.96 (0.47)*	0.00 (0.46)	–[a]
Goodness-of-fit								
-2LL	12256.45	13612.40	13526.09	10501.71	12240.22	13607.11	13525.10	10508.30
AIC	12294.45	13640.40	13564.09	10525.71	12278.22	13635.11	13563.10	10532.30
BIC	12399.02	13718.30	13669.73	10589.10	12382.80	13713.01	13668.73	10595.68

Notes. Unstandardised estimates (Est.) and standard errors (SE) are presented. PS: Perceptual Speed. IM: Immediate Memory. DM: Delayed Memory. VR: Verbal Reasoning. T scores for cognitive measures standardised to the baseline sample (*M*=50, *SD*=10). Time: years in study. PJD: Physical Job Demands. Movement-related job demand: 0=No (sitting), 1=Yes (standing or moving). Strength-related job demand: 0=No (non-heavy), 1=Yes (heavy). Age: baseline age, grand mean centred at 78.09 years. Gender: 0=Male, 1=Female. Edu: Education, grand mean centred at 15 years. Dashes indicate that effect was not estimated. [a]For model convergence, variance component could not be estimated. -2LL = Deviance. AIC: Akaike information criterion. BIC: Bayesian information criterion. *p<.05; **p<.01; ***p<.001.

Model 2A: Age at Retirement

Model 2A added age at retirement as a predictor of both initial status and rate of change. The estimates from Model 2A are presented in Table 5.20. The associations between the physical job demands and levels of cognitive function remained unchanged with the addition of age at retirement, suggesting that the relations of physical job demands with cognitive function are independent of retirement timing and retirement duration.

Model 2B: Occupational Status

Model 2B added occupational status as a predictor of both initial status and rate of change. The estimates from Model 2B are presented in Table 5.21. Occupational status accounted for the previous relationships between movement-related job demand and cognitive function. Strength-related job demand remained a significant predictor of levels of perceptual speed and immediate memory.

Table 5.20

Parameter Estimates from Multilevel Models Examining Physical Job Demands Predicting Cognitive Performance and Change, and Adjusting for Age at Retirement

	Model 2A: Movement-Related Job Demand				**Model 2A: Strength-Related Job Demand**			
	PS Est. (SE)	**IM Est. (SE)**	**DM Est. (SE)**	**VR Est. (SE)**	**PS Est. (SE)**	**IM Est. (SE)**	**DM Est. (SE)**	**VR Est. (SE)**
Fixed Effects								
Intercept, γ_{00}	52.29 (0.63)***	50.22 (0.58)***	49.53 (0.65)***	51.88 (0.67)***	51.77 (0.44)***	50.13 (0.41)***	49.72 (0.47)***	50.72 (0.48)***
Time, γ_{10}	-0.37 (0.29)	-0.55 (0.12)***	-0.84 (0.36)*	-0.27 (0.11)*	-0.32 (0.21)	-0.60 (0.09)***	-1.24 (0.26)***	-0.28 (0.08)***
Time^2, γ_{20}	-0.03 (0.03)	–	0.06 (0.03)	–	-0.03 (0.02)	–	0.08 (0.03)**	–
Age, γ_{01}	-0.66 (0.05)***	-0.44 (0.05)***	-0.42 (0.05)***	-0.26 (0.06)***	-0.67 (0.05)***	-0.45 (0.05)***	-0.42 (0.05)***	-0.26 (0.06)***
Gender, γ_{02}	1.03 (0.71)	1.83 (0.65)**	2.90 (0.73)***	0.40 (0.74)	0.74 (0.71)	1.58 (0.65)*	2.64 (0.74)***	0.44 (0.75)
Edu, γ_{03}	1.16 (0.21)***	0.26 (0.19)	0.47 (0.22)*	1.28 (0.22)***	1.12 (0.21)***	0.20 (0.19)	0.40 (0.22)	1.32 (0.23)***
PJD, γ_{04}	-2.17 (0.68)**	-1.11 (0.62)	-0.58 (0.70)	-1.87 (0.73)*	-2.56 (0.61)***	-1.69 (0.56)**	-1.41 (0.64)*	-0.60 (0.67)
RA, γ_{05}	0.12 (0.05)*	0.07 (0.05)	0.10 (0.06)	0.19 (0.06)**	0.13 (0.05)*	0.07 (0.05)	0.10 (0.06)	0.19 (0.06)**
Time×Age, γ_{11}	-0.09 (0.03)***	-0.02 (0.01)	-0.04 (0.03)	-0.03 (0.01)*	-0.09 (0.03)***	-0.02 (0.01)	-0.04 (0.03)	-0.03 (0.01)*
Time×Gender, γ_{12}	0.25 (0.31)	-0.01 (0.13)	-0.22 (0.39)	-0.07 (0.11)	0.18 (0.32)	0.02 (0.03)	-0.09 (0.40)	-0.06 (0.11)
Time×Edu, γ_{13}	-0.16 (0.10)	0.06 (0.04)	-0.14 (0.12)	0.03 (0.04)	-0.18 (0.10)	0.07 (0.04)	-0.09 (0.12)	0.04 (0.04)
Time×PJD, γ_{14}	-0.20 (0.30)	-0.00 (0.12)	-0.25 (0.38)	-0.00 (0.11)	-0.45 (0.28)	0.13 (0.12)	0.44 (0.36)	0.01 (0.10)
Time×RA, γ_{15}	0.01 (0.03)	-0.01 (0.01)	-0.01 (0.03)	-0.01 (0.01)	0.01 (0.03)	-0.01 (0.01)	-0.01 (0.03)	-0.01 (0.01)
Time^2×Age, γ_{21}	0.01 (0.00)*	–	0.00 (0.00)	–	0.01 (0.00)*	–	0.00 (0.00)	–
Time^2×Gender, γ_{22}	-0.03 (0.03)	–	0.00 (0.04)	–	-0.02 (0.03)	–	-0.01 (0.04)	–
Time^2×Edu, γ_{23}	0.01 (0.01)	–	0.02 (0.01)	–	0.01 (0.01)	–	0.01 (0.01)	–
Time^2×PJD, γ_{24}	0.03 (0.03)	–	0.01 (0.04)	–	0.04 (0.03)	–	-0.04 (0.03)	–
Time^2×RA, γ_{25}	-0.00 (0.00)	–	-0.00 (0.00)	–	-0.00 (0.00)	–	-0.00 (0.00)	–
Random Effects								
Residual, σ^2_ϵ	21.50 (1.19)***	42.01 (2.21)***	38.81 (2.04)***	45.13 (2.92)***	21.44 (1.19)***	41.99 (2.20)***	38.79 (2.03)***	45.15 (2.92)***
Intercept, σ^2_0	45.90 (3.21)***	28.23 (3.36)***	34.73 (3.43)***	43.85 (4.29)***	45.12 (3.17)***	27.80 (3.34)***	34.50 (3.42)***	44.37 (4.33)***
Time, σ^2_1	0.20 (0.05)***	0.21 (0.08)*	0.26 (0.08)**	–[a]	0.21 (0.05)***	0.21 (0.08)*	0.26 (0.08)**	–[a]
Covariance, σ^2_{01}	-0.57 (0.36)	0.90 (0.48)	-0.02 (0.46)	–[a]	-0.66 (0.36)	0.97 (0.47)*	0.04 (0.46)	–[a]

Goodness-of-fit								
-2LL	12248.05	13610.51	13521.46	10490.68	12231.44	13605.13	13520.21	10497.54
AIC	12292.05	13642.51	13565.46	10518.68	12275.44	1363713	13564.21	10525.54
BIC	12413.14	13731.53	13687.77	10592.63	12396.53	13726.15	13686.52	10599.49

Notes. Unstandardised estimates (Est.) and standard errors (SE) are presented. PS: Perceptual Speed. IM: Immediate Memory. DM: Delayed Memory. VR: Verbal Reasoning. T scores for cognitive measures standardised to the baseline sample (*M*=50, *SD*=10). Time: years in study. PJD: Physical Job Demands. Movement-related job demand: 0=No (sitting), 1=Yes (standing or moving). Strength-related job demand: 0=No (non-heavy), 1=Yes (heavy). Age: baseline age, grand mean centred at 78.09 years. Gender: 0=Male, 1=Female. Edu: Education, grand mean centred at 15 years. RA: Retirement age, mean centred at age 61.89. Dashes indicate that effect was not estimated. [a]For model convergence, variance component could not be estimated. -2LL = Deviance. AIC: Akaike information criterion. BIC: Bayesian information criterion. *p<.05; **p<.01; ***p<.001.

Table 5.21

Parameter Estimates from Multilevel Models Examining Physical Job Demands Predicting Cognitive Performance and Change, and Adjusting for Occupational Status

	Model 2B: Movement-Related Job Demand				**Model 2B: Strength-Related Job Demand**			
	PS **Est. (SE)**	**IM** **Est. (SE)**	**DM** **Est. (SE)**	**VR** **Est. (SE)**	**PS** **Est. (SE)**	**IM** **Est. (SE)**	**DM** **Est. (SE)**	**VR** **Est. (SE)**
Fixed Effects								
Intercept, γ_{00}	50.32 (0.77)***	49.16 (0.72)***	48.47 (0.82)***	49.68 (0.84)***	50.33 (0.57)***	49.43 (0.53)***	49.07 (0.60)***	48.83 (0.62)***
Time, γ_{10}	-0.76 (0.35)*	-0.68 (0.15)***	-0.84 (0.45)	-0.28 (0.13)*	-0.59 (0.27)*	-0.74 (0.11)***	-1.36 (0.34)***	-0.29 (0.10)**
Time^2, γ_{20}	0.00 (0.03)	–	0.06 (0.04)	–	-0.04 (0.03)	–	0.09 (0.03)**	–
Age, γ_{01}	-0.64 (0.05)***	-0.43 (0.05)***	-0.39 (0.05)***	-0.22 (0.05)***	-0.64 (0.05)***	-0.43 (0.04)***	-0.39 (0.05)***	-0.22 (0.05)***
Gender, γ_{02}	0.20 (0.66)	1.39 (0.60)*	2.27 (0.69)**	-0.63 (0.70)	-0.06 (0.67)	1.17 (0.61)†	2.06 (0.70)**	-0.52 (0.71)
Edu, γ_{03}	0.92 (0.21)***	0.13 (0.20)	0.34 (0.22)	1.00 (0.23)***	0.88 (0.21)***	0.09 (0.20)	0.30 (0.22)	1.04 (0.23)***
PJD, γ_{04}	-1.16 (0.70)	-0.55 (0.65)	0.00 (0.74)	-0.75 (0.76)	-1.86 (0.63)**	-1.35 (0.58)*	-1.05 (0.66)	-0.33 (0.68)
OccStat, γ_{05}	2.82 (0.64)***	1.49 (0.59)*	1.54 (0.68)*	3.13 (0.69)***	2.70 (0.63)***	1.33 (0.58)*	1.29 (0.66)	3.40 (0.68)***
Time×Age, γ_{11}	-0.10 (0.03)***	-0.02 (0.01)	-0.04 (0.03)	-0.03 (0.01)**	-0.10 (0.03)***	-0.02 (0.01)	-0.04 (0.03)	-0.03 (0.01)**
Time×Gender, γ_{12}	0.17 (0.29)	-0.00 (0.11)	-0.17 (0.37)	-0.05 (0.10)	0.12 (0.30)	0.03 (0.12)	-0.05 (0.37)	-0.05 (0.10)
Time×Edu, γ_{13}	-0.21 (0.10)*	0.04 (0.04)	-0.14 (0.13)	0.03 (0.04)	-0.22 (0.10)*	0.05 (0.04)	-0.11 (0.13)	0.03 (0.04)
Time×PJD, γ_{14}	-0.02 (0.32)	0.04 (0.13)	-0.27 (0.40)	-0.01 (0.11)	-0.32 (0.29)	0.19 (0.12)	0.48 (0.37)	0.00 (0.11)
Time×OccStat, γ_{15}	0.57 (0.29)	0.19 (0.12)	--0.00 (0.37)	0.01 (0.10)	0.48 (0.29)	0.22 (0.12)	0.19 (0.37)	0.01 (0.10)
Time^2×Age, γ_{21}	0.01 (0.00)*	–	0.00 (0.00)	–	0.01 (0.00)*	–	0.00 (0.00)	–
Time^2×Gender, γ_{22}	-0.02 (0.03)	–	0.00 (0.03)	–	-0.01 (0.03)	–	-0.01 (0.04)	–
Time^2×Edu, γ_{23}	0.02 (0.01)*	–	0.02 (0.01)	–	0.02 (0.01)*	–	0.01 (0.01)	–
Time^2×PJD, γ_{24}	0.01 (0.03)	–	0.01 (0.04)	–	0.03 (0.03)	–	-0.04 (0.04)	–
Time^2×OccStat, γ_{25}	-0.05 (0.03)*	–	0.00 (0.04)	–	-0.05 (0.03)	–	-0.01 (0.03)	–
Random Effects								
Residual, σ_{ϵ}^2	21.40 (1.19)***	42.01 (2.21)***	38.90 (2.04)***	45.16 (2.69)***	21.36 (1. 81)***	41.95 (2.02)***	38.88 (2.04)***	45.19 (2.92)***
Intercept, σ_0^2	44.45 (3.14)***	27.91 (3.35)***	34.49 (3.44)***	42.71 (2.24)***	43.82 (3.11)***	27.61 (3.33)***	34.35 (3.43)***	42.73 (4.25)***
Time, σ_1^2	0.21 (0.05)***	0.21 (0.08)*	0.26 (0.08)**	–[a]	0.21 (0.05)***	0.21 (0.08)*	0.26 (0.08)**	–[a]
Covariance, σ_{01}^2	-0.68 (0.36)	0.79 (0.48)	-0.08 (0.47)	–[a]	-0.73 (0.36)*	0.84 (0.47)	-0.05 (0.47)	–[a]

Goodness-of-fit								
-2LL	12218.85	13599.20	13518.45	10477.23	12206.69	13593.93	13517.39	10478.17
AIC	12262.85	13631.20	13562.45	10505.23	12250.69	13625.93	13561.39	10506.17
BIC	12383.93	13720.22	13684.76	10579.18	12371.78	13714.95	13683.70	10580.12

Notes. Unstandardised estimates (Est.) and standard errors (SE) are presented. PS: Perceptual Speed. IM: Immediate Memory. DM: Delayed Memory. VR: Verbal Reasoning. T scores for cognitive measures standardised to the baseline sample (*M*=50, *SD*=10). Time: years in study. PJD: Physical Job Demands. Movement-related job demand: 0=No (sitting), 1=Yes (standing or moving). Strength-related job demand: 0=No (non-heavy), 1=Yes (heavy). Age: baseline age, grand mean centred at 78.09 years. Gender: 0=Male, 1=Female. Edu: Education, grand mean centred at 15 years. OccStat: Occupational Status, 0=blue-collar, 1=white-collar. Dashes indicate that effect was not estimated. [a]For model convergence, variance component could not be estimated. -2LL = Deviance. AIC: Akaike information criterion. BIC: Bayesian information criterion. *p<.05; **p<.01; ***p<.001.

Model 2C: Health and lifestyle factors

Baseline measures of medical conditions, smoking status, and alcohol consumption were added as level-2 predictors of initial status and rates of cognitive change. Depression and the three activity engagement variables were added as level-1 predictors. The estimates from Model 2C are presented in Table 5.22. The relations of movement-related job demand with levels of perceptual speed and verbal reasoning were independent of the additional cognitive ageing correlates. Moreover, the magnitudes of the associations increased marginally by 0.5%.

Similarly the relations of strength-related job demand with levels of perceptual speed and immediate memory were independent of age, gender, education, medical conditions, depression, smoking status, alcohol consumption, and late life activity engagement. In contrast to the results for movement-related demand, the magnitudes of the associations between strength-related job demand with perceptual speed and immediate memory declined by 8% and 10%, respectively. After controlling for the additional covariates, strength-related job demand was no longer a significant predictor of initial delayed memory performance.

Table 5.22

Parameter Estimates from Multilevel Models Examining Physical Job Demands Predicting Cognitive Performance and Change, and Adjusting for Medical Conditions, Alcohol Consumption, Smoking Status, Depression, and Late Life Activity Engagement

	Model 2C: Movement-Related Job Demand				**Model 2C: Strength-Related Job Demand**			
	PS Est. (SE)	**IM Est. (SE)**	**DM Est. (SE)**	**VR Est. (SE)**	**PS Est. (SE)**	**IM Est. (SE)**	**DM Est. (SE)**	**VR Est. (SE)**
Fixed Effects								
Intercept	48.40 (1.08)***	46.32 (1.09)***	46.47 (1.19)***	47.89 (1.217)***	47.70 (1.01)***	46.14 (1.02)***	46.44 (1.12)***	46.56 (1.19)***
Time	-0.55 (0.44)	-0.20 (0.18)	-1.13 (0.56)*	-0.53 (0.17)**	-0.49 (0.40)	-0.22 (0.16)	-1.35 (0.50)**	-0.47 (0.15)**
Time^2	0.01 (0.04)	–	0.12 (0.06)*	–	0.01 (0.04)	–	0.13 (0.05)**	–
Age	-0.60 (0.05)***	-0.40 (0.05)***	-0.35 (0.05)***	-0.18 (0.05)**	-0.61 (0.05)***	-0.41 (0.05)***	-0.36 (0.05)***	-0.18 (0.05)**
Gender	-0.23 (0.70)	0.92 (0.65)	1.88 (0.74)*	-1.11 (0.75)	-0.42 (0.70)	0.75 (0.66)	1.70 (0.75)*	-0.95 (0.76)
Edu	0.98 (0.20)***	0.17 (0.19)	0.41 (0.22)†	1.11 (0.22)***	0.98 (0.20)***	0.14 (0.19)	0.38 (0.22)	1.19 (0.23)***
PJD	-2.28 (0.66)**	-1.22 (0.62)*	-0.78 (0.70)	-1.92 (0.72)**	-2.21 (0.60)***	-1.44 (0.56)*	-1.12 (0.65)	-0.20 (0.67)
MedCdns	-0.70 (0.25)**	-0.40 (0.23)	-0.26 (0.26)	-0.32 (0.27)	-0.68 (0.24)**	-0.40 (0.23)	-0.25 (0.26)	-0.26 (0.27)
Abstain	-1.43 (0.93)	0.58 (0.86)	-0.47 (0.99)	-0.80 (1.01)	-1.23 (0.93)	0.70 (0.86)	-0.37 (1.00)	-0.85 (1.01)
≤ 2 drinks/day	-0.67 (0.84)	1.06 (0.78)	0.52 (0.91)	0.57 (0.91)	-0.54 (0.84)	1.14 (0.78)	0.60 (0.91)	0.56 (0.91)
Never Smoked	1.12 (0.63)	0.24 (0.59)	0.88 (0.67)	1.22 (0.70)	1.04 (0.62)	0.19 (0.59)	0.87 (0.67)	1.12 (0.70)
Former Smoker	-1.91 (1.08)	0.47 (1.00)	1.42 (1.12)	-1.56 (1.13)	-2.15 (1.08)*	0.33 (1.00)	1.29 (1.13)	-1.50 (1.14)
Time×Age	-0.10 (0.03)***	-0.02 (0.01)	-0.07 (0.03)*	-0.03 (0.01)*	-0.10 (0.03)***	-0.01 (0.01)	-0.06 (0.03)*	-0.03 (0.01)*
Time×Gender	0.22 (0.33)	0.09 (0.13)	-0.26 (0.41)	-0.08 (0.12)	0.14 (0.33)	0.12 (0.13)	-0.09 (0.42)	-0.11 (0.12)
Time×Educ	-0.11 (0.10)	0.04 (0.04)	-0.14 (0.13)	0.04 (0.04)	-0.14 (0.10)	0.06 (0.04)	-0.10 (0.13)	0.03 (0.04)
Time×PJD	-0.18 (0.32)	0.02 (0.13)	-0.01 (0.40)	0.05 (0.12)	-0.47 (0.30)	0.11 (0.13)	0.56 (0.38)	-0.07 (0.11)
Time×MedCdns	-0.09(0.12)	0.01 (0.05)	0.02 (0.15)	0.04 (0.05)	-0.10 (0.12)	0.01 (0.05)	0.02 (0.15)	0.04 (0.05)
Time×Abstain	0.09(0.46)	-0.33 (0.19)	-0.43 (0.58)	0.22 (0.17)	0.13 (0.46)	-0.34 (0.19)	-0.49 (0.58)	0.23 (0.17)
Time×≤ 2 drinks/day	0.34 (0.42)	-0.24 (0.17)	-0.06 (0.53)	0.41 (0.16)**	0.36 (0.42)	-0.25 (0.17)	-0.11 (0.53)	0.42 (0.16)**
Time×Never Smoked	-0.20 (0.30)	-0.06 (0.12)	0.46 (0.39)	-0.09 (0.11)	-0.22 (0.30)	-0.06 (0.12)	0.43 (0.38)	-0.08 (0.11)
Time×Former Smoker	1.13 (0.56)*	-0.13 (0.23)	1.14 (0.70)	-0.07 (0.21)	1.08 (0.56)	-0.11 (0.23)	1.21 (0.70)	-0.09 (0.21)
Time^2×Age	0.01 (0.00)**	–	0.01 (0.00)	–	0.01 (0.00)**	–	0.01 (0.00)	–
Time^2×Gender	-0.03 (0.03)	–	0.01 (0.04)	–	-0.02 (0.03)	–	-0.01 (0.04)	–
Time^2×Edu	0.01 (0.01)	–	0.02 (0.01)	–	0.01 (0.01)	–	0.01 (0.01)	–
Time^2×PJD	0.02 (0.03)	–	-0.02 (0.04)	–	0.04 (0.03)	–	-0.06 (0.04)	–
Time^2×MedCdns	0.00(0.01)	–	-0.01 (0.02)	–	0.00 (0.01)	–	-0.01 (0.02)	–
Time^2×Abstain	-0.01 (0.05)	–	0.03 (0.06)	–	-0.02 (0.05)	–	0.03 (0.06)	–

Time^2×≤ 2 drinks/day	-0.04 (0.04)	–	-0.01 (0.05)	–	-0.04 (0.04)	–	-0.01 (0.05)	–
Time^2×Never Smoked	0.01 (0.03)	–	-0.05 (0.04)	–	0.02 (0.03)	–	-0.04 (0.04)	–
Time^2×Former Smoker	-0.10 (0.05)[†]	–	-0.12 (0.07)	–	-0.10 (0.05)	–	-0.13 (0.07)*	–
CES-D	-0.13 (0.03)***	-0.07 (0.03)*	-0.11 (0.03)**	-0.11 (0.04)**	-0.13 (0.03)***	-0.07 (0.03)*	-0.10 (0.03)**	-0.12 (0.04)**
CogAct	0.47 (0.07)***	0.31 (0.09)***	0.29 (0.09)**	0.37 (0.10)***	0.46 (0.07)***	0.30 (0.09)**	0.28 (0.09)**	0.37 (0.10)***
SocAct	0.24 (0.08)**	0.18 (0.09)*	0.06 (0.09)	0.22 (0.11)*	0.23 (0.08)**	0.17 (0.09)	0.06 (0.09)	0.22 (0.11)*
PhysAct	0.00 (0.02)	0.02 (0.02)	0.01 (0.02)	0.02 (0.03)	-0.00 (0.02)	0.02 (0.02)	0.01 (0.02)	0.02 (0.04)
Random Effects								
Residual, σ_ϵ^2	21.58 (1.25)***	43.42 (2.37)***	38.48 (2.12)***	45.69 (3.33)***	21.41 (1.24)***	43.31 (2.37)***	38.37 (2.11)***	45.62 (3.33)***
Intercept, σ_0^2	40.82 (3.01)***	25.38 (3.36)***	32.98 (3.41)***	40.65 (4.59)***	40.65 (2.68)***	25.32 (3.35)***	33.03 (3.41)***	41.28 (4.63)***
Time, σ_1^2	0.11 (0.05)*	0.05 (0.08)	0.17 (0.08)*	–[a]	0.12 (0.05)*	0.05 (0.08)	0.17 (0.08)*	–[a]
Covariance, σ_{01}^2	-0.50 (0.34)	1.01 (0.47)*	0.03 (0.47)	–[a]	-0.59 (0.34)	1.03 (0.47)*	0.07 (0.47)	–[a]
Goodness-of-fit								
-2LL	11546.73	12764.05	12680.98	9859.06	11535.98	12761.75	12681.47	9865.67
AIC	11622.73	12820.05	12756.98	9911.06	11611.98	12817.75	12757.47	9917.67
BIC	11829.97	12974.16	12966.00	10046.81	11819.22	12971.85	12966.49	10053.42

Notes. Unstandardised estimates (Est.) and standard errors (SE) are presented. PS: Perceptual Speed. IM: Immediate Memory. DM: Delayed Memory. VR: Verbal Reasoning. T scores for cognitive measures standardised to the baseline sample (*M*=50, *SD*=10). Time: years in study. PJD: Physical Job Demands. Movement-related job demand: 0=No (sitting), 1=Yes (standing or moving). Strength-related job demand: 0=No (non-heavy), 1=Yes (heavy). Age: baseline age, grand mean centred at 78.09 years. Gender: 0=Male, 1=Female. Edu: Education, grand mean centred at 15 years. Smoking status: reference group is smoker. Alcohol consumption: reference group is Risky (more than 2 drinks daily). MedCdns: Number of medical conditions, grand mean centred (*M*=1.58). CES-D, centred at 16 (scores >16 correspond to the cutoff for depression). CogAct: cognitive activity. SocAct: social activity. PhysAct: physical activity. Dashes indicate that effect was not estimated. [a]For model convergence, variance component could not be estimated. -2LL = Deviance. AIC: Akaike information criterion. BIC: Bayesian information criterion. *p<.05; **p<.01; ***p<.001

Model 3: Movement- and strength-related job demands

Model 3 added movement- and strength-related job demands into the same model. The estimates from Model 3 are presented in Table 5.23. Movement-related job demand was not a significant predictor of cognitive function after controlling for strength-related job demand. Strength-related job demand remained a significant predictor of initial cognitive function.

In a supplementary model, the three complexity variables and the two physical job demand variables were entered in to the same model via simultaneous entry. The parameter estimates for that model are presented in Appendix D. They generally reveal a similar pattern of findings as those presented throughout this chapter. Higher complexity with data was associated with higher levels of perceptual speed and verbal reasoning. Higher complexity with people was associated with higher initial levels of verbal reasoning. Higher complexity with things was associated with lower initial levels of perceptual speed. Movement-related job demand was associated with lower initial levels of verbal reasoning. Strength-related job demand as associated with lower initial levels of immediate memory.

Table 5.23

Parameter Estimates from Multilevel Models Examining Movement- and Strength-Related Job Demands Predicting Cognitive Performance and Change

	Movement-Related Job Demand + Strength-Related Job Demand			
	PS	**IM**	**DM**	**VR**
	Est. (SE)	**Est. (SE)**	**Est. (SE)**	**Est. (SE)**
Fixed Effects				
Intercept	52.71 (0.63)***	50.51 (0.58)***	49.82 (0.66)***	51.98 (0.68)***
Time	-0.29 (0.29)	-0.58 (0.12)***	-0.94 (0.37)*	-0.28 (0.11)*
Time^2	-0.04 (0.03)	–	0.07 (0.04)	–
Age	-0.63 (0.05)***	-0.42 (0.04)***	-0.39 (0.05)***	-0.20 (0.05)***
Gender	0.11 (0.67)	1.24 (0.61)*	2.16 (0.70)**	-0.34 (0.71)
Edu	1.11 (0.21)***	0.20 (0.19)	0.43 (0.22)*	1.32 (0.23)***
Movement	-1.31 (0.72)	-0.49 (0.67)	0.00 (0.75)	-1.86 (0.78)
Strength	-2.07 (0.66)**	-1.51 (0.60)*	-1.37 (0.69)*	0.20 (0.71)
Time×Age	-0.09 (0.03)***	-0.02 (0.01)	-0.04 (0.03)	-0.03 (0.01)**
Time×Gender	0.14 (0.30)	0.05 (0.12)	-0.07 (0.37)	-0.04 (0.10)
Time×Edu	-0.18 (0.10)	0.06 (0.04)	-0.11 (0.12)	0.03 (0.04)
Time×Movement	-0.01 (0.33)	-0.06 (0.13)	-0.48 (0.41)	-0.00 (0.12)
Time×Strength	-0.46 (0.31)	0.15 (0.13)	0.58 (0.38)	-0.00 (0.11)
Time^2×Age	0.01 (0.00)*	–	0.00 (0.00)	–
Time^2×Gender	-0.02 (0.03)	–	-0.01 (0.03)	–
Time^2×Edu	0.02 (0.01)	–	0.02 (0.01)	–
Time^2×Movement	0.01 (0.03)	–	0.03 (0.04)	–
Time^2×Strength	0.04 (0.03)	–	-0.05 (0.04)	–
Random Effects				
Residual, σ_ϵ^2	21.45 (1.19)***	41.98 (2.20)***	38.81 (2.04)***	45.19 (2.93)***
Intercept, σ_0^2	45.34 (3.18)***	27.93 (3.35)***	34.81 (3.44)***	44.65 (4.35)***
Time, σ_1^2	0.20 (0.05)***	0.21 (0.08)*	0.26 (0.08)**	–[a]
Covariance, σ_{01}^2	-0.65 (0.36)	0.93 (0.47)	-0.05 (0.46)	–[a]
Goodness-of-fit				
-2LL	12235.56	13606.07	13521.80	10501.63
AIC	12279.56	13638.07	13565.80	10529.63
BIC	12400.65	13727.09	13688.11	10603.58

Notes. Unstandardised estimates (Est.) and standard errors (SE) are presented. PS: Perceptual Speed. IM: Immediate Memory. DM: Delayed Memory. VR: Verbal Reasoning. T scores for cognitive measures standardised to the baseline sample (*M*=50, *SD*=10). Time: years in study. Movement: 0=No (sitting), 1=Yes (standing or moving). Strength: 0=No (non-heavy), 1=Yes (heavy). Age: baseline age, grand mean centred at 78.09 years. Gender: 0=Male, 1=Female. Edu: Education, grand mean centred at 15 years. Dashes indicate that effect was not estimated. [a]For model convergence, variance component could not be estimated. -2LL = Deviance. AIC: Akaike information criterion. BIC: Bayesian information criterion. *p<.05; **p<.01; ***p<.001.

Modifying role of education, gender, or age at retirement

Model 2 was repeated with terms to allow for interactions among the physical job demands (movement-related and strength-related), the covariates (education and gender), and time (linear and quadratic). Model 2A was repeated with terms to allow for interactions among the physical job demands (movement-related and strength-related), age at retirement, and time (linear and quadratic). Relative model fit indices are provided in Table 5.24 (and parameter estimates are provided in Appendix C).

Deviance-based tests revealed the relationships between movement-related job demand and cognitive ageing did not vary by gender or age at retirement. Also, the relationships between strength-related job demand and cognitive ageing did not vary by education, gender, or age at retirement.

The relationship between movement-related job demand and verbal reasoning did vary by education (Δ-2LL (2) = 6.44, *p*<.05). A post hoc analysis (refer to Appendix C, Table C.2) performed for higher and lower education groups revealed that movement-related job demand was not a predictor of verbal reasoning ability among the higher education group. In the lower education group, movement-related job demand (standing or moving) was associated with lower initial levels of verbal reasoning.

Table 5.24

Relative Model Fit Indices: Physical Job Demands by Education, Gender, and Age at Retirement Predicting Cognitive Performance and Change

	Model 2 + Movement-Related Job Demand × Education				**Model 2 + Strength-Related Job Demand × Education**			
	PS	**IM**	**DM**	**VR**	**PS**	**IM**	**DM**	**VR**
-2LL	12251.78	13609.07	13525.06	10495.27	12236.47	13606.19	13524.07	10507.24
[a]Δ-2LL	4.67	3.33	1.03	6.44*	3.75	0.92	1.03	1.06
Δdf	3	2	3	2	3	2	3	2
AIC	12295.78	13641.07	13569.06	10523.27	12280.50	13638.19	13568.07	10353.24
BIC	12416.86	13730.09	13691.37	10597.22	12401.55	13727.21	13690.38	10609.19
	Model 2 + Movement-Related Job Demand × Gender				**Model 2 + Strength-Related Job Demand × Gender**			
	PS	**IM**	**DM**	**VR**	**PS**	**IM**	**DM**	**VR**
-2LL	12252.69	13612.45	13524.12	10501.10	12238.10	13605.71	13524.02	10503.40
[a]Δ-2LL	3.76	-0.05	1.97	0.61	2.12	1.4	1.08	4.9
Δdf	3	2	3	2	3	2	3	2
AIC	12296.69	13644.25	13568.12	10529.10	12282.10	13637.71	13568.02	10531.40
BIC	12417.77	13733.27	13690.43	10603.05	12403.18	13726.72	13690.33	10605.35
	Model 2A + Movement-Related Job Demand × Age at Retirement				**Model 2A + Strength-Related Job Demand × Age at Retirement**			
	PS	**IM**	**DM**	**VR**	**PS**	**IM**	**DM**	**VR**
-2LL	12242.35	13608.79	13519.09	10490.30	2229.84	13604.55	3518.02	10493.12
[b]Δ-2LL	5.7	1.72	2.37	0.38	1.6	0.58	2.19	4.42
Δdf	3	2	3	2	3	2	3	2
AIC	12292.35	13644.79	13569.09	10522.30	12279.84	13640.55	13568.02	10525.14
BIC	12429.95	13744.94	13708.08	10606.81	12417.44	13740.70	13707.01	10609.64

Notes. PS: Perceptual Speed. IM: Immediate Memory. DM: Delayed Memory. VR: Verbal Reasoning. -2LL = Deviance. [a]Δ-2LL = [-2LLmodel 2] – [-2LLcurrent model]. [b] Δ-2LL = [-2LLmodel 2A] – [-2LLcurrent model]. AIC: Akaike information criterion. BIC: Bayesian information criterion. *p<.05; **p<.01; ***p<.001.

5.4 Discussion

The present study contributes new insights into how occupational complexity is associated with change trajectories in specific cognitive domains. To date, only one study has examined whether and how occupational complexity involving data, people, and things, predict performance and change in different cognitive abilities (Finkel et al., 2009). Few studies have examined the associations between physical job demands and cognitive ageing (Fritsch et al., 2007; Potter et al., 2006), and the present study is the first to examine the associations of movement- related job demand with cognitive ageing. The results are interpreted in the context of these prior studies.

5.4.1 Cognitive change

Average decline was evidenced for all the cognitive outcome measures. Consistent with theoretical perspectives on cognitive ageing (e.g., Baltes, 1987; Horn & Cattell, 1967, also refer to Chapter 2, Section 2.2), faster rates of decline were observed for perceptual speed and memory (fluid abilities). In comparison, decline in verbal reasoning (a crystallized ability) was slower. The results in relation to verbal reasoning are interpreted with caution however, because they showed very little inter-individual differences in change over time (also see, Gerstorf et al., 2009). Delayed memory declined most steeply in the earlier years of the study then increased in the later years. Episodic memory impairment is a symptom of dementia, a risk factor for functional impairment, and a salient complaint of older adults. Previously, a study of attrition and mortality in the ALSA, Anstey and Luszcz (2002b) reported that participants who completed the baseline clinical assessment only were more likely to develop dementia than those who did complete the first two waves of clinical assessments (i.e., Baseline and Wave 3). Therefore, the convex curvature for delayed memory may reflect selective longitudinal attrition. The issue of selective longitudinal attrition is discussed in the final chapter in a section on study limitations (Section 6.5).

5.4.2 Occupational complexity with data and people

The results showed that higher occupational complexity with data and people were associated with higher initial levels of perceptual speed and verbal reasoning, but not with differential rates of cognitive decline. The relationships were robust even when considered in light of differences in age, gender, education (Model 2), age at time of retirement (Model 2A), occupational status (Model 2B), and the additional cognitive ageing correlates (Model 2C). Occupation complexity with data and people were not associated with immediate or delayed memory in unadjusted or adjusted models. Consistent with Study 1, the associations of occupational complexity involving data and people with cognitive ageing did not depend on differences in education, gender, or age at retirement. The modifying roles of education, gender, and at time of retirement had not previously been examined in studies of occupational complexity and change in specific cognitive abilities.

Consistent with previous studies (Finkel et al., 2009; Fritsch et al., 2007), higher occupational complexity involving data and people predicted higher average perceptual speed and verbal reasoning performances, but not memory performance. That higher occupational complexity was not associated with slower rates of change in perceptual speed or verbal reasoning is also consistent with the post-retirement trajectories of cognitive ageing estimated by Finkel et al. (2009). Finkel et al. additionally measured spatial ability and reported higher occupational complexity was associated with faster rates of decline on that ability, post-retirement. Consequently, the associations between occupational complexity and cognitive change might be restricted to cognitive abilities other than those examined in this thesis.

In comparison to complexity with people, the associations between complexity with data and levels of cognitive ability were robust. Indeed, occupational complexity with data accounted for the associations between occupational complexity involving people and levels of perceptual speed and verbal reasoning (Model 3). This finding is *inconsistent* with the findings of Finkel et al. (2009). Finkel et al. reported only occupational complexity with people was associated with cognitive functioning, independently of age and education. The differences between Finkel et al.'s Swedish study and this Australian study might be explained by cross-national differences in labour market characteristics, errors in estimating complexity ratings for occupations in the Swedish and Australian censuses (see Chapter 3), or to differences in statistical approaches. For example, Finkel et al. did not include gender as a covariate in their latent growth curve models because women and men in their sample demonstrated equivalent levels of occupational complexity with people. In this thesis, women demonstrated higher levels of occupational complexity with people and gender was included as a covariate in multilevel growth models.

Only after additional statistical control for current symptoms of depression, and current cognitive and social activity engagement, was higher occupational complexity involving data associated with slower rates of cognitive decline in the present study. Given the small size of the association (which was significant at the .05 level), and that it was observed in a model involving multiple comparisons, the relationship was not taken as substantively significant.

5.4.3 Occupational complexity with things

This is the first study to examine the associations of occupational complexity involving things with change in specific cognitive abilities. Bivariate correlations between occupational complexity with things and the cognitive outcome measures in

Finkel et al.'s (2009) study were not significant, so their analyses focused on occupational complexity with data and people only.

The results showed that higher occupational complexity involving things was associated with lower initial levels of perceptual speed and delayed memory and the associations were robust even in light of differences in age, gender, education (Model 2), age at retirement (Model 2A), occupational status (Model 2B), and the additional cognitive ageing correlates (Model 2C).

The association between occupational complexity with things and cognitive change varied by education, but did not vary by gender or age at retirement. Among people who had lower levels of education, higher complexity with things was associated with lower levels of, and a slower rate of decline in, delayed memory. This result is somewhat counterintuitive. Given that delayed memory exhibited a convex curvature (see Figure 5.1), the interrelations between occupational complexity with things, education, and memory may have been biased by selective longitudinal attrition. Moreover, occupational status accounted for the association between occupational complexity with things and delayed memory (Model 2B). The estimates were also small. Thus, the moderating effect of education on the association between occupational complexity with things and delayed memory is not taken as substantively significant.

5.4.4 Physical job demands

Few studies have examined the associations between physical job demands and cognition (Fritsch et al., 2007; Potter et al., 2006). The present study is the first to examine the relations of movement- and strength-related job demands with change in specific cognitive abilities in late life.

The results showed that movement-related job demand (moving around a lot) was associated with lower initial levels of perceptual speed and verbal reasoning independent of age, gender, education (Model 2), age at retirement (Model 2A), and the additional cognitive ageing correlates (Model 2C). However, the associations were explained by individual differences in occupational status (Model 2B). This finding is somewhat similar to a study by Anttila et al. (2002). They simply classified white-collar occupations as sedentary and blue-collar occupations as physical and reported a decreased risk of dementia 20 years later for sedentary compared to physical occupations. Thus, the types of occupations that required workers in the current study to move around a lot might also have been predominately lower status occupations. The results suggest that the negative association between movement-related job demands and cognitive ability may stem from its relations to other socio-economic or lifestyle factors.

The results showed that the association between movement-related job demand and verbal reasoning varied by education. Analyses performed by lower and higher education groups revealed that movement-related demand was associated with a lower level of verbal reasoning in the lower education group. As the association of movement-related job demand with verbal reasoning was explained by occupational status, the results might seem to suggest that socio-economic disadvantage in terms of lower levels of education attainment, and possibly fewer career opportunities, may be associated with poorer cognitive performance in late life. This finding adds further strength to the hypothesis of preserved differentiation, where jobs with greater cognitive demands, including perhaps jobs with fewer physical demands, are selected by people with higher levels of ability.

Strength-related job demand (i.e., heavy physical exertion) was associated with lower levels of perceptual speed and immediate memory, but not with rates of cognitive change. The associations between strength-related job demand and cognitive change did not depend on differences in education, gender, or age at time of retirement.

The data also showed that people who had a main lifetime occupation characterised by strength-related job demand also had fewer years of schooling, which is consistent with some literature (e.g., Potter et al., 2007). The negative association between heavy physical work and cognitive performance was robust even when considered in light of differences in age, gender, and education (Model 2), and age at retirement (Model 2A). The results were not explained by differences in occupational status (Model 2B), suggesting that the socio-economic aspects of occupations such as income and prestige do not fully explain the negative association between heavy physical exertions at work and cognition. The negative association also remained significant after further statistical control for additional cognitive ageing correlates, including alcohol consumption and smoking status (Model C), which have been proposed as possible explanations for the association between manual work involving goods production and increased dementia risk (Qiu et al., 2003).

The results seem to suggest that jobs involving heavy physical exertion might be associated with lower levels of cognitive function, because they most likely derive their complexity from machines and equipment (i.e., things) rather than from data or people. Also, workers in occupations requiring heavy physical labour might be exposed to adverse working conditions, including environmental pollutants that are detrimental to cognitive functioning (Dik et al., 2003). It has also been suggested that people in manual occupations, which presumably are characterised by physical job demands, may have reduced test taking ability because the skills that they require for their jobs do not match those skills necessary for taking tests (Gow, Avlund, et al., 2012; Helmer et al., 2001). So, this explanation may also account for the negative association between heavy physical exertion in the main lifetime occupation and cognition.

5.4.5 Strengths and limitations

As intended, Study 2 has two notable strengths. Firstly, it was able to exclude data from people who scored less than 24 on the MMSE at any point during the study period because it measured cognitive outcomes using other cognitive tests. Therefore, the impact of including data from people with dementia on the study findings was substantially reduced. Multiple tests of cognition were used, thereby allowing for the possibility that some occupational activity demands act to promote only some cognitive abilities. The breadth of variables in the ALSA enabled the examination of physical job demands in addition to occupational complexity, and also allowed for the statistical control of a broad range of potentially confounding covariates. However, similarly to Study 1, the current study was limited to an extent by a lack of effective control for prior ability and selective longitudinal attrition. Also, as noted in Study 1, self-reported measures of the cognitive effort exerted by individuals in response to the demands of the various jobs that they engaged in over the course of career, may have provided additional insights into the nature of the associations between the functional aspects of occupations and cognitive ageing. These methodological issues are discussed in detail in the next chapter.

5.4.6 Conclusion

In conclusion, the associations between occupational complexity, physical job demands, and cognitive ageing showed the pattern predicted by preserved differentiation. It appears that people with higher average levels of ability select higher complexity occupations, and physically undemanding occupations, and the advantage in ability in maintained over time (Bielak, Cherbuin, Bunce, & Anstey, 2014). The next chapter provides a theoretical interpretation of the main findings, and discusses some practical implications.

CHAPTER 6: GENERAL DISCUSSION

6.1 Chapter overview

This chapter presents a general discussion of the thesis findings. The chapter begins by recapitulating the aim, methods, and main findings of this thesis. The findings in Study 1 and Study 2 were discussed at the empirical level in Chapters 4 and 5, respectively. In this final chapter, a theoretical interpretation of the main findings is provided and practical implications are also identified. The strengths and limitations of this thesis are outlined and methodological recommendations are provided for future researchers seeking to further elucidate the nature of the associations between occupational activity demands and cognitive ageing. Recommendations for future research are also provided. The chapter closes with a concluding summary.

6.2 General research aim

Older people are inherently interested in maintaining their cognitive health and the Australian government is interested in strategies that will keep older adults healthy, independent, and productive. To this end, the Government has prioritised research that seeks to better understand the causes of age-related cognitive decline and dementia. Accordingly, this thesis examined whether and how complex and physical demands in the main lifetime occupation are associated with age-related cognitive decline.

The focus of this thesis was informed by the seminal work of Kohn and Schooler, which shows that dealing with complex occupational demands is one possible way to modify cognitive function in younger and older workers. This thesis was also informed by research which shows complex demands or physical activity at midlife to be associated with favourable cognitive outcomes in late life. This thesis builds on this empirical foundation.

A comprehensive review of the empirical literature revealed that currently very little is known of the long-term protective association between occupational complexity and age-related cognitive decline. To date, the associations have only been examined in a handful of studies and in these studies, education, gender, and age at retirement had been overlooked as possible mediators of the relationship between occupational activity and cognitive ability. Moreover, despite an increased prevalence of sedentary behaviour and the growing body of evidence that shows prolonged sitting and physical inactivity to be associated with risk factors for cognitive impairment (Brown et al., 2012), the review revealed few studies have examined the long-term associations of sedentary, and movement- and strength related job demands with age-associated cognitive decline. Furthermore, the extant literature was limited by a number of methodological limitations. Few studies had taken into account occupational duration or when and if people had retired, even though these factors have been shown to be related to cognitive function. Additionally, few studies had examined outcomes in multiple cognitive domains. This thesis addressed these gaps and methodological limitations.

The purpose of this thesis was to investigate whether and how complexity and physical demands in the main lifetime occupation are associated with cognitive performance and change among older, former workers. Subsidiary aims in this thesis were to explore whether the associations between occupational complexity, physical job demands, and cognitive ageing (a) differ by education, gender, and age at the time of retirement, and (b) hold when the influence of other predictors of cognitive decline are statistically controlled, including the socio-economic aspects of occupations.

The research aims were comprehensively examined in two samples of older Australians, using a multilevel growth modelling approach and 11-year data sourced from two prospective studies of ageing. In Study 1, the association of occupational complexity with levels of, and rates of change in, MMSE scores was examined using data from 1,714 participants initially aged 65 to 98 years in the DYNOPTA project. Age, gender, education, occupational status, age at time of retirement, premorbid ability, and current medical conditions and symptoms of depression were examined as covariates. In Study 2, the associations of occupational complexity and physical job demands with levels of, and rates of change in, perceptual speed, verbal reasoning, and immediate and delayed episodic memory were examined using data from 1,059 participants initially aged 65 to 98 years in the ALSA. Age, gender, education, occupational status, age at time of retirement, medical conditions, smoking status, alcohol consumption, current symptoms of depression, and current activity engagement (mental, social, and physical) were examined as covariates.

The main hypothesis examined was *differential preservation*. That is, it was expected that higher occupational complexity would be related to slower rates of cognitive decline. As the literature on occupational physical activity is equivocal, no specific expectations were proposed about whether and how physical job demands would be associated with cognitive change.

6.3 Summary of key findings

A summary of the significant findings in Study 1 and Study 2 are presented in Table 6.1. In line with the preserved differentiation hypothesis, the table clearly shows multiple associations between the occupational activity demands and levels of cognitive ability, but limited associations between the occupational activity demands and rates of cognitive change.

Individuals in the DYNOPTA and the ALSA who previously held occupations higher in complexity tended to have significantly higher initial levels of cognitive ability than individuals who held occupations lower in complexity, and the advantage was maintained 11 years. The results also showed that individuals who previously performed jobs with physical demands (movement and strength) demonstrated significantly lower initial levels of cognitive ability than individuals who performed jobs with few physical demands, and the disadvantage was maintained over time.

The associations between the occupational activity demands and cognitive change did not vary according to differences in education, gender, or retirement timing and duration. Very few studies have considered whether the associations between previous occupational demands and cognitive outcomes in later life vary according to differences in education and gender. The null findings in relation to education suggest that for the cohort examined, ability was not a key determinant of educational attainment or career prospects, perhaps. The null finding with respect to gender is consistent with the previous literature. This is the first study to have examined whether the associations between previous occupational activity demands and late life cognitive outcomes differ by retirement duration and retirement timing. The null findings indicate that perhaps too much time had passed to detect the potentially more proximal effects of retirement on cognition.

The results differed by complexity type, and revealed complex work demands involving data to be the strongest predictor of cognitive functioning. The positive association between complexity with data and cognitive ageing was robust, even in light of differences in a broad array of cognitive ageing correlates. The positive association between occupational complexity involving people and cognitive ageing was not robust. This is consistent with cross-sectional studies of occupational complexity and cognition (Andel et al., 2007; Correa Ribeiro et al., 2013), but inconsistent with the findings of Finkel et al. (2009). The results in this thesis suggest that the positive association between occupational complexity involving people and cognitive ability may stem from its relations to complexity involving data. It may be that complex work demands involving data require greater cognitive effort than work demands involving people. Indeed, a review study on the longitudinal associations between activity engagement and cognitive ageing (Hertzog et al., 2008), indicated that, compared to activity in other domains, including social activity, cognitive activity tends to be the strongest predictor of cognition.

Findings also varied by cognitive domain. Occupational complexity involving data and people were positively associated with perceptual speed and verbal reasoning (crystallized ability), but not with episodic memory performance. This is consistent with the pattern of associations observed by Finkel et al. (2009). In the current study, the parameter estimates for the associations between occupational complexity and verbal reasoning were marginally larger than the estimates for perceptual speed. This finding is in line with research that suggests stronger associations might be found for contextual factors with crystallized ability (Finkel, Reynolds, McArdle, & Pedersen, 2005). Movement-related job demand (i.e., standing and moving about) was also associated with perceptual speed and verbal reasoning. However, the association was negative and the results indicated that the association between the movement-related job demand and cognition might stem from its relations to other socio-economic or lifestyle factors.

Table 6.1

Summary of Significant Research Findings by Occupational Activity Demand and Cognitive Test (Unstandardised Coefficients, β)

		STUDY 1		STUDY 2							
		MMSE		Perceptual Speed		Immediate Memory		Delayed Memory		Verbal Reasoning	
Occupational Activity Demand	**Covariates controlled**	**Level (*β*)**	**Change (*β*)**	**Level (*β*)**	**Change (*β*)**	**Level (*β*)l**	**Change (*β*)**	**Level (*β*)**	**Change (*β*)**	**Level (*β*)**	**Change (*β*)**
Complexity with Data		0.52***	0.16**	0.63***						0.81***	
	Age, gender, education	0.46***	0.16**	0.66***						0.74***	
	[b]Age at retirement	0.47***	0.16**	0.65***						0.72***	
	[b]Occupational status	0.26*		0.40*						0.48**	
	[ab]Additional covariates	0.13		0.61***			0.06*			0.64***	
	[b]People, Things	0.43***	0.16**	0.58***						0.63***	
Complexity with People		0.40***		0.55***						0.59***	
	Age, gender, education	0.33**		0.52***						0.49***	
	[b]Age at retirement	0.34**		0.52***						0.48***	
	[b]Occupational status			0.36**						0.33*	
	[ab]Additional covariates			0.42**						0.40**	
	[b]Data, Things										
Complexity with Things		-0.34***		-0.67***		-0.34**		-0.47**			
	Age, gender, education	-0.22**		-0.49***				-0.26*			
	[b]Age at retirement	-0.22**		-0.45***				-0.26*			
	[b]Occupational status		0.15*	-0.26*							
	[ab]Additional covariates		0.14*	-0.42***				-0.24*			
	[b]Data, People			-0.38**				-0.30*			
Movement-related				-3.40***		-1.91**		-1.62*		-2.69***	
	Age, gender, education			-2.11**						-1.79*	
	[b]Age at retirement			-02.17**						-1.87*	
	[b]Occupational status										
	[ab]Additional covariates			-2.28**		-1.22*				-1.83**	
	[b]Strength										
Strength-related				-3.37***		-2.22***		-2.24**		-1.37*	
	Age, gender, education			-2.49***		-1.66**		-1.35*			
	[b]Age at retirement			-2.56***		-1.69**		-1.41*			
	[b]Occupational status			-1.86**		-1.35*					
	[ab]Additional covariates			-2.21***		-1.44*					
	[b]Movement			-2.07**		-1.51*		-1.37*			

Notes. T scores for cognitive measures. [a] Additional covariates in Study 1 were baseline NART scores and time varying measures of medical conditions and depression; Additional covariates in Study 2 were time-invariant measures of medical conditions, smoking status, alcohol consumption, and time-varying measures of depression and activity engagement. [b] Also controlled for age, gender, and education. *p<.05; **p<.01; ***p<.001

Higher occupational complexity with things was associated with lower initial levels of processing speed and episodic memory. The negative association between things and cognitive ability is consistent with the findings of Andel et al. (2007). The finding that occupational activities involving complex interactions with things and heavy physical exertion were similarly associated with lower episodic memory performance, suggests that complexity with things is qualitatively different from data and people in terms of cognitive stimulation (Harvey, 2004). Furthermore, the finding in this thesis that higher complexity with things was associated with slower rates of MMSE decline (after controlling for occupational status, premorbid ability, and health factors), and the finding by Correa Ribeiro et al. (2013) that intermediate levels of complexity with things were associated with higher levels of MMSE, suggest that the equivocal nature of the extant results in relation to complexity with things may stem, in part, from differences in the actual work profiles of the samples studied.

The associations between strength-related job demand and immediate memory performance were robust, and remained significant after adjustments for age, gender, education, age at retirement, occupational status, the other occupational activity demands, and a broad range of late life health and lifestyle factors. Thus, it appears that there is something unique about the link between previous physical exertion at work and memory performance in later life. This finding highlights the utility of measuring cognitive outcomes in multiple domains.

6.4 Theoretical interpretation of key findings

The findings are supportive of the preserved differentiation hypothesis. That is, the associations of previous occupational activity demands with late life cognitive functioning reflect long-term differences in average cognitive ability. The findings are generally inconsistent with the hypothesis of differential preservation, suggesting that previous occupational activity demands do not alter rates of cognitive decline in later life.

The environmental complexity and cognitive reserve hypotheses provide the theoretical basis of this thesis. The environmental complexity hypothesis describes a reciprocal and causal relationship between complex occupational demands and cognitive functioning. It proposes that people who work in occupations that require them to deal with complex demands will exercise their cognitive skills and raise them to a higher level, whilst those people who work in occupations that require them to deal with simple demands, will not exercise their cognitive skills sufficiently and will not raise them to a higher level. How this occurs is not yet well understood. One key hypothesis is that complex, cognitively demanding activity stimulates structural and functional changes in the brain, such as increasing dendritic branching, creating new synaptic connections and increasing cognitive processing efficiency. In essence, the environmental complexity hypothesis suggests that the stimulation provided by complex demands in the main lifetime occupation will alter trajectories of cognitive change. Contrary to this expectation, the results in this study and in other studies (Gow, Avlund, et al., 2012) indicate that occupational complexity (or physical job demands) at midlife do not significantly alter trajectories of cognitive decline among former workers in later life. The results show instead, that older adults who previously held a main lifetime occupation characterised by higher levels of complexity (and perhaps with few physical demands), had higher levels of cognitive ability in late life, on average, than older adults who previously held a main lifetime occupation characterised by lower levels of complexity (and perhaps with more physical demands), and the advantage was maintained over time. This pattern is consistent with preserved differentiation.

Although the results are supportive of preserved differentiation, the data cannot clarify whether (a) people who previously held occupations involving higher levels of complexity always had higher levels of ability, or (b) if the people who performed well on tests of perceptual speed and verbal reasoning engaged in more complex occupational activity during their career (Bielak, Cherbuin, et al., 2014). Similarly, this thesis cannot separate out the direction of the association between heavy physical work and poorer immediate memory performance (Bielak, Cherbuin, et al., 2014). The samples of older adults in this thesis had been retired about 17 years. So, it is plausible that in the intervening period between work and the baseline cognitive assessment, any benefits from occupational complexity in terms of slower rates of cognitive decline, were washed out by other influences on cognitive performance and change during this interval.

6.5 Practical implications of key findings

In addition to contributing to the theoretical debate on the causes of age-related cognitive decline, the findings in this thesis have implications for policy. In the context of an ageing population, the optimising of cognitive health has become an increasingly important societal and public health goal. Moreover, occupational activity encompasses the mid part of the life course, and midlife has been identified as key point in the lifespan for interventions to optimise cognitive health. Even though the present study suggests that occupational activity does not change the course of cognitive decline in old age, the findings of support for preserved differentiation “still adds positively to the larger aim of how to possibly improve cognitive functioning” (Bielak, Cherbuin, et al., 2014, p. 529; Hertzog et al., 2008). Thus, the results suggest that there may be scope for workplace interventions, such as vocational training opportunities which require the processing of information or data, to provide a “one time boost” to cognition (Bielak, Cherbuin, et al., 2014, p. 7; Gow, Bielak, et al., 2012). Indeed, the World Health Organization's (World Health Organization, 2002), strategy for "active ageing"[17] includes a recommendation to "provide education and learning opportunities throughout the life course" (p. 51).

As Australians live longer they may be more inclined to remain active in the workforce for longer, either through choice or financial necessity (Australian Human Rights Commission, 2012). Encouraging older workers to remain in the workforce for longer is also an aim of the Australian government, as evidenced by policy to gradually increase the qualifying age for the pension to 67 by 1 July 2023 (Commonwealth of Australia, 2010). Given that cognitive decline might impact on the ability of older workers to participate in paid work (Westerlund et al., 2009), workplace interventions offering a "one time boost" to cognition may also assist in keeping older people active in the workforce for longer (Avolio & Waldman, 1990). Indeed, Kohn and Schooler's research program suggests that the greatest gains from substantively complex work might be for older adults (Schooler & Caplan, 2009). Yet, discriminatory employment and training practices suggest that older adults are less likely than younger adults to receive workplace training (Australian Human Rights Commission, 2012). Therefore, increased advocacy and formal policy to increase the delivery of training initiatives targeted at older workers should be encouraged.

6.6 Strengths

This thesis was able to contribute new knowledge on the associations of occupational complexity and physical job demands with cognition by addressing a number of gaps and methodological limitations in the literature. First, data were drawn from two large population-based longitudinal studies of ageing. The large sample sizes afforded by the DYNOPTA and the ALSA suggest the null findings in

[17] The World Health Organization (2002, p. 12) defined active ageing as "the process of optimizing opportunities for health, participation and security in order to enhance quality of life as people age"

this thesis are less likely to be due to statistical power (Hertzog, Lindenberger, Ghisletta, & Oertzen, 2006). Second, four wave data permitted the modelling of non-linear cognitive change that might occur in later years and when the protective effects of occupational complexity might be more pronounced (Christensen et al., 2001). Third, multiple tests of cognition were used measuring abilities in the fluid and crystallized domains, thereby addressing the possibility that occupational complexity or physical job demands might be associated with decline in some cognitive domains but not others. Fourth, this thesis extended and validated the findings of Finkel et al. (2009) with an Australian measure of occupational complexity involving data, people, and things. Fifth, the analyses were comprehensive and explored the potential moderating roles of education, gender, and age at retirement on the associations between occupational complexity, physical job demands and cognitive ageing. Many studies have overlooked the moderating roles of education, gender, and age at time of retirement (i.e., retirement timing and retirement duration). Finally, an array of potentially confounding covariates, which may have distorted the associations of occupational complexity and physical job demands with cognitive ageing, were examined. Several limitations also need to be acknowledged.

6.7 Limitations and outlook

6.7.1 Prior ability

The main limitation in this study concerns the lack of effective control for prior ability. Some researchers have suggested that education may be a reasonable proxy for early life ability (Mackinnon, Christensen, Hofer, Korten, & Jorm, 2003) and to some extent it may determine occupational placement. In the current study associations between the occupational activity demands and cognitive function were shown to be independent of education. However, education might be less relevant as a proxy for prior ability in this study's cohort, because educational attainment may have been principally determined by socio-economic factors rather than ability. Thus, the associations between the occupational activity demands and cognition may have been overestimated.

This thesis was also unable to separate out the directionality of the relations between the occupational activity demands and cognition. A key challenge for future researchers it to unravel the causal relations between occupational activity and cognitive ageing. This challenge will be met through a greater emphasis on longitudinal research designs that track people over multiple life course transitions, including the transitions in and out of work. Evidence of the growing awareness for such research designs, is the establishment over the past decade of studies such as the US Health and Retirement Study and the English Longitudinal Study of Ageing, which track people pre-and post-retirement, and the PATH Through Life Project in Australia, which tracks people in three different age cohorts. It is expected that findings from these studies will contribute greatly to our understanding of the interrelationships between occupation activity demands and cognitive ageing.

6.7.2 Sample characteristics

Due to the effects of selection and attrition, caution should be taken when generalising the findings of this thesis to the general Australian population. Lower functioning people are less likely to participate in longitudinal studies of ageing (Morrell, Brant, & Ferrucci, 2009). As a result, the ALSA and DYNOPTA samples were likely to have been higher functioning than the general population.

Attrition due to mortality is also a limitation in longitudinal studies of cognitive ageing because it means that over time, the sample becomes less representative of the general population (Hofer et al., 2012). The potentially confounding effects of mortality were somewhat minimised in this thesis by controlling for variables that are informative of mortality (Anstey et al., 2001). Nevertheless, occupational complexity has been associated with reduced mortality risk in men (Moore & Hayward, 1990), and low socioeconomic status, physical inactivity, and prolonged sitting at work have been linked to all-cause mortality (Dunstan, Howard, Healy, & Owen, 2012; Gilson, Burton, van Uffelen, & Brown, 2011; Konlaan, Theobald, & Bygren, 2002; Mummery, Schofield, Steele, Eakin, & Brown, 2005; van der Ploeg, Chey, Korda, Banks, & Bauman, 2012). If those people who previously held occupations lower in complexity, or with sedentary job demands, experienced faster rates of cognitive decline and were more likely to die, then the true effects of the occupational activity demand variables on cognitive decline would be underestimated.

Selective, non-random attrition may also be a limitation, particularly in relation to delayed memory. Specifically, if people with lower levels of cognitive function are less likely to remain in a study and to contribute data at all waves than people with higher levels of functioning, then true cognitive change and associated between-person variation will be underestimated (Gerstorf, Herlitz, & Smith, 2006; Lindenberger, Singer, & Baltes, 2002). This could potentially lead to ambiguous inferences about the role of occupational complexity in explaining individual differences in cognitive ageing (Hofer et al., 2012). Nevertheless, the results from studies 1 and 2, are generally consistent and they are also largely consistent with studies using data from other longitudinal studies of ageing (Finkel et al., 2009; Gow, Avlund, et al., 2012). Nonetheless, it is important that the findings reported in this thesis be validated in future studies.

Although the study samples were restricted to people who reported a retirement age of 40 years or more, it was not possible to directly control for differences in occupational duration because this information was not available in the data sources used (Gow, Avlund, et al., 2012, was also not able to control for occupation duration). Moreover, this method did not guarantee that those people who did retire after age 40 were engaged continuously in the labour market prior to that age. If a substantial portion of the samples held their main lifetime occupation for less than 23 years, then perhaps the likelihood of observing an association between occupational complexity and cognition was reduced. However, the results showed that the associations between the predictor variables and the cognitive outcome variables were independent of age at retirement. If age at retirement functions as a rough proxy for occupational duration, then the potentially confounding effects of occupational duration did not appear to be pervasive in this thesis.

Studies have demonstrated asymmetrical relationships in cognitive change between older spouses. For example, using 11-year data from the ALSA, Gerstorf et al. (2009) found that husbands' perceptual speed performance preceded and predicted subsequent changes in wives' perceptual speed performance. As a possible explanation for their findings, Gerstorf and colleagues suggested that husbands accumulated cognitive resources during their career that benefited the couple in old age. As women in this cohort were likely to have had reduced employment and career opportunities, a fruitful area of future research might be to explore whether the cognitive resources acquired by husbands via occupational activity provide cognitive benefits to wives. Correspondingly, the equivalent findings for men and women reported in this thesis and in other studies (Gow, Avlund, et al., 2012) might potentially be explained by spousal dynamics.

6.7.3 Occupation measures

Occupational information was collected retrospectively and was indicated by a single question about the main lifetime occupation. Therefore, some misclassification of occupation and measurement of occupational complexity was possible. However, job mobility was likely to be low in this cohort (Broom et al., 1976), meaning that the main lifetime occupation was likely to be representative of a person's career. Also, if 'end of career' occupational pursuits are affected by the effects of dementing processes on cognition, as reported by Smyth et al. (2004), then taking a person's main lifetime occupation rather than their last job, or the job from which they retired, may have reduced this confounding effect.

The occupational complexity measure assumes equivalence in intellectual challenge between people and over time. However, this is unlikely to be true. As such, the effects of occupational complexity on cognitive ageing may have been underestimated (Finkel et al., 2009). Additional insights into the associations between occupational complexity and cognitive ageing may be revealed from a combination of measures based on objective criteria and subjective measures that capture individual variability of intellectual challenges. Occupations vary in a number of regards other than complexity levels or physical demands. Future research that incorporates measures of complexity as well as those characteristics described by Karasek as psychosocial work factors (Rijs et al., 2013), will also be useful in providing a richer account of how the wider occupational environment might potentially be modified to optimise cognitive health and wellbeing (Andel et al., 2011; Gow, Avlund, et al., 2012).

In relation to physical job demands, the dichotomous measures may have represented a too heterogeneous grouping to detect cognitive benefits from occupation-based physical activity or the detrimental effects of sedentary job behaviour. Using metabolic equivalent values to distinguish between sedentary behaviour (<1.5 MET, Brown et al., 2012) and light activities (1.6 to 2.9 METs, Brown et al., 2012) in the workplace might offer richer insights into the relationship between occupational physical demands and cognitive functioning. Given the increased prevalence of prolonged sitting at work, and the detrimental effects of physical inactivity or sedentary behaviour on physical health, the relationship between these factors and cognitive ageing is a fruitful area for future research.

6.7.4 Cognitive outcome measures

The choice of cognitive outcome measures was constrained somewhat by the available data. Consequently, cognition was measured using individual tests, which might be less optimal than using composite measures (Wilson et al., 2002). Nevertheless, the results reported in this thesis in relation to perceptual speed, memory, and verbal reasoning are largely equivalent to those reported by Finkel et al. (2009). Estimates of cognitive change using individual cognitive tests may also be biased by retest or practice effects (Rabbitt, Diggle, Smith, Holland, & Mc Innes, 2001). However, the average linear decline on the cognitive measures suggests that practice effects were not pervasive in this thesis. The use of the MMSE as an index of cognitive performance and change might also be considered a limitation of this thesis. As discussed in Chapter 4, the MMSE is not a very sensitive measure of cognitive decline, and the decline that is evidence by the MMSE may in fact represent underestimates of true declines. Nevertheless, the MMSE is commonly used in studies of cognitive ageing, partly because the test features in most longitudinal studies. Also, as dementia is predicted by declines of the MMSE, changes on this test are of interest to researchers of cognitive ageing (Piccinin et al., 2013).

6.7.5 Measuring time

This thesis used time in study as a metric of time because the samples were age heterogeneous and the use of this metric has been recommended in such conditions (Hofer et al., 2012). However, process-models of change, such as models indexing cognitive change over time since retirement, or change point models comparing rates of change before and after retirement (e.g., Finkel et al., 2009), may reveal further insights into the complex interrelations between cognition, occupation, and retirement. The examination of cognitive change pre- and post-retirement is a promising area for future research and was not feasible with the datasets under investigation in this thesis.

6.8 Final conclusion

This study provided a comprehensive examination of the long-term protective associations between occupational complexity and later life cognitive abilities and found evidence supporting preserved differentiation rather than differential preservation. People who held occupations higher in complexity with data, performed at a higher average level on a range of cognitive tests compared to people who held occupations lower in complexity, and those average differences were maintained over an 11 year period, even when differences in other influences on cognitive performance and change, such as differences in the timing and duration of retirement and current symptoms of depression and late life cognitive activity, were considered. The evidence in relation to physical job demands provided additional support for preserved differentiation. People, who previously performed work with physical demands, particularly work requiring heavy physical exertion, performed at a lower average level on tests of cognition than people who performed work that was not physically demanding, and the average disadvantage was maintained over time. Therefore, the late life associations of occupational complexity and physical job demands with age-associated cognitive decline appear to reflect the persistence of long-term differences in average cognitive ability. A better understanding of the relationships between occupational complexity and normal cognitive decline has potentially broad implications for designing interventions for optimising cognitive health among both current and former workers. Therefore, future research in this area is warranted. The results in this thesis, suggest that future research might benefit from a focus on complex occupational activities involving data; from examining cognitive outcomes in multiple domains; and, from including measures of cognitive ability at early and midlife. Studies using brain imaging techniques and biomarkers will also prove valuable in contributing knowledge about the mechanisms that may underpin the occupational activity and cognitive ageing relationship. Understanding the long-term associations between sedentary work behaviour and normal cognitive decline will also become increasingly important as the prevalence of sedentary work behaviour increases. Future research in this area will benefit from using indices of prolonged sitting rather than using dichotomous measures of sitting versus moving. In conclusion, longitudinal data do not currently support a long-term protective association between complex demands in the main lifetime occupation and age-associated cognitive decline among former workers.

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APPENDICES

Appendix A: Multilevel Modelling

Multilevel growth modelling decomposes variance in an outcome measure, such as cognition, across within-person and between-person levels and explains that variance with variables specified at each level (Ram & Grimm, 2007). It is a commonly used approach for examining human development, where repeated observations are taken from the same individuals (i.e., where observations are nested within individuals).

The basic multilevel model can be expressed by sub-models at two levels (Shaw & Liang, 2013; Singer & Willett, 2003). The level-1, or within-person, model takes the following basic form:

$$Cognition_{ij} = \beta_{0i} + \beta_{1i}(Time_{ij}) + \varepsilon_{ij}$$

where, $Cognition_{ij}$, represents the outcome variable (i.e. cognitive functioning) for person *i* at time *j*; β_{0i} is the starting point (intercept), which is defined as an individual's cognition score when time equals zero (baseline); *Time* represents the amount of time (years since baseline); β_{1i} is the rate of change (slope) in cognition for individual *i* over time; and, ε_{ij} represents random error of individual *i* at occasion *j*, or that portion of individual *i*'s cognition score that is unpredicted or remains to be explained on occasion *j*.

The level-1 model is referred to a within-person model because it estimates the starting point and the rate of change in cognition over repeated measures of cognition for each individual in the dataset (Shaw & Liang, 2013). The individual growth parameters, β_{0i} and β_{1i}, in the level-1 model can be decomposed into fixed and random effects in a level-2, or between-person, model, as follows:

$$\beta_{0i} = \gamma_{00} + \mu_{0i}$$

$$\beta_{1i} = \gamma_{10} + \mu_{1i}$$

where, γ_{00} ,is a fixed effect and represents the average cognition score when time equals zero (baseline) for the sample as a whole; γ_{10} is a fixed effect and represents the average within-person change in cognition scores over time (years since baseline) for the sample; μ_{0i} is a random effect and represents the degree to which each individual's cognition score at the intercept (when time equals zero) deviates from the mean; and μ_{1i} is a random effect representing the degree to which individuals' cognitive change rates deviate from the average. Thus, fixed effects represent the average intercept and slope for the sample as a whole, whereas random effects represent between-person variability in intercepts and slopes (Shaw & Liang, 2013). The random effects play an important role in answering questions about between-person (inter-individual) differences in within-person (intra-individual) change. The level-1 and level-2 models can be combined and re-expressed as a composite.

This thesis was primarily concerned about whether cognitive trajectories differed as a function of occupational complexity or physical job demands. Thus, these time invariant, predictor variables were added to the level-2 (between-person) model, as follows:

$$\beta_{0i} = \gamma_{00} + \gamma_{01}(Occupatonal\ Complexity) + \mu_{0i}$$

$$\beta_{1i} = \gamma_{10} + \gamma_{11}(Occupational\ Complexity_i) + \mu_{1i}$$

so that, γ_{00} represents the average cognition score at baseline and occupational complexity equals zero[18] for the sample as a whole; γ_{01} represents the effect of a one unit increase in occupational complexity on cognition at baseline; γ_{10} represents the average within-person change in cognition over years since baseline when occupational complexity equals zero; and γ_{11} represents the effect of a one unit increase occupational complexity on within-person change in cognition over years since baseline for the sample. When the new level-2 equations are combined with the Level-1 equation, occupational complexity is specified as having a main effect on cognition as well as being part of an interaction effect with time.

MLM assumes that the level-1 residual (ε_{ij}) are independently drawn from a normal distribution with mean 0 and variance σ_{ϵ}^2, are uncorrelated with the level-1 predictor (Time), and are homoscedastic across occasions (Singer & Willett, 2003). MLM also assumes that the level-2 residuals, (μ_{1i} and, μ_{1i}) are bivariate normal with mean 0, unknown variances, σ_0^2 and σ_1^2, and unknown covariance σ_{01}. MLM also assumes that the level-2 residuals are independent of the level-1 residual and of the model's predictors (Singer & Willett, 2003).

Analyses using MLM are carried out under the assumption that missing data are *missing at random* (MAR: Little & Rubin, 2002). MAR means that the likelihood of having missing data on a given variable may depend on other observed information, but does not depend on the data that would have been observed but were in actuality missing (Singer & Willett, 2003; West, Welch, & Galecki, 2007). Under the MAR assumption, "inferences based on methods of ML estimation in [MLM] are valid" (West et al., 2007). Compared to other ways of dealing with missing data (e.g., listwise deletion, regression imputation, mean imputations), FIML estimation produces more precise and less biased estimates (Schafer & Graham, 2002). Thus, the accepted practice in cognitive ageing research is to assume that data are MAR and to include covariates in analyses that are informative of missingness (Anstey et al., 2003; Gerstorf et al., 2009; Wagner et al., 2013). This was the approach taken in this thesis.

[18] In this thesis, occupational complexity was grand mean centred, so 'zero' represented the average level of complexity for the sample as a whole.

Appendix B: Parameter Estimates from Multilevel Models Examining Occupational Complexity by Education, Gender, and Age at Retirement Predicting Cognitive Performance and Change

Table B.1

Parameter Estimates from Multilevel Models Examining Occupational Complexity × Education Predicting Cognitive Performance and Change

	Model 2 + Data × Education				**Model 2 + People × Education**				**Model 2 +Things × Education**			
	PS Est. (SE)	**IM Est. (SE)**	**DM Est. (SE)**	**VR Est. (SE)**	**PS Est. (SE)**	**IM Est. (SE)**	**DM Est. (SE)**	**VR Est. (SE)**	**PS Est. (SE)**	**IM Est. (SE)**	**DM Est. (SE)**	**VR Est. (SE)**
Fixed Effects												
Intercept	50.56 (0.35)***	49.36 (0.33)***	49.12 (0.37)***	50.45 (0.39)***	50.81 (0.35)***	49.45 (0.32)***	49.22 (0.36)***	50.56 (0.38)***	50.92 (0.35)***	49.49 (0.32)***	49.31 (0.36)***	50.65 (0.38)***
Time	-0.50 (0.17)**	-0.57 (0.08)***	-1.10 (0.21)***	-0.29 (0.07)***	-0.52 (0.16)**	-0.56 (0.07)***	-1.05 (0.21)***	-0.28 (0.06)***	-0.50 (0.17)**	-0.56 (0.07)***	-1.13 (0.21)***	-0.29 (0.06)***
Time^2	-0.01 (0.02)	–	0.07 (0.02)**		-0.01 (0.02)	–	0.07 (0.02)**		-0.01 (0.02)	–	0.07 (0.02)***	
Age	-0.64 (0.05)***	-0.43 (0.05)***	-0.39 (0.05)***	-0.23 (0.05)***	-0.64 (0.05)***	-0.43 (0.05)***	-0.39 (0.05)***	-0.23 (0.05)***	-0.62 (0.05)***	-0.42 (0.05)***	-0.39 (0.05)***	-0.21 (0.05)***
Gender	1.14 (0.66)	1.79 (0.60)**	2.61 (0.68)***	0.21 (0.70)	0.67 (0.66)	1.63 (0.60)**	2.48 (0.68)***	-0.38 (0.70)	0.08 (0.68)	1.37 (0.62)*	2.07 (0.70)**	-0.39 (0.72)
Edu	1.06 (0.21)***	0.24 (0.20)	0.44 (0.22)*	1.17 (0.23)***	1.17 (0.21)***	0.29 (0.19)	0.49 (0.22)*	1.23 (0.22)***	1.17 (0.21)***	0.28 (0.19)	0.45 (0.21)*	1.37 (0.22)***
OC	0.67 (0.14)***	0.24 (0.13)	0.20 (0.14)	0.72 (0.15)***	0.57 (0.14)***	0.17 (0.12)	0.12 (0.14)	0.43 (0.14)**	-0.46 (0.11)***	-0.19 (0.10)	-0.28 (0.12)**	-0.10 (0.12)
Edu×OC	0.05 (0.10)	0.03 (0.09)	0.03 (0.10)	-0.05 (0.10)	-0.14 (0.08)	-0.03 (0.08)	-0.04 (0.09)	0.11 (0.09)	-0.01 (0.08)	-0.03 (0.07)	-0.01 (0.03)	-0.06 (0.08)
Time×Age	-0.09 (0.03)	-0.02 (0.01)	-0.04 (0.03)	-0.03 (0.01)**	-0.09 (0.03)***	-0.02 (0.01)	-0.04 (0.03)	-0.03 (0.01)**	-0.09 (0.03)***	-0.02 (0.01)	-0.04 (0.03)	-0.03 (0.01)**
Time×Gender	0.22 (0.29)	0.03 (0.11)	-0.14 (0.37)	0.05 (0.10)	0.23 (0.29)	0.01 (0.11)	-0.15 (0.37)	-0.03 (0.10)	0.14 (0.30)	0.02 (0.12)	-0.13 (0.37)	-0.05 (0.10)
Time×Edu	-0.14 (0.10)	0.04 (0.04)	-0.16 (0.12)	0.03 (0.04)	-0.14 (0.10)	0.06 (0.04)	-0.12 (0.12)	0.04 (0.03)	-0.16 (0.10)	0.06 (0.04)	-0.13 (0.12)	0.02 (0.04)
Time×OC	-0.00 (0.06)	0.05 (0.03)	0.05 (0.08)	0.01 (0.02)	0.01 (0.06)	0.01 (0.03)	-0.01 (0.08)	0.00 (0.01)	-0.08 (0.05)	0.01 (0.02)	0.04 (0.06)	-0.01 (0.02)
Time×Edu×OC	-0.02 (0.05)	0.01 (0.02)	0.07 (0.06)	0.01 (0.02)	0.02 (0.04)	0.01 (0.02)	0.01 (0.05)	-0.02 (0.02)	-0.03 (0.04)	-0.01 (0.01)	-0.11 (0.04)**	-0.02 (0.01)
Time^2×Age	0.02 (0.00)*	–	0.00 (0.00)	–	0.01 (0.00)*	–	0.00 (0.00)	–	0.01 (0.00)*	–	0.00 (0.00)	–
Time^2×Gender	-0.02 (0.03)	–	0.00 (0.03)	–	-0.02 (0.03)	–	0.00 (0.03)	–	-0.02 (0.03)	–	0.00 (0.03)	–
Time^2×Edu	0.01 (0.01)	–	0.02 (0.01)	–	0.01 (0.01)	–	0.02 (0.01)	–	0.01 (0.01)	–	0.02 (0.01)	–

$Time^2$×OC	0.00 (0.01)	–	-0.00 (0.01)	–	0.00 (0.01)	–	0.00 (0.01)	–	0.01 (0.00)	–	0.00 (0.01)	–
$Time^2$×Edu×OC	-0.00 (0.00)	–	-0.01 (0.01)	–	-0.00 (0.00)	–	0.00 (0.01)	–	0.00 (0.00)	–	0.01 (0.00)*	–
Random Effects												
Residual, σ_{ϵ}^2	21.50 (1.19)***	42.03 (2.21)***	38.84 (2.04)***	45.07 (2.90)***	21.50 (1.19)***	42.14 (2.22)***	38.91 (2.04)***	45.25 (2.94)***	21.45 (1.19)***	42.14 (2.22)***	38.62 (2.03)***	45.03 (2.92)***
Intercept, σ_0^2	45.62 (3.18)***	28.29 (3.37)***	34.89 (3.45)***	42.78 (4.23)***	46.18 (3.21)***	28.34 (3.38)***	34.96 (3.46)***	43.86 (4.33)***	45.64 (3.19)***	28.08 (3.37)***	34.41 (3.42)***	45.12 (4.36)***
Time, σ_1^2	0.20 (0.05)***	0.20 (0.08)*	0.26 (0.08)**	–[a]	0.21 (0.05)***	0.21 (0.08)*	0.26 (0.08)**	–[a]	0.21 (0.05)***	0.20 (0.08)*	0.25 (0.08)**	–[a]
Covariance, σ_{01}^2	-0.74 (0.35)*	0.83 (0.47)	-0.07 (0.47)	–[a]	-0.80 (0.36)*	0.86 (0.48)	-0.02 (0.47)	–[a]	-0.73 (0.36)*	0.93 (0.48)	0.09 (0.46)	–[a]

Notes. Unstandardised estimates (Est.) and standard errors (SE) are presented. PS: Perceptual Speed. IM: Immediate Memory. DM: Delayed Memory. VR: Verbal Reasoning. T scores for cognitive measures standardised to the baseline sample (*M*=50, *SD*=10). Time: years in study. Data: Occupational complexity with data, grand mean centred (M=3.67). People: Occupational complexity with people, grand mean centred (*M*=1.32). Things: Occupational complexity with things, grand mean centred (*M*=2.35). OC: Occupational complexity, higher scores indicate greater complexity. Age: baseline age, grand mean centred at 78.09 years. Gender: 0=Male, 1=Female. Edu: Education, grand mean centred at 15 years. Dashes indicate that effect was not estimated. [a]For model convergence, variance component could not be estimated. *p<.05; **p<.01; ***p<.001

Table B.2

Parameter Estimates from Multilevel Models Examining Occupational Complexity Involving Things Predicting Cognitive Performance and Change in Lower and Higher Education Groups

	Low Education	High Education
	Est. (SE)	**Est. (SE)**
Fixed Effects		
Intercept	48.81 (0.43)***	49.99 (0.53)***
Time	-0.97 (0.24)***	-1.35 (0.30)***
Time^2	0.05 (0.02)*	0.09 (0.03)**
Age	-0.37 (0.06)***	-0.37 (0.07)***
Gender	2.26 (0.87)*	1.77 (0.96)
OC (Things)	-0.30 (0.14)*	-0.36 (0.17)*
Time×Age	-0.02 (0.04)	-0.07 (0.04)
Time×Gender	-0.14 (0.45)	0.12 (0.51)
Time×OC (Things)	0.17 (0.07)*	-0.03 (0.09)
Time^2×Age	-0.00 (0.00)	0.00 (0.00)
Time^2×Gender	0.01 (0.04)	-0.00 (0.05)
Time^2×OC (Things)	-0.01 (0.01)	0.01 (0.01)
Random Effects		
Residual, σ_ϵ^2	36.34 (2.34)***	42.01 (3.02)***
Intercept, σ_0^2	36.94 (4.17)***	39.92 (5.01)***
Time, σ_1^2	0.39 (0.11)***	0.14 (0.11)
Covariance, σ_{01}^2	-0.55 (0.58)	0.88 (0.63)
Goodness-of-fit		
-2LL	9221.86	6996.03
AIC	9253.86	7028.03
BIC	9336.71	7106.33

Notes. Unstandardised estimates (Est.) and standard errors (SE) are presented. T scores for cognitive measures standardised to the baseline sample (*M*=50, *SD*=10). Time: years in study. Things: Occupational complexity with things, grand mean centred (*M*=2.35) and higher scores indicate greater complexity. Age: baseline age, grand mean centred at 78.09 years. Gender: 0=Male, 1=Female. -2LL = Deviance. AIC: Akaike information criterion. BIC: Bayesian information criterion. *p<.05; **p<.01; ***p<.001.

Table B.3

Parameter Estimates from Multilevel Models Examining Occupational Complexity × Gender Predicting Cognitive Performance and Change

	Model 2 + Data × Gender				**Model 2 + People × Gender**				**Model 2 + Things × Gender**			
	PS Est. (SE)	**IM Est. (SE)**	**DM Est. (SE)**	**VR Est. (SE)**	**PS Est. (SE)**	**IM Est. (SE)**	**DM Est. (SE)**	**VR Est. (SE)**	**PS Est. (SE)**	**IM Est. (SE)**	**DM Est. (SE)**	**VR Est. (SE)**
Fixed Effects												
Intercept	50.60 (0.34)***	49.38 (0.32)***	49.12 (0.36)***	50.42 (0.38)***	50.75 (0.34)***	49.43 (0.32)***	49.19 (0.36)***	50.63 (0.38)***	50.95 (0.35)***	49.53 (0.32)***	49.31 (0.36)***	50.71 (0.38)***
Time	-0.51 (0.17)**	-0.56 (0.07)***	-1.02 (0.21)***	-0.29 (0.06)***	-0.51 (0.16)**	-0.55 (0.07)***	-1.04 (0.21)***	-0.28 (0.06)***	-0.52 (0.16)**	-0.56 (0.07)***	-1.09 (0.21)***	-0.29 (0.06)***
Time^2	-0.01 (0.02)	–	0.06 (0.02)**	–	-0.01 (0.02)	–	0.06 (0.02)**	–	-0.01 (0.02)	–	0.07 (0.02)**	–
Age	-0.64 (0.05)***	-0.43 (0.05)***	-0.39 (0.05)***	-0.23 (0.06)***	-0.64 (0.05)***	-0.43 (0.05)***	-0.39 (0.05)***	-0.22 (0.05)***	-0.62 (0.05)***	-0.42 (0.05)***	-0.38 (0.05)***	-0.20 (0.05)***
Gender	1.01 (0.67)	1.75 (0.61)**	2.50 (0.69)***	0.25 (0.70)	0.66 (0.66)	1.59 (0.60)**	2.47 (0.68)***	-0.29 (0.70)	0.38 (0.71)	1.58 (0.64)*	2.12 (0.73)**	-0.10 (0.75)
Edu	1.09 (0.21)***	0.26 (0.19)	0.47 (0.22)*	1.14 (0.22)***	1.15 (0.21)***	0.27 (0.19)	0.49 (0.22)*	1.26 (0.22)***	1.19 (0.21)***	0.29 (0.19)	0.45 (0.21)*	1.40 (0.22)***
OC	0.72 (0.15)***	0.27 (0.14)*	0.31 (0.16)*	0.70 (0.16)***	0.56 (0.15)***	0.08 (0.14)	0.11 (0.16)	0.56 (0.16)**	-0.53 (0.12)***	-0.24 (0.12)*	-0.27 (0.13)*	-0.17 (0.14)
Gender×OC	-0.32 (0.32)	-0.20 (0.29)	-0.54 (0.33)	0.16 (0.33)	-0.16 (0.28)	0.23 (0.26)	-0.04 (0.29)	-0.27 (0.30)	0.34 (0.27)	0.25 (0.24)	0.02 (0.28)	0.35 (0.29)
Time×Age	-0.09 (0.03)***	-0.02 (0.01)	-0.04 (0.03)	-0.03 (0.01)**	-0.09 (0.03)***	-0.02 (0.01)	-0.04 (0.03)	-0.03 (0.01)**	-0.09 (0.03)***	-0.02 (0.01)	-0.04 (0.03)	-0.03 (0.01)**
Time×Gender	0.20 (0.29)	0.04 (0.11)	-0.08 (0.37)	-0.06 (0.10)	0.22 (0.29)	0.02 (0.11)	-0.17 (0.37)	-0.04 (0.10)	-0.03 (0.31)	0.01 (0.12)	-0.06 (0.38)	-0.06 (0.10)
Time×Edu	-0.13 (0.10)	0.04 (0.04)	-0.15 (0.12)	0.04 (0.04)	-0.14 (0.10)	0.06 (0.04)	-0.13 (0.12)	0.04 (0.04)	-0.17 (0.10)	0.06 (0.04)	-0.11 (0.12)	0.03 (0.03)
Time×OC	0.02 (0.07)	0.03 (0.03)	-0.06 (0.09)	0.03 (0.03)	0.00 (0.07)	0.05 (0.03)	-0.05 (0.09)	0.00 (0.03)	-0.01 (0.06)	0.02 (0.03)	0.05 (0.07)	-0.01 (0.02)
Time×Gender×OC	-0.11 (0.14)	0.05 (0.06)	0.39 (0.18)*	-0.08 (0.05)	0.04 (0.12)	-0.08 (0.05)	0.13 (0.15)	-0.01 (0.04)	-0.30 (0.11)*	-0.03 (0.04)	0.00 (0.14)	-0.01 (0.04)
Time^2×Age	0.01 (0.00)*	–	0.00 (0.00)	–	0.01 (0.00)*	–	0.00 (0.00)	–	0.01 (0.00)*	–	0.00 (0.00)	–
Time^2×Gender	-0.02 (0.03)	–	-0.00 (0.03)	–	-0.02 (0.03)	–	0.00 (0.03)	–	-0.00 (0.03)	–	-0.00 (0.04)	–

Time^2×Edu	0.01 (0.01)	–	0.02 (0.01)	–	0.01 (0.01)	–	0.02 (0.01)	–	0.01 (0.01)	–	0.02 (0.01)	–
Time^2×OC	0.00 (0.01)	–	0.01 (0.01)	–	0.00 (0.01)	–	0.01 (0.01)	–	0.00 (0.01)	–	0.00 (0.01)	–
Time^2×Gender×OC	0.01 (0.01)	–	-0.04 (0.02)*	–	-0.01 (0.01)	–	-0.02 (0.01)	–	0.03 (0.01)*	–	-0.00 (0..01)	–
Random Effects												
Residual, σ_ϵ^2	21.53 (1.19)***	42.06 (2.21)***	38.73 (2.03)***	44.51 (2.87)***	21.52 (1.19)***	42.07 (2.21)***	38.80 (2.04)***	45.28 (2.94)***	21.34 (1.18)***	42.17 (2.22)***	38.89 (2.04)***	45.18 (2.93)***
Intercept, σ_0^2	45.54 (3.18)***	28.22 (3.36)***	34.79 (3.44)***	43.50 (4.24)***	46.24 (3.21)***	28.36 (3.38)***	34.96 (3.45)***	43.88 (4.33)***	45.72 (3.19)***	28.03 (3.37)***	34.36 (3.43)***	44.99 (4.36)***
Time, σ_1^2	0.20 (0.05)***	0.20 (0.08)*	0.26 (0.08)**	–[a]	0.21 (0.05)***	0.21 (0.08)*	0.26 (0.08)**	–[a]	0.21 (0.05)***	0.20 (0.08)*	0.24 (0.08)**	–[a]
Covariance, σ_{01}^2	-0.72 (0.35)*	0.83 (0.47)	-0.07 (0.47)	–[a]	-0.77 (0.36)*	0.85 (0.48)	-0.01 (0.47)	–[a]	-0.74 (0.36)*	0.95 (0.48)*	0.16 (0.46)	–[a]

Notes. Unstandardised estimates (Est.) and standard errors (SE) are presented. PS: Perceptual Speed. IM: Immediate Memory. DM: Delayed Memory. VR: Verbal Reasoning. T scores for cognitive measures standardised to the baseline sample (*M*=50, *SD*=10). Time: years in study. Data: Occupational complexity with data, grand mean centred (*M*=3.67). People: Occupational complexity with people, grand mean centred (*M*=1.32). Things: Occupational complexity with things, grand mean centred (*M*=2.35). OC: Occupational complexity, higher scores indicate greater complexity. Age: baseline age, grand mean centred at 78.09 years. Gender: 0=Male, 1=Female. Edu: Education, grand mean centred at 15 years. Dashes indicate that effect was not estimated. [a]For model convergence, variance component could not be estimated. *p<.05; **p<.01; ***p<.001

Table B.4

Parameter Estimates from Multilevel Models Examining Occupational Complexity × Age at Retirement Predicting Cognitive Performance and Change

	Model 2A + Data × Age at Retirement				**Model 2A + People × Age at Retirement**				**Model 2A + Things × Age at Retirement**			
	PS Est. (SE)	**IM Est. (SE)**	**DM Est. (SE)**	**VR Est. (SE)**	**PS Est. (SE)**	**IM Est. (SE)**	**DM Est. (SE)**	**VR Est. (SE)**	**PS Est. (SE)**	**IM Est. (SE)**	**DM Est. (SE)**	**VR Est. (SE)**
Fixed Effects												
Intercept	50.49 (0.35)***	49.30 (0.32)***	49.03 (0.37)***	50.24 (0.38)***	50.61 (0.35)***	49.36 (0.32)***	49.08 (0.37)***	50.44 (0.38)***	50.77 (0.35)***	49.47 (0.33)***	49.20 (0.37)***	50.47 (0.39)***
Time	-0.52 (0.17)**	-0.56 (0.08)***	-1.04 (0.21)***	-0.28 (0.07)***	-0.52 (0.17)**	-0.54 (0.08)***	-1.03 (0.21)***	-0.27 (0.07)***	-0.49 (0.17)**	-0.55 (0.08)***	-1.06 (0.21)***	-0.27 (0.07)***
Time^2	-0.01 (0.02)	–	0.06 (0.02)**	–	-0.01 (0.02)**	–	0.06 (0.02)**	–	-0.01 (0.02)	–	0.07 (0.02)***	–
Age	-0.67 (0.05)***	-0.45 (0.05)***	-0.42 (0.05)***	-0.29 (0.05)***	-0.68 (0.05)***	-0.45 (0.05)***	-0.42 (0.05)***	-0.28 (0.06)***	-0.66 (0.05)***	-0.44 (0.05)***	-0.42 (0.05)***	-0.26 (0.06)***
Gender	1.66 (0.71)*	1.96 (0.65)**	3.01 (0.74)***	0.89 (0.74)	1.22 (0.71)	1.90 (0.64)**	2.92 (0.73)***	0.44 (0.73)	0.64 (0.72)	1.66 (0.66)*	2.56 (0.75)***	0.43 (0.75)
Edu	1.06 (0.21)***	0.25 (0.19)	0.44 (0.22)*	1.13 (0.22)***	1.11 (0.21)***	0.27 (0.19)	0.47 (0.22)*	1.22 (0.22)***	1.15 (0.21)***	0.27 (0.19)	0.43 (0.21)*	1.35 (0.22)***
OC	0.64 (0.13)***	0.22 (0.12)	0.18 (0.14)	0.72 (0.14)***	0.53 (0.13)***	0.15 (0.12)	0.09 (0.13)	0.49 (0.14)***	-0.45 (0.11)***	-0.19 (0.10)	-0.26 (0.12)*	-0.10 (0.12)
Retire	0.11 (0.05)*	0.06 (0.05)	0.10 (0.06)*	0.16 (0.06)**	0.12 (0.05)*	0.06 (0.05)	0.10 (0.06)	0.18 (0.06)**	0.12 (0.05)*	0.06 (0.05)	0.10 (0.06)	0.19 (0.06)**
OC×Retire	-0.01 (0.02)	0.03 (0.02)	0.01 (0.02)	0.01 (0.02)	-0.02 (0.02)	0.00 (0.02)	0.01 (0.02)	-0.01 (0.02)	0.01 (0.02)	-0.02 (0.02)	-0.00 (0.02)	0.01 (0.02)
Time×Age	-0.10 (0.03)***	-0.02 (0.01)	-0.04 (0.03)	-0.03 (0.01)*	-0.09 (0.03)***	-0.02 (0.01)	-0.04 (0.03)	-0.02 (0.01)*	-0.09 (0.03)***	-0.02 (0.01)	-0.03 (0.03)	-0.03 (0.01)*
Time×Gender	0.21 (0.32)	0.02 (0.13)	-0.16 (0.40)	-0.06 (0.11)	0.23 (0.31)	-0.02 (0.12)	-0.22 (0.39)	-0.07 (0.11)	0.18 (0.32)	0.01 (0.13)	-0.11 (0.40)	-0.09 (0.11)
Time×Edu	-0.14 (0.10)	0.05 (0.04)	-0.14 (0.12)	0.03 (0.04)	-0.14 (0.10)	0.06 (0.04)	-0.12 (0.12)	0.04 (0.03)	-0.16 (0.10)	0.06 (0.04)	-0.11 (0.12)	0.03 (0.03)
Time×OC	0.00 (0.06)	0.04 (0.03)	0.03 (0.08)	0.01 (0.02)	0.01 (0.06)	0.02 (0.03)	-0.01 (0.07)	-0.01 (0.02)	-0.08 (0.05)	0.01 (0.02)	0.04 (0.06)**	-0.02 (0.02)
Time×Retire	0.01 (0.03)	-0.00 (0.01)	-0.01 (0.03)	-0.00 (0.01)	0.01 (0.03)	-0.01 (0.01)	-0.01 (0.03)	-0.01 (0.01)	0.01 (0.03)	-0.00 (0.01)	-0.01 (0.03)	-0.01 (0.01)
Time×OC×Retire	0.01 (0.01)	-0.00 (0.00)	-0.01 (0.01)	-0.00 (0.00)	0.01 (0.01)	0.00 (0.00)	0.01 (0.01)	-0.00 (0.00)	-0.00 (0.01)	0.00 (0.00)	-0.01 (0.01)	-0.00 (0.00)
Time^2×Age	0.01 (0.00)*	–	0.00 (0.00)	–	0.01 (0.00)*	–	0.00 (0.00)	–	0.01 (0.00)*	–	0.00 (0.00)	–
Time^2×Gender	-0.03 (0.03)	–	-0.00 (0.04)	–	-0.03 (0.03)	–	0.00 (0.04)	–	-0.03 (0.03)	–	-0.00 (0.04)	–

$Time^2$×Edu	0.01 (0.01)	–	0.02 (0.01)	–	0.01 (0.01)	–	0.02 (0.01)	–	0.01 (0.01)	–	0.02 (0.01)	–
$Time^2$×OC	0.00 (0.01)	–	0.00 (0.01)	–	0.00 (0.01)	–	0.00 (0.01)	–	0.01 (0.00)	–	0.00 (0.01)	–
$Time^2$×Retire	-0.00 (0.00)	–	-0.00 (0.00)	–	-0.00 (0.00)	–	-0.00 (0.00)	–	-0.00 (0.00)	–	0.00 (0.00)	–
$Time^2$×OC×Retire	-0.00 (0.00)	–	0.00 (0.00)	–	-0.00 (0.00)	–	-0.00 (0.00)	–	0.00 (0.00)	–	0.00 (0.00)	–
Random Effects												
Residual, σ_ϵ^2	21.51 (1.19)***	42.08 (2.21)***	38.85 (2.04)***	45.05 (2.90)***	21.54 (1.19)***	42.09 (2.21)***	38.82 (2.04)***	45.22 (2.93)***	21.49 (1.19)***	42.16 (2.22)***	38.84 (2.04)***	45.06 (2.92)***
Intercept, σ_0^2	45.05 (3.16)***	27.93 (3.35)***	34.58 (3.43)***	42.11 (4.20)***	45.61 (3.18)***	28.27 (3.37)***	34.76 (3.44)***	43.15 (4.29)***	45.07 (3.17)***	27.90 (3.36)***	34.05 (3.41)***	44.39 (4.32)***
Time, σ_1^2	0.20 (0.05)***	0.20 (0.08)*	0.26 (0.08)**	–[a]	0.20 (0.05)***	0.21 (0.08)*	0.26 (0.08)**	–[a]	0.20 (0.05)***	0.20 (0.08)*	0.22 (0.08)**	–[a]
Covariance, σ_{01}^2	-0.67 (0.35)	0.85 (0.47)	-0.02 (0.46)	–[a]	-0.68 (0.36)	0.86 (0.48)	-0.00 (0.47)	–[a]	-0.66 (0.36)	0.98 (0.48)*	0.24 (0.46)	–[a]

Notes. Unstandardised estimates (Est.) and standard errors (SE) are presented. PS: Perceptual Speed. IM: Immediate Memory. DM: Delayed Memory. VR: Verbal Reasoning. T scores for cognitive measures standardised to the baseline sample (*M*=50, *SD*=10). Time: years in study. Data: Occupational complexity with data, grand mean centred (*M*=3.67). People: Occupational complexity with people, grand mean centred (*M*=1.32). Things: Occupational complexity with things, grand mean centred (*M*=2.35). OC: Occupational complexity, higher scores indicate greater complexity. Age: baseline age, grand mean centred at 78.09 years. Gender: 0=Male, 1=Female. Edu: Education, grand mean centred at 15 years. Retire: Age at retirement, grand mean centred at age 61.89. Dashes indicate that effect was not estimated. [a]For model convergence, variance component could not be estimated. *p<.05; **p<.01; ***p<.001.

Appendix C: Parameter Estimates from Multilevel Models Examining Physical Job Demands by Education, Gender, and Age at Retirement Predicting Cognitive Performance and Change

Table C.1

Parameter Estimates from Multilevel Models Examining Physical Job Demands × Education Predicting Cognitive Performance and Change

	Model 2 + Movement-Related Job Demand× Education				Model 2 + Strength-Related Job Demand × Education			
	PS Est. (SE)	**IM** Est. (SE)	**DM** Est. (SE)	**VR** Est. (SE)	**PS** Est. (SE)	**IM** Est. (SE)	**DM** Est. (SE)	**VR** Est. (SE)
Fixed Effects								
Intercept	52.66 (0.64)***	50.47 (0.59)***	49.65 (0.66)***	50.44 (0.67)***	51.86 (0.44)***	50.22 (0.41)***	49.81 (0.47)***	49.42 (0.46)***
Time	-0.40 (0.29)	-0.56 (0.13)***	-0.89 (0.37)*	-0.26 (0.14)	-0.31 (0.21)	-0.62 (0.09)***	-1.24 (0.26)***	-0.28 (0.10)**
Time^2	-0.03 (0.03)	–	0.06 (0.04)	–	-0.03 (0.02)	–	0.08 (0.03)**	–
Age	-0.62 (0.05)***	-0.42 (0.04)***	-0.38 (0.05)***	-0.27 (0.05)***	-0.63 (0.05)***	-0.42 (0.04)***	-0.39 (0.05)***	-0.28 (0.05)***
Gender	0.50 (0.66)	1.54 (0.60)*	2.42 (0.69)***	-0.18 (0.68)	0.17 (0.67)	1.26 (0.61)*	2.17 (0.70)**	-0.26 (0.68)
Edu	0.48 (0.40)***	-0.31 (0.38)	0.42 (0.42)	0.76 (0.43)	1.31 (0.26)***	0.12 (0.24)	0.45 (0.27)	1.69 (0.27)***
PJD	-2.33 (0.68)**	-1.23 (0.63)	-0.57 (0.71)	-1.80 (0.71)*	-2.60 (0.62)***	-1.60 (0.57)**	-1.37 (0.65)*	-1.25 (0.65)
Edu×PJD	0.96 (0.47)*	0.78 (0.43)	0.10 (0.49)	0.97 (0.49)*	-0.42 (0.43)	0.28 (0.39)	-0.05 (0.45)	-0.52 (0.45)
Time×Age	-0.09 (0.03)***	-0.02 (0.01)	-0.04 (0.03)	-0.04 (0.01)**	-0.09 (0.03)***	-0.02 (0.01)	-0.04 (0.03)	-0.04 (0.01)**
Time×Gender	0.21 (0.29)	0.02 (0.11)	-0.17 (0.37)	0.01 (0.12)	0.14 (0.30)	0.05 (0.12)	-0.06 (0.37)	0.00 (0.13)
Time×Edu	-0.06 (0.18)	0.07 (0.07)	-0.07 (0.23)	0.14 (0.08)	-0.13 (0.12)	0.09 (0.05)	-0.06 (0.15)	0.08 (0.05)
Time×PJD	-0.15 (0.31)	0.00 (0.13)	-0.23 (0.39)	-0.02 (0.14)	-0.50 (0.29)	0.11 (0.12)	0.41 (0.36)	-0.02 (0.13)
Time×Edu×PJD	-0.13 (0.21)	-0.02 (0.09)	-0.09 (0.27)	-0.11 (0.10)	-0.16 (0.20)	-0.08 (0.09)	-0.08 (0.26)	-0.08 (0.10)
Time^2×Age	0.01 (0.00)*	–	0.00 (0.00) *	–	0.01 (0.00)*	–	0.00 (0.00)	–
Time^2×Gender	-0.02 (0.03)	–	0.00 (0.03)	–	-0.02 (0.03)	–	-0.01 (0.04)	–
Time^2×Edu	0.01 (0.02)	–	0.01 (0.02)	–	0.01 (0.01)	–	0.01 (0.01)	–
Time^2×PJD	0.03 (0.03)	–	0.01 (0.04)	–	0.05 (0.03)[†]	–	-0.04 (0.03)	–
Time^2×Edu×PJD	0.00 (0.02)	–	0.02 (0.03)	–	0.02 (0.02)	–	0.00 (0.02)	–
Random Effects								
Residual, σ^2_ϵ	21.50 (1.19)***	42.05 (2.21)***	38.83 (2.04)***	54.08 (2.64)***	21.41 (1.18)***	42.03 (2.21)***	38.86 (2.04)***	54.18 (2.64)***
Intercept, σ^2_0	46.13 (3.22)***	28.07 (3.36)***	34.98 (3.45)***	49.33 (4.05)***	45.62 (3.19)***	27.84 (3.35)***	34.74 (3.44)***	49.51 (4.07)***
Time, σ^2_1	0.20 (0.05)***	0.21 (0.08)*	0.26 (0.08)**	–[a]	0.21 (0.05)***	0.21 (0.08)*	0.26 (0.08)**	–[a]
Covariance, σ^2_{01}	-0.58 (0.36)	0.90 (0.47)[†]	-0.04 (0.46)	–[a]	-0.70 (0.36)[†]	0.96 (0.47)*	0.00 (0.46)	–[a]

Notes. Unstandardised estimates (Est.) and standard errors (SE) are presented. PS: Perceptual Speed. IM: Immediate Memory. DM: Delayed Memory. VR: Verbal Reasoning. T scores for cognitive measures standardised to the baseline sample (*M*=50, *SD*=10). Time: years in study. PJD: Physical Job demands. Movement-related job demand: 0=No (sitting), 1=Yes (standing or moving). Strength-related job demand: 0=No (non-heavy), 1=Yes (heavy). Age: baseline age, grand mean centred at 78.09 years. Gender: 0=Male, 1=Female. Edu: Education, grand mean centred at 15 years. Dashes indicate that effect was not estimated. [a]For model convergence, variance component could not be estimated. *p<.05; **p<.01; ***p<.001.

Table C.2

Parameter Estimates from Multilevel Models Examining Movement-Related Job Demand Predicting Cognitive Performance and Change in Lower and Higher Education Groups

	Lower Education	**Higher Education**
	Est. (SE)	**Est. (SE)**
Fixed Effects		
Intercept	51.98 (0.95)***	52.63 (0.86)***
Time	-0.44 (0.15)**	-0.08 (0.13)
Age	-0.26 (0.07)***	-0.04 (0.08)
Gender	-0.80 (0.92)*	0.66 (1.00)
MJD	-3.22 (1.00)**	-0.29 (0.96)
Time×Age	-0.04 (0.01)**	-0.01 (0.01)
Time×Gender	-0.11 (0.13)	0.13 (0.14)
Time×MJD	0.14 (0.15)	-0.21 (0.14)
Random Effects		
Residual, σ_{ϵ}^2	52.33 (4.05)***	28.88 (3.35)***
Intercept, σ_0^2	49.50 (5.89)***	32.10 (5.36)***
Time, σ_1^2	–[a]	–[a]
Covariance, σ_{01}^2	–[a]	–[a]
Goodness-of-fit		
-2LL	7434.18	3066.03
AIC	7454.18	3086.03
BIC	7503.36	3127.12

Notes. Unstandardised estimates (Est.) and standard errors (SE) are presented. T scores for cognitive measures standardised to the baseline sample (*M*=50, *SD*=10). Time: years in study. Movement-related job demand (MJD): 0=No (sitting), 1=Yes (standing or moving). Age: baseline age, grand mean centred at 78.09 years. Gender: 0=Male, 1=Female. Dashes indicate that effect was not estimated. [a]For model convergence, variance component could not be estimated. -2LL = Deviance. AIC: Akaike information criterion. BIC: Bayesian information criterion. *p<.05; **p<.01; ***p<.001.

Table C.3

Parameter Estimates from Multilevel Models Examining Physical Job Demands × Gender Predicting Cognitive Performance and Change

	Model 2 + Movement-Related Job Demand × Gender				**Model 2 + Strength-Related Job Demand × Gender**			
	PS	**IM**	**DM**	**VR**	**PS**	**IM**	**DM**	**VR**
	Est. (SE)	**Est. (SE)**	**Est. (SE)**	**Est. (SE)**	**Est. (SE)**	**Est. (SE)**	**Est. (SE)**	**Est. (SE)**
Fixed Effects								
Intercept	52.95 (0.74)***	50.22 (0.69)***	49.61 (0.77)***	51.03 (0.78)***	52.04 (0.46)***	50.30 (0.43)***	49.81 (0.49)***	50.71 (0.52)***
Time	-0.66 (0.34)	-0.58 (0.15)***	-0.60 (0.43)	-0.34 (0.17)*	-0.36 (0.22)	-0.65 (0.10)***	-1.20 (0.28)***	-1.42 (0.29)***
Time^2	-0.01 (0.03)	–	0.03 (0.04)	–	-0.03 (0.02)	–	0.08 (0.03)**	–
Age	-0.62 (0.05)***	-0.42 (0.05)***	-0.38 (0.05)***	-0.27 (0.05)***	-0.63 (0.05)***	-0.43 (0.04)***	-0.39 (0.05)***	-0.24 (0.05)***
Gender	-0.89 (1.17)	1.66 (1.08)	2.37 (1.21)	-2.18 (1.23)	-0.25 (0.78)	1.02 (0.71)	2.15 (0.81)**	-0.85 (0.86)
Edu	1.19 (0.21)***	0.27 (0.19)	0.49 (0.22)*	1.48 (0.21)***	1.15 (0.21)***	0.22 (0.19)	0.43 (0.22)*	1.41 (0.23)***
PJD	-2.83 (0.84)**	-1.02 (0.78)	-0.54 (0.88)	-2.68 (0.88)**	-2.84 (0.69)***	-1.88 (0.64)**	-1.35 (0.73)	-1.24 (0.78)
Gender×PJD	2.00 (1.40)	-0.20 (1.28)	0.06 (1.44)	2.81 (1.45)	1.63 (1.47)	0.88 (1.32)	0.05 (1.52)	2.43 (1.55)
Time×Age	-0.09 (0.03)***	-0.02 (0.01)	-0.04 (0.03)	-0.04 (0.01)**	-0.09 (0.03)***	-0.02 (0.01)	-0.04 (0.03)	-0.13 (0.03)***
Time×Gender	0.87 (0.51)	0.07 (0.21)	-0.72 (0.65)	0.23 (0.23)	0.30 (0.35)	0.13 (0.14)	-0.13 (0.44)	-0.44 (0.44)
Time×Edu	-0.16 (0.10)	0.06 (0.04)	-0.14 (0.12)	0.06 (0.04)	-0.18 (0.10)	0.07 (0.04)	-0.10 (0.12)	0.17 (0.13)
Time×PJD	0.19 (0.39)	0.03 (0.17)	-0.58 (0.49)	0.10 (0.19)	-0.33 (0.33)	0.22 (0.14)	0.34 (0.41)	-0.69 (0.43)
Time×Gender×PJD	-0.96 (0.61)	-0.07 (0.25)	-0.76 (0.77)	-0.32 (0.27)	-0.62 (0.65)	-0.29 (0.25)	0.26 (0.80)	0.61 (0.81)
Time^2×Age	0.01 (0.00)*	–	0.00 (0.00)	–	0.01 (0.00)*	–	0.00 (0.00)	–
Time^2×Gender	-0.09 (0.05)	–	0.07 (0.06)	–	-0.03 (0.03)	–	0.01 (0.04)	–
Time^2×Edu	0.01 (0.01)	–	0.02 (0.01)	–	0.01 (0.01)	–	0.01 (0.01)	–
Time^2×PJD	-0.01 (0.04)	–	0.05 (0.05)	–	0.04 (0.03)	–	-0.03 (0.04)	–
Time^2×Gender×PJD	0.09 (0.06)	–	-0.09 (0.07)	–	0.04 (0.06)	–	-0.05 (0.07)	–
Random Effects								
Residual, σ_ϵ^2	21.49 (1.19)***	41.95 (2.21)***	38.81 (2.04)***	54.08 (2.64)***	21.43 (1.19)***	42.07 (2.21)***	38.94 (2.05)***	50.53 (2.08)***
Intercept, σ_0^2	46.40 (3.23)***	28.27 (3.36)***	34.94 (3.45)***	49.33 (4.05)***	45.70 (3.19)***	27.83 (3.35)***	34.68 (3.44)***	50.08 (3.68)***
Time, σ_1^2	0.20 (0.05)***	0.21 (0.08)*	0.26 (0.08)**	–[a]	0.21 (0.05)***	0.20 (0.08)*	0.25 (0.08)**	–[a]
Covariance, σ_{01}^2	-0.62 (0.36)	0.89 (0.48)	-0.03 (0.47)	–[a]	-0.71 (0.36)*	0.97 (0.47)*	0.02 (0.46)	–[a]

Notes. Unstandardised estimates (Est.) and standard errors (SE) are presented. PS: Perceptual Speed. IM: Immediate Memory. DM: Delayed Memory. VR: Verbal Reasoning. T scores for cognitive measures standardised to the baseline sample (*M*=50, *SD*=10). Time: years in study. PJD: Physical Job demands. Movement-related job demand: 0=No (sitting), 1=Yes (standing or moving). Strength-related job demand: 0=No (non-heavy), 1=Yes (heavy). Age: baseline age, grand mean centred at 78.09 years. Gender: 0=Male, 1=Female. Edu: Education, grand mean centred at 15 years. Dashes indicate that effect was not estimated. [a]For model convergence, variance component could not be estimated. -2LL = Deviance. AIC: Akaike information criterion. BIC: Bayesian information criterion. *p<.05; **p<.01; ***p<.001.

Table C.4

Parameter Estimates from Multilevel Models Examining Physical Job Demands × Age at Retirement Predicting Cognitive Performance and Change

	Model 2A + Movement-Related Job Demand × Age at Retirement				**Model 2A + Strength-Related Job Demand × Age at Retirement**			
	PS	**IM**	**DM**	**VR**	**PS**	**IM**	**DM**	**VR**
	Est. (SE)	**Est. (SE)**	**Est. (SE)**	**Est. (SE)**	**Est. (SE)**	**Est. (SE)**	**Est. (SE)**	**Est. (SE)**
Fixed Effects								
Intercept	52.37 (0.63)***	50.12 (0.59)***	49.42 (0.66)***	51.83 (0.68)***	51.76 (0.44)***	50.14 (0.41)***	49.73 (0.47)***	50.73 (0.48)***
Time	-0.30 (0.29)	-0.52 (0.13)***	-0.73 (0.37)†	-0.27 (0.11)*	-0.30 (0.21)	-0.61 (0.09)***	-1.26 (0.26)***	-0.26 (0.08)**
Time^2	-0.04 (0.03)	–	0.05 (0.04)	–	-0.03 (0.02)	–	0.09 (0.03)**	–
Age	-0.66 (0.05)***	-0.44 (0.05)***	-0.42 (0.05)***	-0.25 (0.06)***	-0.67 (0.05)***	-0.45 (0.05)***	-0.42 (0.05)***	-0.26 (0.06)***
Gender	1.05 (0.71)	1.83 (0.65)**	2.90 (0.73)***	0.38 (0.74)	0.70 (0.71)	1.59 (0.65)*	2.66 (0.74)***	0.55 (0.75)
Edu	1.16 (0.21)***	0.26 (0.19)	0.47 (0.22)*	1.28 (0.22)***	1.12 (0.21)***	0.20 (0.19)	0.40 (0.22)	1.31 (0.23)***
PJD	-2.24 (0.68)**	-1.00 (0.63)	-0.46 (0.71)	-1.81 (0.74)*	-2.56 (0.61)***	-1.71 (0.56)**	-1.42 (0.64)*	-0.56 (0.67)
RA	0.21 (0.09)*	-0.00 (0.09)	0.03 (0.10)	0.14 (0.10)	0.11 (0.06)	0.08 (0.06)	0.12 (0.06)	0.24 (0.07)**
PJD×RA	-0.11 (0.10)	0.10 (0.10)	0.11 (0.11)	0.07 (0.11)	0.06 (0.10)	-0.02 (0.09)	-0.04 (0.10)	-0.14 (0.11)
Time×Age	-0.10 (0.03)***	-0.02 (0.01)	-0.04 (0.03)	-0.03 (0.01)*	-0.09 (0.03)***	-0.02 (0.01)	-0.04 (0.03)	-0.02 (0.01)*
Time×Gender	0.25 (0.31)	-0.01 (0.12)	-0.23 (0.39)	-0.07 (0.11)	0.21 (0.32)	0.02 (0.13)	-0.12 (0.40)	-0.08 (0.11)
Time×Edu	-0.16 (0.10)	0.06 (0.04)	-0.14 (0.12)	0.03 (0.04)	-0.18 (0.10)	0.07 (0.04)	-0.09 (0.12)	0.03 (0.04)
Time×PJD	-0.29 (0.31)	-0.04 (0.13)	-0.38 (0.39)	0.00 (0.11)	-0.46 (0.28)	0.15 (0.12)	0.47 (0.36)	-0.03 (0.11)
Time×RA	0.05 (0.04)	0.01 (0.02)	0.06 (0.05)	-0.01 (0.02)	0.03 (0.03)	-0.01 (0.01)	-0.03 (0.04)	-0.00 (0.01)
Time×PJD×RA	-0.05 (0.05)	-0.02 (0.02)	-0.09 (0.06)	-0.00 (0.02)	-0.05 (0.05)	0.01 (0.02)	0.07 (0.06)	-0.01 (0.02)
Time^2×Age	0.01 (0.00)*	–	0.00 (0.00)	–	0.01 (0.00)*	–	0.00 (0.00)	–
Time^2×Gender	-0.03 (0.03)	–	0.00 (0.04)	–	-0.03 (0.03)	–	-0.01 (0.04)	–
Time^2×Edu	0.02 (0.01)	–	0.02 (0.01)	–	0.02 (0.01)	–	0.01 (0.01)	–
Time^2×PJD	0.04 (0.03)	–	0.02 (0.04)	–	0.04 (0.03)	–	-0.04 (0.03)	–
Time^2×RA	-0.01 (0.00)	–	-0.01 (0.01)	–	-0.00 (0.00)	–	0.00 (0.00)	–
Time^2×PJD×RA	0.01 (0.00)	–	0.01 (0.01)	–	0.00 (0.00)	–	-0.01 (0.01)	–
Random Effects								
Residual, σ_ϵ^2	21.40 (1.18)***	41.95 (2.20)***	38.77 (2.03)***	45.14 (2.92)***	21.38 (1.18)***	41.99 (2.20)***	38.70 (2.03)***	45.01 (2.91)***
Intercept, σ_0^2	45.74 (3.20)***	28.28 (3.36)***	34.72 (3.43)***	43.80 (4.30)***	45.17 (3.17)***	27.74 (3.34)***	34.44 (3.41)***	44.25 (4.31)***
Time, σ_1^2	0.20 (0.05)***	0.21 (0.08)*	0.26 (0.08)**	–[a]	0.20 (0.05)***	0.20 (0.08)*	0.26 (0.08)**	–[a]
Covariance, σ_{01}^2	-0.54 (0.36)	0.89 (0.47)	-0.02 (0.46)	–[a]	-0.65 (0.36)	1.00 (0.47)*	0.07 (0.46)	–[a]

Notes. Unstandardised estimates (Est.) and standard errors (SE) are presented. PS: Perceptual Speed. IM: Immediate Memory. DM: Delayed Memory. VR: Verbal Reasoning. T scores for cognitive measures standardised to the baseline sample (*M*=50, *SD*=10). Time: years in study. PJD: Physical Job Demands. Movement-related job demand: 0=No (sitting), 1=Yes (standing or moving). Strength-related job demand: 0=No (non-heavy), 1=Yes (heavy). Age: baseline age, grand mean centred at 78.09 years. Gender: 0=Male, 1=Female. Edu: Education, grand mean centred at 15 years. RA: Retirement age, mean centred at age 61.89. Dashes indicate that effect was not estimated. [a]For model convergence, variance component could not be estimated. -2LL = Deviance. AIC: Akaike information criterion. BIC: Bayesian information criterion. *p<.05; **p<.01; ***p<.001.

Appendix D: Parameter Estimates from Multilevel Models Examining Occupational Complexity and Physical Job Demands Predicting Cognitive Performance and Change

	Data + People + Things + Movement + Strength			
	Perceptual Speed (PS) Est. (SE)	**Immediate Memory (IM)** Est. (SE)	**Delayed Memory (DM)** Est. (SE)	**Verbal Reasoning (VR)** Est. (SE)
Fixed Effects				
Intercept	52.18 (0.63)***	50.32 (0.60)***	49.53 (0.67)***	51.71 (0.69)***
Time	-0.32 (0.29)	-0.58 (0.13)***	-0.92 (0.37)*	-0.29 (0.11)**
Time^2	-0.04 (0.03)	–	0.07 (0.04)	–
Age	-0.65 (0.05)***	-0.43 (0.05)***	-0.39 (0.05)***	-0.23 (0.05)***
Gender	0.25 (0.68)	1.30 (0.63)*	2.05 (0.71)**	0.20 (0.72)
Education	0.87 (0.21)***	0.14 (0.20)	0.37 (0.22)	1.05 (0.23)***
Data	0.54 (0.14)***	0.18 (0.13)	0.20 (0.15)	0.60 (0.16)***
People	0.13 (0.15)	-0.03 (0.15)	-0.16 (0.16)	0.40 (0.17)*
Things	-0.27 (0.13)*	-0.10 (0.12)	-0.26 (0.14)	0.13 (0.14)
Movement	-1.19 (0.72)	-0.40 (0.68)	0.28 (0.77)	-2.16 (0.79)**
Strength	-1.18 (0.68)	-1.28 (0.63)*	-1.07 (0.72)	0.73 (0.73)
Time×Age	-0.09 (0.03)***	-0.02 (0.01)	-0.04 (0.03)	-0.03 (0.01)**
Time×Gender	0.07 (0.30)	0.07 (0.12)	0.01 (0.38)	-0.06 (0.10)
Time×Education	-0.17 (0.10)	0.05 (0.04)	-0.13 (0.13)	0.03 (0.04)
Time×Data	-0.02 (0.07)	0.04 (0.03)	0.03 (0.08)	0.01 (0.02)
Time×People	-0.04 (0.07)	0.02 (0.03)	0.04 (0.09)	-0.02 (0.03)
Time×Things	-0.08 (0.06)	0.02 (0.02)	0.05 (0.07)	-0.02 (0.02)
Time×Movement	0.03 (0.330	-0.08 (0.14)	-0.56 (0.42)	0.01 (0.12)
Time×Strength	-0.39 (0.32)	0.18 (0.13)	0.59 (0.41)	0.02 (0.12)
Time^2×Age	0.01 (0.00)*	–	0.00 (0.00)	–
Time^2×Gender	-0.01 (0.03)	–	-0.01 (0.04)	–
Time^2×Education	0.01 (0.01)	–	0.02 (0.01)	–
Time^2×Data	0.00 (0.01)	–	-0.00 (0.01)	–
Time^2×People	0.01 (0.01)	–	-0.00 (0.01)	–
Time^2×Things	0.01 (0.01)	–	0.00 (0.01)	–
Time^2×Movement	0.01 (0.03)	–	0.03 (0.04)	–
Time^2×Strength	0.04 (0.03)	–	-0.06 (0.04)	–

Random Effects				
Residual, σ_ϵ^2	21.57 (1.20)***	42.07 (2.21)***	38.81 (2.04)***	45.38 (2.92)***
Intercept, σ_0^2	42.87 (3.07)***	27.68 (3.35)***	34.23 (3.43)***	41.36 (4.20)***
Time, σ_1^2	0.19 (0.05)***	0.20 (0.08)*	0.24 (0.08)**	–[a]
Covariance, σ_{01}	-0.67 (0.36)	0.85 (0.48)	0.02 (0.47)	–[a]
Goodness of fit				
-2LL	12191.94	13596.58	13507.01	10512.95
AIC	12253.94	13640.58	13569.01	10552.95
BIC	12424.56	13762.98	13741.36	10958.69

Notes. Unstandardised estimates (Est.) and standard errors (SE) are presented. T scores for cognitive measures standardised to the baseline sample (*M*=50, *SD*=10). Time: years in study. Data: Occupational complexity with data, grand mean centred (*M*=3.67). People: Occupational complexity with people, grand mean centred (*M*=1.32). Things: Occupational complexity with things, grand mean centred (*M*=2.35). Occupational complexity, higher scores indicate greater complexity. Movement: 0=No (sitting), 1=Yes (standing or moving). Strength: 0=No (non-heavy), 1=Yes (heavy). Age: baseline age, grand mean centred at 78.09 years. Gender: 0=Male, 1=Female. Education, grand mean centred at 15 years. Dashes indicate that effect was not estimated. [a]For model convergence, variance component could not be estimated. -2LL = Deviance. AIC: Akaike information criterion. BIC: Bayesian information criterion. *p<.05; **p<.01; ***p<.001.