Inequalities in Children's Working Memory: Variation by Socioeconomic Disadvantage and Ethnicity

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Abstract

Working memory is a limited capacity system that allows the storage and manipulation of information over short time periods. It is crucial for children's learning ability in the classroom, and for children's educational attainment. Previously, researchers have disagreed regarding the extent to which working memory is associated with external factors, such as socioeconomic disadvantage and ethnicity. In this thesis, I investigate the associations between socioeconomic position, ethnicity and children's working memory, and the potential causal factors between these associations.

In a systematic review, I found that children with lower socioeconomic position have worse working memory. I also found that ethnic minority children tended to have lower working memory scores, however, I could not make any definitive conclusions about this due to methodological constraints. This systematic review informed three further studies using data from a longitudinal cohort study - Born in Bradford.

In the cohort analysis, children from socioeconomically disadvantaged families had worse working memory equivalent to an age difference of 16 months, and the home learning environment did not mediate this association. Substantial variation was found in working memory by ethnic group, and children from ethnic majority backgrounds had stronger associations between disadvantage and working memory than ethnic minority groups. Finally, neither own ethnic density nor Mosque attendance were significant positive factors for ethnic minority children's working memory.

My thesis provides evidence of an association between socioeconomic position and children's working memory, contributing to a body of evidence demonstrating the longstanding and profound effects of social inequality on children's development. It is one of the first studies to investigate and reveal substantial variation both across and within ethnic majority and minority groups. Future research prioritisations are to investigate the mechanisms underlying these associations, and investigate the implications of these associations for social inequalities in children's educational attainment.

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Authors Declaration

I declare that this thesis is a presentation of original work and I am the sole author. This work has not previously been presented for an award at this, or any other, University. All sources are acknowledged as References.

Parts of this thesis have been disseminated at two conferences:

- Mooney, K.E., Pickett, K.E., Shire, K., Allen, R.J., and Waterman, A.H. (2021). Society for Social Medicine & Population Health Virtual Annual Scientific Meeting. Socioeconomic disadvantage and ethnicity are associated with large differences in cognitive abilities that underlie children's educational outcomes: analysis of a prospective birth cohort study. Oral presentation. (Chapter 4)
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Thesis Outline

This thesis consists of three sections: A) Background (Chapters 1-2), B) Cohort study analysis (Chapters 3-6), and C) Discussion (Chapter 7).

In Section A, I provide the background for the study across two chapters. In Chapter 1, I define and conceptualise the outcome of interest (working memory) and the two exposures (socioeconomic position and ethnicity). I then describe the theoretical background to studying associations between child socioeconomic position and outcomes, and ethnic group and outcomes. I also describe the profound educational inequalities present in the UK by socioeconomic position and ethnicity. In Chapter 2, I conduct a systematic review of the literature asking 1) what is the association between socioeconomic position and working memory in children?; and 2) what is the association between ethnic minority status and working memory in children?

In Section B, I use data from the Born in Bradford cohort study to answer further research questions across four chapters. In Chapter 3, I will provide the research setting, and describe the variables include in the analyses. In Chapters 4-6, I answer specific research questions around the nature of working memory: 1) a study of how working memory scores are patterned by personal demographic characteristics, 2) a study of the associations between socioeconomic position, the home learning environment, and working memory across two ethnic groups, and 3) a study of potential positive factors for ethnic minority children's working memory.

In Section C, I revisit and discuss the results from all of the studies. I summarise the key findings and implications, the strengths and limitations of the cohort study data, and make recommendations for future research and practice.

Section A: Background

This section contains the background for my thesis across two chapters:

- Chapter 1 defines the concepts of interest and provides the theoretical background to studying the associations between them. It also describes inequalities in educational attainment by socioeconomic position and ethnicity.
- Chapter 2 provides a systematic review of the literature about the associations socioeconomic position and working memory, and ethnicity and working memory.

Chapter 1. Introduction

1.1 Definitions

1.1.1 Working Memory

Working Memory (WM) is a limited capacity system that allows the storage and manipulation of information over short time periods (Baddeley, 2010; Cowan, 2017). It supports ongoing cognitive activity, and underpins the ability to learn new information (Cowan, 2014). It is important also to note that working memory is considered as part of the broader construct of 'executive function'; an umbrella term that encompasses the processes responsible for purposeful, goal-directed behaviour. The three core executive function components are inhibition, cognitive flexibility, and working memory (Anderson, 2002; Diamond and Lee, 2011). The outcome of interest in my thesis is only working memory, rather than any other executive functions. Every day examples of when we use our working memory are:

- Following a conversation and remembering what has been said
- Mental arithmetic
- Reading steps in a recipe and remembering what steps to take next
- Following instructions to complete a task

My thesis is concerned with *children's* working memory. Research has shown that working memory scores generally increase with age throughout early to late childhood. Linear increases in working memory scores were found by age with 736 children aged 4-15 (Gathercole et al., 2004a), and in over 15,000 children aged 7-10 years (Hill et al., 2021b). Further, working memory ability tends to decrease during adulthood (Quentin and Cohen, 2019). A study comparing 29 year olds to 59 year olds showed the older group had lower scores on more challenging working memory tasks (Mattay et al., 2006). A large study of visual working memory in 55,753 individuals aged between 8 and 75 showed that average visual working memory scores peaked at age 20, and then declined. By age 55, adults had worse visual working memory scores than 8 and 9 year olds (Brockmole and Logie, 2013).

Two major issues that have dominated theoretical models of working memory are 1) how they conceptualise whether working memory encompasses the ability to only process information, or to both store *and* process information and 2) how they conceptualise the storage of information as either domain general or domain specific (see Baddeley 2012, for a review). Whilst working memory is generally conceptualised as distinct from long term memory, it is seen as closely related to short term memory (or seen as a system that encompasses short-term memory) (Alloway and Copello, 2013). To explain this theoretical issue further, three key models that I contrast here are the attentional control model (Engle and Kane, 2004), the embedded processes model (Cowan, 1999), and the multicomponent working memory (MCWM) model (Baddeley, 2010).

In Engle and Kane's (2004) attentional control model, working memory is a 'domain general' executive attention capacity, where attention is required to maintain task goals and inhibit interfering information (Engle and Kane, 2004). This view separates working memory from short-term memory and describes working memory as a 'processing' capability *only* (Cowan, 2008). By this definition, a test of short-term memory storage is not actually considered a working memory test (Cowan, 2017). Additionally, the attentional control model considers verbal and visuospatial material to be processed in the same storage system – making it domain general. In Cowan's (1999) embedded processes model, working memory is organised into two embedded levels: a first level with unlimited sets of long-term memory representations, and a second embedded level which focuses attention on a specific set of those long-term memory representations. This model views working memory as a 'subset' of long-term memory. Again, this model is domain general, as it does not consider verbal and visuospatial material to be processed in separate storage systems (Cowan, 1999).

Finally, perhaps the most widely-cited model of working memory is the Multicomponent working memory (MCWM) model first proposed by Baddeley and Hitch in 1974 (Baddeley and Hitch, 1974), which has since been substantially updated and developed (Baddeley, 2000; Baddeley, Hitch and Allen, 2021). I use this model throughout this thesis to guide the methods and presentation of results regarding working memory. In the following sections I describe the MCWM model in detail and the rationale for using this model to situate the current research.

Whilst there are differences between models, there is also much that is common between them. All the main theories of working memory believe it is a limited capacity system that operates over short time periods, and that it helps with on-going cognitive activity. Indeed, this is why working memory is so essential for educational attainment, and I describe studies that have investigated its importance for educational attainment in Section 1.3.

1.1.1.1 The Multicomponent Working Memory Model

The MCWM model comprises four separable components (see Figure 1), each responsible for different activities within working memory.

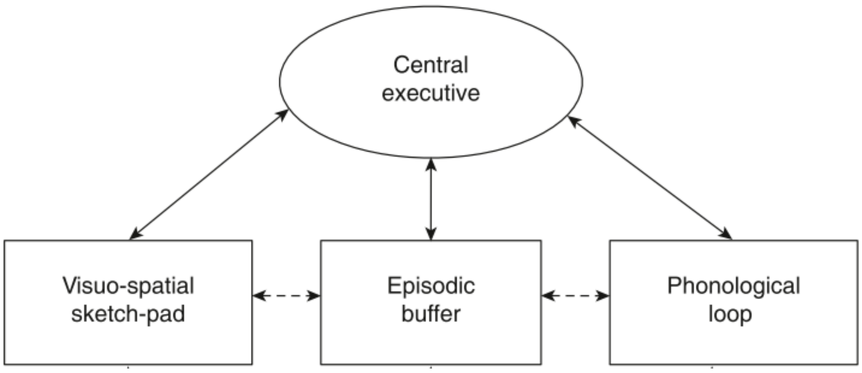


Figure 1. The Multicomponent Working Memory Model (Baddeley, 2010)

- **The Phonological Loop** holds verbal and acoustic information using a temporary store and an articulatory rehearsal system, and is concerned with the short term storage of verbal information (Baddeley and Hitch, 1974; Baddeley, 2010). A classic test to measure the capacity of the phonological loop is to ask participants to listen to, and then repeat, a series of digits in the same order they heard them.
- **The Visuospatial Sketchpad** is complimentary to the phonological loop, as it is concerned with the short term storage of visuospatial information

(Baddeley and Hitch, 1974; Baddeley, 2010). This is often measured by asking participants to observe, and then copy, a spatial pattern tapped out on a series of blocks.

- Aided by the phonological loop and visuospatial sketchpad, the **Central Executive** is an attentional control system concerned with both storage, processing and manipulation of information (Baddeley, 2003, 2010). In contrast to simple storage, attentionally demanding tasks place specific demands on the central executive. A standard task to measure the central executive is to ask participants to listen to, and repeat, a series of digits, but in the *reverse* order. This requires the participant both to store and manipulate the information in order to complete the task.
- Finally, the most recently developed component of the model, the **Episodic Buffer** stores information in a multi-dimensional code and provides a temporary interface between the phonological loop, visuospatial sketchpad, and the central executive (Baddeley, 2000). Whilst each of the previously described components are measured with specific tests, the Episodic Buffer is not as easily measurable, and not typically assessed in studies looking at the association between working memory and education, or between working memory and sociodemographic variables.

1.1.1.2 Rationale for the MCWM

I have chosen to use the MCWM for several reasons. First, the MCWM model allows for an investigation of both "storage" and "processing" capabilities, rather than simply focusing on the processing aspects of working memory (e.g., Engle and Kane, 2004). This will allow a broader perspective on which aspects of working memory (if any) that both socioeconomic position and ethnicity are associated with, and will allow researchers to interpret my results regardless of which working memory model they apply.

Second, in investigations about associations between educational attainment and working memory, many researchers use tests to measure working memory that relate to the components represented in the MCWM model (Fenesi et al., 2015). For instance, the most widely used developmental assessment tools of working memory, such as the Automated Working Memory Assessment (AWMA; Alloway et al., 2008) and the Working Memory Test Battery for Children (WMTB-C; Pickering and Gathercole, 2001) include separate working memory tasks that reflect distinct components of the MCWM model (e.g., verbal storage, visuospatial storage, and attentional control). Studies of working memory abilities usually present results for each test, which in turn represent each component of it. It therefore makes sense practically to examine these components separately, rather than combine them and lose potentially important information about the variability between the tests and/or components of working memory.

Third, in connection to the above point, it is important to gauge a child's working memory profile across different input modalities, materials, and levels of task complexity, in line with natural variation in working memory task contexts encountered in the real world.

Finally, another reason for use of the MCWM model is that although the different components are likely related to one another, there is substantial evidence to suggest that the abilities are separable. In a study of the functional organisation of working memory, 633 children aged 4-6 were tested on different components of working memory. Factor analysis found evidence for a measurement model that incorporated constructs representing the central executive, phonological loop, and episodic buffer components of working memory (Alloway et al., 2004). A similar study regarding the structure of verbal and visuospatial working memory tested 709 children aged 4-11 on four tasks. Confirmatory factor analysis again indicated that the structure represented the central executive, phonological loop, and visuospatial sketchpad (Alloway, Gathercole and Pickering, 2006). Further, the factor structure based on the MCWM model is consistent by age in years, demonstrated by a factor analysis study including 736 children aged 6 to 15 years. (Gathercole et al., 2004a)

Further evidence to suggest the components are separable comes from studies that investigate the association between components of working memory and activation in particular brain areas. Tasks that assess complex working memory have long been uniquely associated with brain activation in the prefrontal cortex (D'Esposito and Postle, 2015; D'esposito et al., 1995), whereas passive storage is related to activation within different networks, such as Broca's and Wernicke's area and the right hemisphere (Chai, Abd Hamid and Abdullah, 2018). In terms of modality, an empirical study of children completing mathematical tasks found verbal and spatial working memory to also be separable; where verbal working memory tasks were associated with brain activation in the left temporal cortex, and visuospatial working memory tasks were associated with the right parietal cortex (Demir, Prado and Booth, 2014). A recent review has summarised much of the neurocognitive literature, providing evidence to suggest that verbal working memory activates Broca's and Wernicke's areas while visuospatial information is associated with the right hemisphere (Chai, Abd Hamid and Abdullah, 2018).

Studies have also shown how different aspects of working memory contribute to specific abilities in children, further indicating it is important to consider the components separately. A study with 196 children aged 6–13 years showed all four working memory components provided significant and independent contributions to intelligence (measured by Raven's Progressive Matrices), providing strong evidence for domain specific models of working memory (Tillman, Nyberg and Bohlin, 2008). In a study exploring mathematics skills, simple verbal working memory and complex verbal working memory predicted mathematical reasoning in 2nd grade, whilst simple visuospatial working memory predicted both mathematical reasoning and numerical operations skills in 3rd grade in 48 children aged 7 -8-year olds. The authors propose that these results reflect a shift from prefrontal to parietal cortical brain area function during mathematical skill acquisition (Meyer et al., 2010). In another study where children aged 5-6 years old were assessed on all components of working memory, verbal complex working memory ability at 5 years old was the only significant predictor of children's reading abilities at age 6 (Nevo and Breznitz, 2011).

It follows that since the behavioural and neurocognitive evidence suggests that working memory components are separable, any disparity in working memory between socioeconomic or ethnic groups may be inconsistent across the components of working memory. Given that socioeconomic disadvantage has been shown to have different patterns of association with different aspects of cognition (Farah et al., 2006; Engel, Santos and Gathercole, 2008) and that different components of working memory are associated with different underlying neurological structures, socioeconomic disadvantage may also have specific associations with different components of working memory. Indeed, previous studies have shown that the magnitude of the association between socioeconomic disadvantage and working memory does change dependent on whether the task material is verbal or visuospatial (Tine, 2014; Vandenbroucke et al., 2016), and how working memory capacity is measured (St. John, Kibbe and Tarullo, 2018). Further, some researchers have argued that simple storage may be more reliant on knowledge structures, which in turn are related to crystallized intelligence, and therefore may be more sensitive to the effects of socioeconomic disadvantage than attentional control, which is related more to fluid intelligence (Alloway & Copello, 2013). However, there is not yet any empirical evidence to address this claim.

1.1.1.3 Working Memory is key for educational attainment

Within this section, I describe the rationale for why working memory is an important ability – primarily due to its very strong associations with general learning and cognitive abilities, and with educational attainment.

As I have already described, working memory is important for many everyday activities. For instance, following a conversation and remembering what has been said, or reading steps in a recipe and remembering which steps to take next (Section 1.1.1). It follows from this that working memory is clearly important for children in educational settings, where they are constantly encountering new information and following instructions. An empirical study of 42 children aged 7-11 years found that assessments of working memory were strongly associated with children's ability to follow instructions in a classroom setting (Jaroslawska et al., 2016b), demonstrating the importance of working memory for educational settings.

It is therefore unsurprising that working memory is strongly associated with children's educational attainment. There is not scope in my thesis to describe the many pathways by which children's working memory could influence their educational attainment, however, a review paper has summarised some of these. It is hypothesised that working memory ability could underlie differences in general cognition; through having strong predictive associations with intelligence, reasoning, multitasking, verbal comprehension and verbal fluency. It has also been suggested that working memory underlies important differences in social cognition; through mentalising, stereotyping and self-regulation (see Gruszka and Nęcka, 2017, for a review).

More broadly, working memory underlies general learning and academic attainment. Mental arithmetic illustrates how children use their working memory, as it requires holding number combinations, and updating the contents of working memory to include calculations as they are updated (Gathercole and Alloway, 2008). Reading further illustrates use of working memory, as working memory is needed to keep relevant speech sounds in the mind, match them up with corresponding letters, and combine them to read words (Alloway and Copello, 2013). Working memory is required for forming new concepts, where two ideas must exist in working memory simultaneously for a new concept to be learned (e.g. to learn that a stripy cat is a tiger) (Cowan, 2014). It is also required for remembering instructions and staying on task (Alloway et al., 2009). Finally, it is essential for the successful application of mnemonic strategies, where chunking combines information into categories, and rehearsal allows for information to be repeated, stored and recalled (Cowan, 2014). Without sufficient working memory ability, it would not be possible to carry out many complex mental activities (Gathercole and Alloway, 2008).

Working memory has been found to be a significant predictor of performance on general learning measures such as the Wechsler Intelligence Scale for Children (WISC), Wechsler Objective Reading Dimensions (WORD), and Wechsler Objective Numerical Dimensions

(WOND) (Wechsler, 1993, 1996, 2003). Working memory measured at age 5 has been found to be a better predictor than IQ for later literacy and numeracy (measured with WISC, WORD, and WOND scales) with 98 children aged 11 (Alloway and Alloway, 2010). In another study, Alloway et al., (2009) identified 308 5-11 year olds as having very low working memory, and found that the majority performed poorly in the learning measures of WISC and WORD assessments. Further, the children were judged by teachers as having attentional issues, having problems with monitoring the quality of their work, and having difficulties in generating new solutions to problems.

Numerous observational studies have investigated how working memory relates to performance on Key Stage tests, demonstrating how it is associated with children's 'real-world' school-based assessments. St Clair-Thompson and Gathercole (2006) assessed working memory in 51 children aged 11-12 in the North East of England. They found working memory to be associated with national curriculum attainment in both English and Mathematics. Gathercole, Brown, & Pickering (2003) investigated working memory in 54 children aged 4 from a suburban area of a city in south-west England, and Key Stage 1 attainment at age 7. Working memory scores were found to be highly significant predictors of subsequent attainment in Literacy, but not in Maths.

Gathercole, Pickering, Knight, & Stegmann (2004) found working memory to have associations with attainment in English, Maths, and Science in 40 children aged 7 recruited from a state secondary school in the southeast of England. When tested again at age 14, working memory was associated with attainment in Maths and Science, but no longer associated with English. Although it is not clear why skills in Key Stage 2 English were not associated with working memory skills, Gathercole et al. suggest that working memory capacity may be more important for early literacy skills than higher-level skills of comprehension and analysis. Jarvis and Gathercole (2003) found evidence to suggest a distinct role for different components of working memory with particular curriculum areas. In 55 children aged 10-11 and 73 children aged 13-14, all tasks of working memory were correlated with attainment in Key Stage tests, however, tasks of complex working memory showed the strongest associations. With regards to storage components, simple verbal working memory had unique associations with English and Maths, and simple visuospatial working memory had unique associations with Maths and Science.

Several meta-analyses have summarised the literature investigating associations between working memory and learning abilities. Two meta-analyses have revealed working memory to be related to mathematical performance at a medium effect size; first, in 4-12 year old children in 29 studies (Friso-Van Den Bos et al., 2013), and second, across the lifespan in 110 studies (Peng et al., 2016). Further, a recent systematic review (with no meta-analysis) found visuospatial working memory to be associated with mathematics performance in children aged up to 16 in 35 studies (Allen, Higgins and Adams, 2019). Finally, working memory has been found to be correlated with reading comprehension skills in 18 studies using meta-analysis, where the size of effect ranged from small to large dependent on the type of working memory task (Carretti et al., 2009).

Another significant aspect of working memory is its potential as an endophenotype underpinning several developmental disorders. Children with difficulties with working memory are judged by their teachers to be easily distracted, or disinterested (Alloway et al., 2009). Meta-analysis of 45 studies found that children with ADHD exhibit significant working memory deficits relative to their typically developing peers (Kasper, Alderson and Hudec, 2012). Dyslexia and dyscalculia – learning disorders associated with impairments in reading and mathematics, respectively – are associated with significant working memory impairments. In a meta-analysis synthesising the research regarding children with reading disabilities, such children were significantly disadvantaged compared with average readers on working memory tasks (Swanson, Xinhua Zheng and Jerman, 2009). A meta-analysis synthesized research on working memory deficits amongst children with difficulties in reading, mathematics, or both. In 29 studies that compared children with disorders to typically developing children, all learning difficulty groups demonstrated deficits in working memory (Peng and Fuchs, 2016).

Altogether this evidence emphasises the advantages of better working memory for typically developing children, and the incidence of working memory deficits in children with learning difficulties. Although the associations between specific components of working memory and particular curriculum areas is not always consistent, the evidence nonetheless indicates the importance of working memory for learning new information and attainment on Key Stage tests.

Another significant aspect of working memory is its potential to have implications for broader health outcomes throughout the life course. In this section, I have already demonstrated that working memory is important for cognition, learning, and educational attainment. It is generally agreed that increased years in education and educational attainment is related to a variety of health outcomes (Silles, 2009; Amin, Behrman and Spector, 2013; Powdthavee, 2014), and it follows from this that higher working memory ability may act as a route to improved health through higher educational attainment. Indeed, high executive functions (including working memory) have been found to predict better health outcomes in 6069 participants in the Avon Longitudinal Study of Parents and Children (ALSPAC). In particular, better working memory scores predicted not being overweight (Stautz et al., 2016).

1.1.2 Socioeconomic Position

Although the terms socioeconomic status, social class, and socioeconomic position are at times used interchangeably without consideration of the different meanings (McCartney et al., 2019), I have purposefully chosen the term socioeconomic position to use in my thesis.

The concept of socioeconomic position is premised on social class, which reflects the social groups that arise from interdependent economic relationships among people. The concept of socioeconomic position has theoretical origins in both Karl Marx and Max Weber's sociological theories (McCartney et al., 2019; Galobardes et al., 2006a). Karl Marx's view of social class asserted that an individual's position in a class hierarchy related to their role in the production process. It follows from this that a class shares common economic interests, is conscious of those interests, and acts collectively to advance those interests (Marx, 1875; Galobardes et al., 2006a). In contrast, Max Weber's view of social class postulated society as hierarchically stratified along many dimensions to create groups where individuals share common positions (Galobardes et al., 2006a). Importantly, social classes exist only in relationship to one another and co-define one another – where a group's location within the economy defines their social class. As such, social class is expressed in the distribution of occupations, incomes, wealth, education, and social status (Galobardes et al., 2006a).

Within this thesis, I study socioeconomic position; which I conceptualise as both the social and economic factors that influence what positions individuals or groups hold within the hierarchical structure of a society. It aggregates both resource-based components, referring to material assets such as income and wealth, and prestige-based components, referring to an individual's access to and consumptions of goods such as education, occupation and their societal position (Krieger, Williams and Moss, 1997; Galobardes et al., 2006a, 2006b). I employ socioeconomic *position* rather than the more commonly used phrase "socioeconomic status", as socioeconomic status oversimplifies the distinction between two different aspects of socioeconomic position: (a) actual resources, and (b) status, meaning prestige or rank-related characteristics (Krieger, Williams and Moss, 1997). In other words, socioeconomic position emphasises the mechanism of *position* in society, and describes the places and experiences that different groups have within social processes that stem from the relations between groups (McCartney et al., 2019). I also use the term socioeconomic disadvantage throughout this thesis, to refer to those with low socioeconomic position characteristics.

It is clear that socioeconomic position is a complex construct with many indicators, and each indicator comes with its own theoretical bases, strengths, and limitations (for a full review see Galobardes et al., 2006a, 2006b). The following table outlines some indicators of socioeconomic position that are relevant to my thesis, all of which have been broadly agreed to reflect family socioeconomic position.

Table 1. Indicators of socioeconomic position

Indicator and theoretical bases	Example tools
Occupational status Reflects a person's place in society related to their social standing.	The National Statistics Socioeconomic Classification (NS-SEC) has 14 operational categories that can be abbreviated to a three-category version to represent hierarchy: (1) higher occupations, (2) intermediate occupations, and (3) lower occupations (Rose and Pevalin, 2011) Hollingshead (1975) index where occupational code is rated on a 9-point scale (Hollingshead, 1975)
Educational attainment Assumes that an increase in time spent in education, or an increase in the number of educational milestones completed, translates into a change in socioeconomic position.	Can be measured as a continuous variable (e.g. years of completed education) Or as a categorical variable by assessing educational milestones (e.g. primary or high school, higher education diplomas, or degrees).
Income Directly measures the material resources of an individual or household.	Can be measured as a continuous absolute income, or can be placed within predefined categories. Income may be measured as a relative indicator establishing levels of poverty in a neighbourhood (e.g. percentage above or below the official poverty level). Additional information on family size or the number of people dependent on the reported income can give an 'income-to-needs' ratio.
Free school meals (FSM) As above	Free School Meals (FSM) eligibility is essentially a proxy measure for low parental income, where children may be eligible for a free school meal if their parent receives income benefits, child tax credit, or universal credit (Gorard, 2012)
Neighbourhood deprivation	The Index of Multiple Deprivation (IMD) is the official measure of relative

Goes beyond individual or household level of measurement, and provides an estimate of the social circumstances in the area that a person or family live in.	deprivation for local councils in England. The IMD ranks every small area in England from 1 (most deprived area) to 32,844 (least deprived area) (Ministries of Housing Communities and Local Government, 2019b)
Housing characteristics Measures the material aspects of socioeconomic position relating to housing characteristics. Household amenities are markers of material circumstances	Housing tenure— whether housing is owner occupied (owned outright or being bought with a mortgage), or rented from a private or social landlord. Household amenities (e.g. access to hot and cold water in the house, having central heating and carpets).
Subjective social status Reflects a person's own view about their own position in the social hierarchy.	'Ladder' tool where subjects indicate on which rung of the social ladder they consider themselves to be (e.g. Singh-Manoux, Adler and Marmot, 2003)
Resource access Disadvantage is relative to the society in which an individual lives, and is concerned with not only income, but access to resources that are customary or widely accepted in societies in which they belong (Main and Bradshaw, 2016)	Questions about access to amenities such as children having two pairs of shoes, family holidays and expenditure on hobbies or social visits.
Single parent status Growing up with one parent is associated with economic hardship, where children of unmarried mothers tend to have lower educational attainment and occupational status (Mikkonen et al., 2016)	Binary indicator where child either lives with one parent or both (e.g. Sarsour et al., 2011)

My thesis focuses on child socioeconomic position, which encompasses a child's early exposure to social position and the different opportunities that this confers. The measurement of which therefore has the potential to examine exposures during 'critical periods' in early life, to establish what factors may have longstanding associations with different outcomes (McCartney et al., 2019). However, the measurement of childhood socioeconomic position is also accompanied by specific considerations. In the following paragraphs, I describe some issues to consider when measuring and describing socioeconomic differences among children.

First, childhood socioeconomic position is commonly measured by using indicators in Table 1 but for that child's parent at the individual level (e.g. parent occupation, education or income). It is important to acknowledge that individual indicators summarise not just the socioeconomic position of that child, but the socioeconomic position of an entire family or household, and this may affect whether we see meaningful socioeconomic differences. A single indicator of family income or occupation cannot possibly encapsulate the dynamic economic needs of an entire family. Adults tend to determine the allocation of resources within a family, and it cannot be known whether the needs of both adults and children are being met by a singular income (Bradbury, Jenkins and Micklewright, 2001, p.39). For example, a survey of carers of British children found that one half of parents who are defined as poor themselves have children who are 'not poor', due to a large proportion of mothers going without items for themselves in order to provide for their children instead (Adelman, Middleton and Ashworth, 1999).

Second, although cross-sectional research can effectively capture socioeconomic position at one point in time, dynamic family and economic circumstances can expose children to ever-changing socioeconomic experiences during childhood – and it is often not a static characteristic (Bradley and Corwyn, 2002; Ursache and Noble, 2016). For instance, a quarter of the children interviewed in two-parent households of the British Household Panel Survey had a change of head of household 6 years later, and marital splits are associated with decreases in family income (Jarvis and Jenkins, 1999).

Finally, the age at which a child experiences low socioeconomic position may have differential effects on child development, with socioeconomic disadvantage in early life being particularly harmful for children (Duncan, Magnuson, and Votruba-Drzal, 2017). It is therefore important to consider the age at which socioeconomic position is being measured and relate it to the timepoint where the outcome is measured. Relevant to this, the time spent living in a socioeconomically disadvantaged family can also impact development. In a study of 8741 children in the Millennium Cohort Study, children born into poverty had worse cognitive development than those not in poverty in the Bracken School Readiness assessment at ages 3, 5, and 7. Further, continuously living in poverty had a cumulatively worse effect on development compared to those who had not experienced poverty (Dickerson and Popli, 2014).

1.1.3 Ethnicity

Within this thesis, I choose to focus on the concept of ethnicity rather than race. Although race and ethnicity may have been conceptualised as interchangeable concepts in the past, race and ethnicity are different analytical concepts within the social sciences. 'Race' implies relatedness through genes, whereas ethnicity implies relatedness through shared history and culture. The theory that differences in biological races can predict intellectual, moral, or social qualities is now unsustainable and unjustifiable (Chattoo and Atkin, 2019, p.27). This is because it is now widely recognised that there are huge variations in physical characteristics within, as well as between, racial groups, and that the boundaries of racial groups are ever-changing due to constant movements and intermingling between people from different geographical parts of the world (Chattoo & Atkin, 2019, p.27).

Ethnicity is premised on notions of shared descent, heritage and culture – and encompasses religion, tradition and language (The Oxford Dictionary, 2010 in Chattoo & Atkin 2019, p.22). Ethnicity is both the social construction and social mobilisation of descent and culture. Fenton (2003) describes how:

> *'people or peoples do not just possess cultures or share ancestry; they elaborate these into the idea of a community founded upon these attributes' (cited in Chattoo & Atkin 2019, p. 23).*

This description emphasises that ethnicity is not a fixed or essential characteristic that people 'have' but is an active process of self-identity and differentiation involving negotiation of boundaries of inclusion and exclusion between groups. Alike to the interactions between social classes (Krieger, Williams and Moss, 1997), these boundaries shift according to the context of social interaction and struggles over power and resources over time (Hall, 1996, cited in Chattoo & Atkin 2019, p.22-23). In England, the term 'ethnicity' is usually used to designate immigrants and minority cultures/groups, who tend to experience higher levels of socioeconomic disadvantage. It acts as a source of social stratification, perpetuating forms of disadvantage and discrimination (Modood, 2008, cited in Chattoo & Atkin 2019, p.23).

Throughout this thesis, I make contrasts about working memory between ethnic majority and ethnic minority groups, and about socioeconomic position within these groups. Although the term Black and Minority Ethnic (BAME) has recently become commonly used, I do not use this since it homogenises people from a variety of different ethnic backgrounds, and this may mask inequalities experienced by particular ethnic groups (Black British Academics, 2021).

In the systematic review in this thesis (Chapter 2), I also use the term 'ethnic minority status' to refer to any ethnic minority group in any country. This is because the systematic review included participants from any country, and whether a child belongs to an ethnic minority group depends on their country of birth and country of residence.

Within Section B of this thesis (Chapters 3-6), I consider the ethnic majority group to be White British in contrast to all other ethnic minority groups, as they are the most populous ethnic group within England. When describing differences across ethnic groups, I avoid combining 'other' ethnic groups into one homogenous group where possible. Instead, I aim to describe ethnic groups using the most discrete group available in the data (e.g. instead of combining Pakistani, Bangladeshi, and Indian groups into one South Asian group, they are described separately).

1.2 Theoretical Background: Associations Between Socioeconomic Position, Ethnicity, and Child Outcomes

1.2.1 Socioeconomic Position and Child Outcomes

Although it is not possible to investigate causality in my thesis, I apply a view of 'social causation', as this allows for an investigation and discussion of the potential mechanisms of socioeconomic position and ethnicity on working memory. In the context of health, the social causation hypothesis asserts that socioeconomic disadvantage increases the risk of worse health, whereas the social selection or 'drift' hypothesis asserts that poor health inhibits socioeconomic attainment and leads people to 'drift' into socioeconomic disadvantage (Mossakowski, 2014). I therefore view any socioeconomic differences in children's working memory to be due to the effects of social causation where socioeconomic disadvantage has caused worse working memory, rather than due to low working memory causing a drift into low socioeconomic position.

Sen (1999) developed the 'capability approach'; a framework that claims that freedom to achieve well-being is of primary moral importance, and that wellbeing should be understood in terms of people's capabilities and functions. The framework also describes that the development of capabilities relies upon a person's access to socioeconomic resources. In other words, if the environments which people are born into are favourable, then they will have more control to develop capability and influence their lives (Marmot et al., 2010; Sen, 1999). I view working memory as a capability that requires a suitable environment to be developed. However, not all children are born into such environments. As defined in Section 1.1.2, socioeconomic position (the social and economic factors that influence what positions individuals or groups hold) is an environmental factor that may make a child's environment less favourable and influence their working memory capability. Socioeconomic position has been hypothesised to influence child outcomes through a number of pathways, and I describe those that may be relevant to working memory here.

1.2.1.1 Family Stress Perspective

Socioeconomic disadvantage is hypothesised to influence child outcomes negatively through experiences of stress – otherwise known as the 'family stress perspective' (Bornstein, 2009; Duncan, Magnuson and Votruba-Drzal, 2017). Lower socioeconomic position families tend to experience more stressful life events, such as family dissolution, household moves, unstable employment, and persistent economic hardship (Bradley and Corwyn, 2002). Research has shown that early childhood poverty is associated with increased allostatic load, a measure of physiological stress which can have numerous negative lifelong consequences (Lupien et al., 2001; Bradley and Corwyn, 2002). Higher levels of child physiological stress are suggested to interfere with healthy development of stress responses and of the brain (Duncan, Magnuson and Votruba-Drzal, 2017). In the context of working memory, a longitudinal study of 195 participants found that the association between early disadvantage and adult working memory was mediated by chronic stress (Evans and Schamberg, 2009)

However, it is important to acknowledge an emerging body of work that explores whether early adversity may also enhance particular cognitive skills. The ***hidden talents approach*** acknowledges that poverty and adversity are harmful, but seeks to understand the mental abilities that may be enhanced through adversity. It proposes that adversity may shape abilities in different directions; for example, enhance one ability whilst impairing another (Frankenhuis, Young and Ellis, 2020). The approach proposes that stress-adapted skills represent a form of adaptive intelligence that enables individuals to function within the constraints of harsh and unpredictable environments (Ellis et al., 2020). For instance, in a study of 104 deprived and nondeprived Nigerian children, the deprived group had significantly better scores on a working memory task, but not on a set-shifting or inhibition task. This was interpreted as evidence of the hidden talents approach, and that deprived children in Nigeria may rely on working memory to attain success (Nweze et al., 2021). This approach highlights the importance of understanding the nature between socioeconomic deprivation and precise cognitive abilities (such as working memory), rather than looking at broader constructs or composites of several abilities (such as executive functions).

1.2.1.2 Resource and Investment Perspective

Socioeconomic position is also hypothesised to influence child development through lack of access to resources to enhance the home learning environment – otherwise known as the 'resource and investment perspective'. For example, children from poorer families have less access to learning materials and experiences such as visiting libraries and museums, and are less likely to be given extra tuition or lessons to develop skills (Bradley and Corwyn, 2002). Further, parents in low socioeconomic position may be less able to purchase educational materials for the home, and may have less time to invest in their children due to less flexible work schedules (Duncan, Magnuson and Votruba-Drzal, 2017). Related to this, lower family income is associated with lower levels of cognitive stimulation in the home environment (Votruba-Drzal, 2006). Indeed, the home learning environment (measured as the frequency of activities such as reading, drawing, and learning songs) explained some socioeconomic gaps in child development in a study of approximately 30,000 children in the UK Millennium Cohort Study (Kelly et al., 2011).

Amso and Lynn (2017) argue that the positive enrichment and opportunities gained from higher socioeconomic position are *more* important for child cognitive development than the negative experiences of stress through low socioeconomic position. They propose that the effects of adversity (as explained in the previous section) and the effects of socioeconomic position have separate and distinct biological mechanisms related to cognitive development. They argue that high socioeconomic position is consistently associated with higher levels of cognitive enrichment and parental closeness, whereas low socioeconomic position does not always mean a high level of stressful experiences (Amso, Salhi and Badre, 2018). Indeed, it has previously been found that socioeconomic position is associated with working memory via cognitive enrichment, but not via stressful experiences (Amso, Salhi and Badre, 2018).

1.2.1.3 Cultural Perspective

Socioeconomic position has been hypothesised to influence child development via a culture of poverty – otherwise known as the 'cultural perspective' (Duncan, Magnuson and Votruba-Drzal, 2017). Cultural explanations have previously suggested that high levels of *"nonmarital childbearing, joblessness, female-headed households, criminal activity, and welfare dependency"* among lower socioeconomic position families were likely to be transmitted from parents to children (Duncan, Magnuson and Votruba-Drzal, 2017, p.421). However, this perspective has been criticised for failing to explain how the conditions experienced by lower socioeconomic position families result in the transition of culture between parents and families (Small, Harding and Lamont, 2010).

Within the cultural perspective, different parenting styles, beliefs, and goals are relevant to child development (Hoff et al., 2002). In terms of beliefs and goals, higher socioeconomic position parents tend to give earlier age estimates for developmental milestones and goals. In terms of parenting styles, higher socioeconomic position parents tend to have more 'democratic' and child centred homes, whereas lower socioeconomic position parents tend to have a style which is oriented to 'maintaining order' and obedience (Hoff et al., 2002). Qualitative work shows that higher socioeconomic position parents provide multiple stimulating learning activities and social interactions that parents believe will improve their child's development, whereas lower socioeconomic position parents direct their efforts towards keeping children safe, enforcing discipline, and behaviour regulation (Lareau, 2003). However, these parenting styles are not consistently associated with child outcomes. In the Midlife in the United States study of 7,108 participants aged 24-75 years, higher paternal discipline was positively related to cognitive function in those with lower childhood socioeconomic position, whereas it was negatively related to cognitive function for those with higher childhood socioeconomic position (Liu and Lachman, 2019).

Further, children from socioeconomically disadvantaged families face significant difficulties with beliefs about themselves at school. Reay's (2017) interviews with children from working-class families reveals how children from working class backgrounds struggle with school:

> *"working class children have often said that they feel stupid, rubbish, 'no good', or even that they 'count for nothing' in the school context"* (Reay, 2018, p.77)

Reay interviewed people from working class backgrounds, including adults about their experiences with school and with current students. An adult woman recalled her experience of school:

> *"My whole sense of myself when I was at school was that I was no good at anything, that I was hopeless at learning" (Reay, 2018, p.68)*

Further, secondary school students describe difficulties with teacher perceptions and concentration:

> *"Some kids they just can't do it, like they find the work too hard, or they can't concentrate because too much is going on for them" (Reay, 2018, p.79)*

> *"Those teachers look down on you" (Reay, 2018, p.80)*

Clearly, socioeconomically disadvantaged students in England have difficulties in school that manifest as feeling they are unable to succeed. This is very likely to impact on their educational outcomes.

1.2.1.4 Transactional Models

It is important to acknowledge that it is not only socioeconomic position that may influence a child's development, but a range of other environmental and genetic factors. A recent body of evidence has begun to demonstrate associations between genes and childhood cognition (Tucker-Drob, Briley and Harden, 2013). However, transactional models posit that associations between genes, cognitive development, and academic outcomes are much more strongly related in more advantaged socioeconomic circumstances (Tucker-Drob, Briley and Harden, 2013; Peng and Kievit, 2020). In other words, children do not have chances to fully realise their potential in environments of socioeconomic disadvantage. Whilst I recognise that socioeconomic position is not the only factor to influence child development, and that genes may also have an influence, the influence of genes exceeds the scope of my PhD and is not explored in this thesis.

1.2.2 Ethnicity and Child Outcomes

Whilst much of the development of the theory about ethnic group and child outcomes has taken place in the US and is dominated by US scholars, many of these models are applicable and relevant to England. Historically, research investigating associations between ethnic group and outcomes had taken a 'deficit' perspective. The deficit perspective identified the cause of ethnic educational inequality as a function of 'deficits' affecting ethnic minority groups, and emphasised that the more groups become assimilated into society, the more success they would experience in education and in income. These models suggested that ethnic minority groups give up their cultural background (or suppress it), and assimilate into 'White' ways of knowing, being, and speaking, in order to achieve upward mobility in terms of education (Cabrera, 2019).

More recently, researchers have largely moved to more progressive models that incorporate understanding about the sociology of ethnicity, culture, and racism, and socioeconomic disadvantage within ethnic groups. Alike to my view of the effects of socioeconomic position, I view any effects of ethnicity on children's working memory to be due to social causation, where socioeconomic disadvantage or other environmental factors associated with ethnicity may cause differences in working memory. Ethnic minority groups tend to experience higher levels of socioeconomic disadvantage than ethnic majority groups in England (Chattoo and Atkin, 2019; United Nations, 2019), therefore, many ethnic group differences in child outcomes are often ascribed to be due to social position.

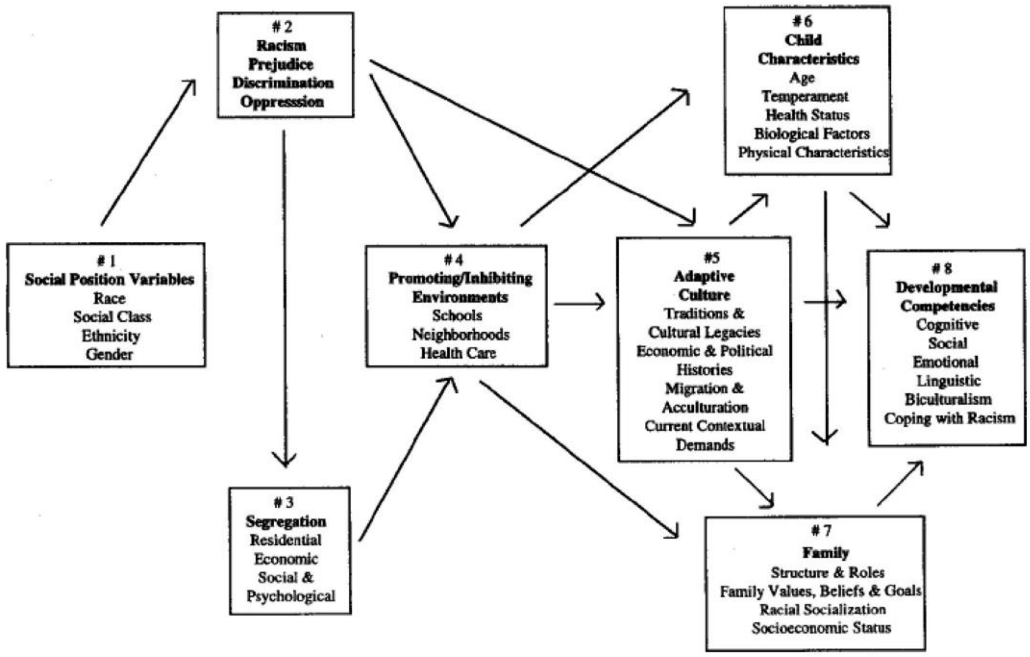
Even if studies adjust for socioeconomic position in their analyses and still see an association between ethnicity and working memory, these studies may be subject to problems in measurement error or statistical modelling. One such problem is confounding due to measurement error in a confounder, otherwise known as residual confounding (Fewell, Davey Smith and Sterne, 2007). Residual confounding reduces our ability to control for confounding in analysis, and is likely present in investigations that explore ethnic differences whilst adjusting for socioeconomic position. Studies that control for one aspect of socioeconomic position and ascribe ethnic differences in an outcome to racial or genetic differences are assuming that ethnic minority groups have equal social positions in all other aspects – which is unlikely to be true (Kaufman, Cooper and McGee, 1997).

A further statistical modelling problem that modifies the association between the exposure and the outcome is when a mediator is conditioned upon. In this case, socioeconomic position is a mediator since it may be caused by ethnicity (and obviously socioeconomic position cannot cause ethnicity), and may be caused by an unobserved variable. Conditioning on socioeconomic position creates a conditional dependency between ethnicity, an unobserved mediator-outcome confounder and, in turn, working memory. The estimated effect of ethnicity on working memory may therefore be distorted by this problem (Cole et al., 2010; Pearl and Mackenzie, 2018). When I examine the cohort study data for ethnic differences in working memory, I do not adjust for socioeconomic position partly for this reason.

However, there are other factors to consider beyond socioeconomic position in ethnic group differences, and I describe some of these in the following sections.

1.2.2.1 Integrative Model for the Study of Developmental Competencies in Ethnic Minority Children

Consistent with the social causation view is the 'integrative model for the study of developmental competencies in ethnic minority children' (García et al., 1996). The model has been used to investigate the environmental forces which drive ethnic minority children's development (Marks and Garcia Coll, 2018).



<u>Figure 2. Integrative model for the study of developmental competencies in minority children (Garcia Coll et al., 1996)</u>

Seen in Figure 2, the model emphasises the importance of the variables that affect a child from birth (e.g. socioeconomic position, race, and gender). Treating ethnicity as a fixed construct with direct impacts on development serves largely to perpetuate 'deficit' models of development, and does not acknowledge the social construction of, and negative social forces associated with, ethnicity. The model highlights many of the ways in which socioeconomic consequences of being an ethnic minority may impact on child development, which are consistent with the previously discussed perspectives around socioeconomic position (section 1.2.1). For example, box #7 in the model describes the importance of family values, beliefs, and goals, which is consistent with the cultural perspective (section 1.2.1.3) that these impact on child development.

In addition, the model highlights the environmental forces of racism, prejudice, discrimination, oppression, and segregation on child development for ethnic minority children. Indeed, empirical evidence indicates that mothers experiences of perceived racism are associated with increased risk of child socioemotional difficulties and spatial abilities, although not with verbal or non-verbal ability scores in the UK Millennium Cohort Study (Kelly, Becares and Nazroo, 2013). Further, a review of 40 articles on racism and child health found most studies find significant associations between perceived racism and behavioural and mental health (Pachter and García Coll, 2009). With respect to the population that is included in my study in Section B, qualitative work with Pakistani children in Bradford indicates that they do experience racism from other children at school (Din, 2006, p.60) – though the impact of this upon their development remains unknown.

Further, the model also notes the potential 'promoting' factors for child development, including schools, neighbourhood and health care. This highlights that there may be a number of 'protective' or 'buffering' factors that mean children are less affected by negative effects of socioeconomic disadvantage. The next section considers potential protective factors for ethnic minority children's development: ethnic density, and culture, community, and religion.

1.2.2.2 Potential Protective Factors for Ethnic Minority Children

Ethnic density

Own ethnic density is the density of one's own ethnic group in the same space – whether in a residential area, such as a neighbourhood, or an institution, such as a school or workplace. Ethnic minorities may be protected from some of the social disadvantage associated with ethnic minority status by high own ethnic density. Increased own ethnic density has been hypothesised to have an influence on health through the positive effects of social integration, and reduced exposure to the negative effects of stigma and racism (Pickett and Wilkinson, 2008). A systematic review found that, although many studies reported a null association between ethnic density and health, own ethnic density was more likely to be protective of physical health, mortality, and health behaviours than to have negative effects (Bécares et al., 2012). A narrative review found that ethnic density may protect against adult mental disorders, however, could only make tentative conclusions due to the heterogeneity of study designs and limited statistical power in studies of ethnic density (Shaw et al., 2012).

Since these two reviews, an investigation of 8610 mothers and infants from the Born in Bradford cohort study found that for South Asian women, higher ethnic minority density was associated with lower odds of smoking during pregnancy, but not with higher birth weight or lower odds of preterm birth (Uphoff et al., 2016). Only one study has investigated how ethnic density may influence a child's development in school. Zhang *et al.*, 2017 investigated the influence of own ethnic density on children's cognitive and behavioural outcomes in different ethnic minorities in a cohort study in England (Millennium Cohort Study) and in the US (Early Childhood Longitudinal Cohort Study). Here, I describe the findings for the measures of cognitive development.

In England, increased own ethnic density was associated with reduced expressive vocabulary scores (measured by the British Ability Scores) for most ethnic groups. After adjusting for other covariates including first language and area deprivation (measured using IMD), this association only remained significant for Bangladeshi children. In the US, increased own ethnic density showed mixed and non-significant effects on reading ability (measured by a tool designed by the Early Childhood Longitudinal Study) for all racial/ethnic groups – except for a negative effect for Hispanic children. After adjusting for other covariates including first language and area deprivation, there were no longer any significant associations. The authors conclude that the difference across countries may be due to the measures not being comparable, or may be due to differences in the national contexts influencing the effects of ethnic density (Zhang et al., 2017). Again, the results regarding the influence of ethnic density on ethnic minority children's cognitive development is mixed, and requires further investigation.

Culture, Community and Religion

Related to high levels of own ethnic density, ethnicity can be a positive aspect of one's identity through a sense of group belonging, immersion in culture, and an increased sense of community. For instance, Pakistani Muslim families living in Bradford are thought to build social capital by drawing on ethnic and religious identities and practices. They build social capital not only within and between families, but also make friendships, to generate social resources. This building of social capital may assist in overcoming lack of economic and human capital. For example, Pakistani Muslim parents who describe being unable to support their children educationally can rely on older siblings and others in the community for this sort of support (Thapar-Bjorkert and Sanghera, 2010). Related to high levels of own ethnic density, this is likely possible in Bradford due to very high levels of the Pakistani population living there.

Religion can also be a positive aspect of identity for ethnic minority children. The majority of Pakistani children report that they attend Mosque, which is usually accompanied by learning to read the Quran by heart (Dogra, Barber and Sheard, 2020; Din, 2006, p.131). Qualitative work with children in Bradford indicates attending Mosque creates a sense of community, and that children describe Islam as 'important' to themselves (Din, 2006, p.132). However, the impact that these mechanisms may have on child development outcomes remains largely unknown.

1.2.3 Beyond Competencies: Pygmalion Effect and Stereotype Threat

The theories discussed in sections 1.2.1-1.2.2 only encompass the ways in which socioeconomic position and ethnicity influence a child's *actual* ability or competency. Beyond children's ability, we can also consider how their outcomes may be affected by factors specific to test taking settings. In other words, disadvantaged children may have equal capabilities to their more advantaged peers, but do not score as well in test taking settings.

One such factor is the 'Pygmalion effect'; a phenomenon where teacher expectations for lower performance subconsciously affect both teacher behaviour and student performance (White and Locke, 2000). The Pygmalion effect describes how people do better when more is expected of them. For example, teachers unconsciously mark work from ethnic minority children with lower scores when comparing national tests marked remotely to marks given by teachers in the classroom (Burgess and Greaves, 2013, cited in Pickett and Vanderbloemen, 2015), and secondary teachers have lower expectations for ethnic minority children and students from disadvantaged backgrounds (Boser, Wilhelm and Hanna, 2014). Students may react to this discrimination by becoming demotivated or confrontational, and this reinforces the social stereotyping by teachers and encourages a vicious circle of low attainment for these students (Strand, 2011b). Importantly, expectations from both the teacher and the students have been found to be significant predictors of college graduation rates (Boser, Wilhelm and Hanna, 2014).

Further, a contextual factor that may induce differences in outcomes is ‘stereotype threat’. Stereotype threat occurs when people are, or feel themselves to be, at risk of conforming to stereotypes about their own social group, and has been discussed as a contributing factor to the achievement gap between children of low and high socioeconomic status (Spencer and Castano, 2007) and children from different ethnic groups (Appel and Kronberger, 2012). Schmader, Johns and Forbes (2008) theorise that for those at risk of being negatively stereotyped about their abilities, stereotype threat increases physiological stress at the time of testing, active monitoring of performance, and efforts to suppress negative thoughts. These physiological and psychological mechanisms consume executive resources needed to perform well on cognitive tasks, including tasks of working memory. Whilst the majority of experiments investigating stereotype threat explicitly prime stereotypes prior to test tasking (Désert, Préaux and Jund, 2009; Tine and Gotlieb, 2013), children may still be aware of their disadvantage in a test setting without explicit priming. As socioeconomically disadvantaged children become aware of their relative disadvantage early in life (Heberle and Carter, 2015), it seems plausible that stereotype threat may underpin some socioeconomic and ethnic differences in working memory scores in formal test settings.

1.2.4 Intersection Between Ethnicity and Socioeconomic Position

Intersectionality recognises that people's identities and social positions are shaped by multiple factors. A person's age, disability, ethnicity, gender, gender identity, religion and belief, sexual orientation and socioeconomic background combine in unique ways to create different experiences of discrimination and privilege (Cho, Crenshaw and McCall, 2013). Recently, intersectional approaches have been key in identifying interactions between ethnicity, gender, and socioeconomic position in predicting child outcomes. For example, in comparison to most other ethnic groups, White children at the lowest levels of socioeconomic position tend to be at higher risk for both lower social emotional scores in the U.S. (Kuo et al., 2020) and low educational achievement in England (Strand, 2014). Both Kuo et al. (2020) and Strand (2014) argue that accounts of outcomes framed exclusively in terms of social class, ethnicity or gender are insufficient, emphasising an intersectional approach for understanding such data.

Related to this, there may be problems with using the same measures of socioeconomic position across all ethnic groups. Research shows that social gradients are less pronounced in ethnic minority groups for maternal and child health (Mallicoat, Uphoff and Pickett, 2020; Uphoff, Pickett and Wright, 2016), and child social and emotional scores (Kuo et al., 2020). This lack of social gradients could be due to insensitive measurement of socioeconomic position in ethnic minority groups, as traditional measures of socioeconomic position may not be valid across all ethnic groups. For instance, educational attainment received in a different county may not be recognised in another, meaning it does not gain the expected income or occupation (Kelaher et al., 2009). These studies emphasise the importance of careful consideration when selecting and interpreting socioeconomic measures for ethnic minority groups, and the important of investigating socioeconomic differences within ethnic groups.

1.3 The Educational Divide

In this section I describe the evidence showing that socioeconomic disadvantage and ethnicity are associated with differences in educational attainment. Although a large body of evidence exists demonstrating very early socioeconomic inequalities in a variety of child development outcomes prior to beginning school and persisting throughout childhood (Feinstein, 2003; Vignoles, Jerrim and Vignoles, 2011; Kelly et al., 2011; Linberg et al., 2019), I focus only on inequalities in child educational attainment.

I focus only on educational attainment for several reasons. First, England provides a large, representative database for children's educational attainment, and this does not exist for other developmental outcomes. Further, the age at which children have national tests recorded in the database is closer to the age where children took working memory tests in the Born in Bradford study, which is the setting for my research. Second, educational attainment is undoubtedly an important predictor of later health and success in life (Silles, 2009; Amin, Behrman and Spector, 2013), whilst the evidence regarding cognition and health is only just emerging (Stautz et al., 2016). Third, child poverty is a rising issue which is likely to be affecting children's classroom abilities (United Nations, 2019). A recent survey of 1026 teachers found that a large majority of UK Teachers consider poverty to negatively affect the learning of their students (91%). Teachers noted a wide range of signs of poverty in their classrooms including: hunger (83%), ill health (80%), lack of concentration (93%), tiredness (95%), poor behaviour (94%) and being bullied (64%) (National Education Union and Child Poverty Action Group, 2018). The fourth and final reason is that socioeconomic disadvantage and ethnicity may be associated with differences in attainment via working memory. This last point is particularly significant: differences in working memory may provide a pathway for understanding why educational inequalities manifest in the first place.

The Department for Education provides the National Pupil Database (NPD). The NPD contains pupil attainment data for individuals in state funded education aged 2-21, and is linked to personal and school characteristics (GOV.UK). Educational attainment or achievement refers to the completion of educational benchmarks, exams, or qualifications. The most commonly undertaken assessments in England are:

- At age 4-5, at the end of Reception, teachers provide Early Years Foundation Stage Profile (EYFSP) assessments of children (GOV.UK).
- At age 5-6, in Year 1, children are tested with a teacher administrated phonics check (GOV.UK, 2018a).
- At age 7 for Key Stage 1, and at age 11 for Key Stage 2, both English (grammar and reading) and Mathematics (arithmetic and reasoning) are tested by Standard Attainment Tests (SATs). A teacher assessment of the SAT's is provided for reading, writing, math and science (GOV.UK, 2018b, 2018a).
- An Attainment 8 score refers to a student's average score across 8 subjects, and is used to illustrate a child's GCSE attainment at ages 14 and 15 (AQA).

1.3.1 Socioeconomic Gaps in Educational Attainment

Parsons (2019) analysed two different cohorts of pupils through KS1 to KS4, reaching age 16 in 2012 and 2015. The Income Deprivation Affecting Children Index (IDACI) is a neighbourhood measure of deprivation, calculated according to the proportion of families in that area in receipt of benefits.

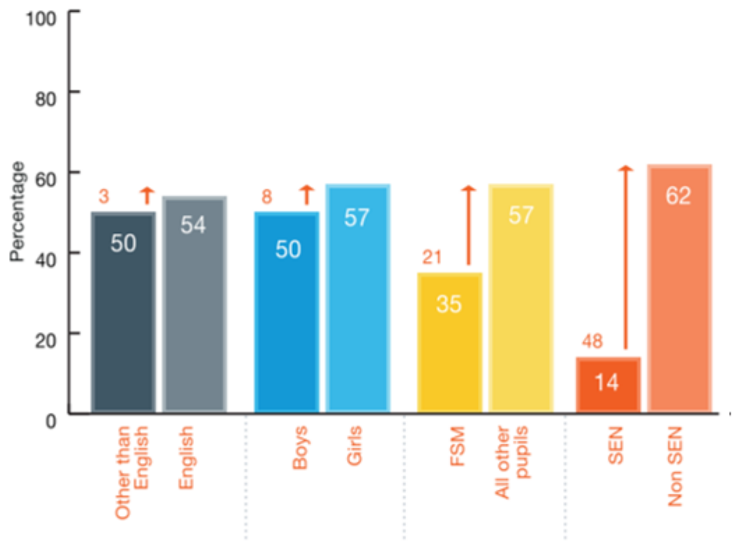
Table 2. Percentage of pupils achieving expected levels at Key Stages 1 and 2, and achieving GCSEs.

	Cohort reaching 16 in 2012			Cohort reaching 16 in 2015		
IDACI decile	KS1 reading, writing & maths (%)	KS2 reading, writing & maths (%)	Five A*-C GCSEs including English and maths (%)	KS1 reading, writing & maths (%)	KS2 reading, writing & maths (%)	Five A*-C GCSEs including English and maths (%)
Poorest 10%	66.7	57.0	34.9	73.4	63.3	39.2
11-20%	71.1	59.7	37.6	76.3	65.0	40.9
21-30%	74.6	63.9	42.0	79.3	68.0	44.7
31-40%	77.4	66.9	45.5	81.3	70.6	48.6
41-50%	80.2	70.0	50.2	83.7	73.9	53.0
51-60%	82.5	74.0	55.3	85.8	76.6	57.7
61-70%	84.7	76.5	59.7	87.2	79.0	61.6
71-80%	86.1	78.8	63.6	88.6	81.2	65.4
81-90%	87.9	81.3	67.4	89.8	83.5	68.8
Most affluent 10%	90.1	84.6	73.0	91.6	86.4	74.6
Total numbers	***464,100***	***537,553***	***560,165***	***496,030***	***516,399***	***536,394***

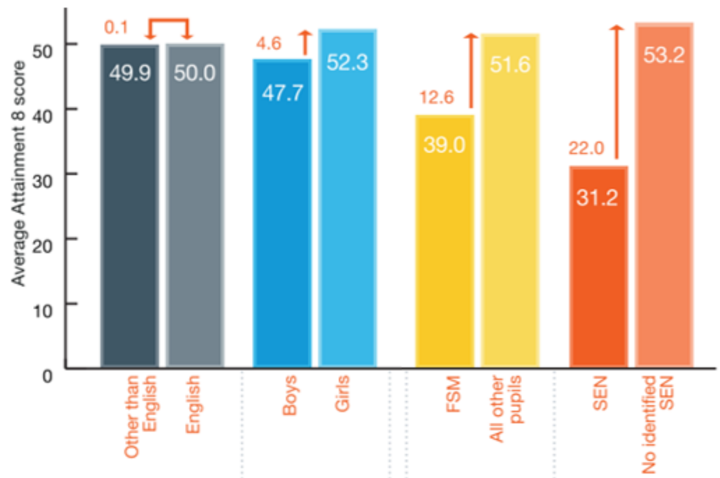
Source: National Pupil Database analyses of two longitudinal cohorts (reproduced from Parsons, 2019)

Table 2 shows a clear social gradient in achieving the expected levels at all Key Stages, across each decile from poorest to most affluent. This analysis has allowed insight into trends in socioeconomic differences in attainment levels. The same social gradient is demonstrated both in 2012 and 2015 – although the gap between poorest and most affluent decreases by 4-6% in 2015. The gap between the poorest 10% and most affluent 10% of children widens considerably at each stage of attainment for both cohorts – (2012 data 24%, 27%, 39%; 2015 data 18%, 21%, 35%) (Parsons, 2019).

The Education Endowment Foundation (2018) report describes gaps in attainment levels in 2016, reporting on differences between pupils with different characteristics.



<u>Figure 3. Percentage reaching the expected standard in reading, writing, and mathematics for different pupils aged 11 in England, 2016 (state funded schools). Source: Education Endowment Foundation, 2018.</u>



<u>Figure 4. Average Attainment 8 scores in GCSE's for different pupils aged 16 in England, 2016 (state funded schools). Source: Education Endowment Foundation, 2018.</u>

Figure 3 outlines the substantial attainment gap in 2016 for disadvantaged pupils aged 11 in Key Stage 2 reading, writing and maths, with only 35% of pupils receiving free school meals (FSM) reaching expected levels, compared to 57% of all other pupils reaching expected levels. Figure 4 shows that the gap persists at age 16, with FSM eligible pupils scoring an average GCSE Attainment 8 score of only 39, compared to all other pupils achieving 51.6. Further data (not pictured) show that only 50% of disadvantaged pupils achieve A*-C GCSE's in English and Maths, in comparison to 75% of non-disadvantaged pupils. As seen in Figure's 3 and 4, the Special Educational Needs and Disability (SEND) attainment gap is the only gap that is larger than the socioeconomic disadvantage gap. The SEND gap is also closely linked to socioeconomic disadvantage, with 27% of pupils with SEND being eligible for FSM, compared to only 12% without SEN.

In the most recent NPD statistics available online, it is clear that the attainment gap is persisting in recent times. Only 70% of children receiving FSM achieved the expected standard in phonics assessments at age 5-6 in 2018, compared to 84% of children who do not receive FSM (GOV.UK, 2018a). This gap widens by Key Stage 1 teacher assessments in maths, writing, and reading at age 7, where 20% more of non-FSM pupils achieve the expected standard (GOV.UK, 2018a). The disadvantage gap was very similar in the latest data in 2019, where 20% more of non-disadvantaged children reached the expected standard in maths, writing, and reading (Department for Education, 2019).

Regrettably, the COVID-19 pandemic is likely to exacerbate and widen educational inequality. An ongoing study indicates that primary school children have significantly lower achievement in reading and mathematics overall, likely due to missed learning. Further, the disadvantage gap has widened compared to 2019, with disadvantaged children achieving less in reading and mathematics, and being less likely to attempt questions towards the end of assessments (Education Endowment Foundation, 2021).

Failure to achieve these core qualifications significantly hinders progression into further employment or further education. The cumulative impact of being without these fundamental skills in Maths and English leads to long-term challenges for both the individual and the nation as a whole. Addressing these continued inequalities in educational attainment is crucial for reducing consequential health inequalities

(Marmot et al., 2010). Disappointingly, the socioeconomic attainment gap is closing at an extremely slow rate; with the Education Policy Institute estimating it will take around 50 years for it to close at its current trajectory (Andrews, Robinson and Hutchinson, 2017). However, this analysis may underestimate the closing of the attainment gap due to the ongoing COVID-19 pandemic, meaning it will take even longer than 50 years.

1.3.2 Ethnic Group Differences in Educational Attainment

Pupils belonging to ethnic minority groups made up 31.8% of the total school population in 2017, up 7.5% from 2011. Whilst no individual minority group constitutes more than 4% of the total school population, they are not evenly spread throughout local authorities. Manchester, Birmingham and Leicester have over 60% of their students belonging to ethnic minority groups, and Inner London has over 80% (Parsons, 2016, 2019). Since White British are the ethnic majority group in England, I make contrasts between them and the ethnic minority groups in the following section.

Table 3. Attainment at KS1, KS2 and KS4 by ethnic group for two longitudinal national cohorts of pupils (reproduced from Parsons, 2019)

	Cohort reaching 16 in 2012			Cohort reaching 16 in 2015		
Ethnic group	KS1 reading, writing & maths %	KS2 reading, writing & maths	Five A*-C GCSEs including English and maths	KS1 reading, writing & maths %	KS2 reading, writing & maths	Five A*-C GCSEs including English and maths
White British	80.7	71.8	55.8	84.3	75.4	54.2
Mixed White and Black Caribbean	77.0	67.0	47.3	80.8	71.5	45.3
Mixed White and Black African	78.1	68.6	59.4	82.3	74.1	55.3
Indian	82.6	76.0	74.1	86.2	80.1	71.3
Pakistani	69.5	58.9	50.1	75.0	65.2	49.3
Bangladeshi	67.1	63.8	58.8	76.5	70.3	59.8
Black Caribbean	72.0	59.0	46.2	78.0	66.6	42.6
Black African	69.8	59.1	56.5	77.4	67.6	54.1
Other Black background	70.9	57.4	48.4	76.2	64.6	44.6
Gypsy/Traveller/Roma	41.6	27.5	8.7	54.2	24.5	8.5

Parsons (2019) provides descriptive results for attainment at key timepoints by ethnic group from the NPD, and table 3 presents attainment at three stages by ethnic group for two cohorts of pupils. The groups with consistently worse attainment than White British pupils at KS1, KS2, and KS4 across the two cohorts are shaded in grey. Gypsy/Traveller/Roma children consistently have the worst attainment of all ethnic groups. Black Caribbean, Mixed White and Black Caribbean, Other Black background and Pakistani pupils all do relatively poorly at all stages. In contrast, Black African and Bangladeshi pupils have similar outcomes to White British pupils at KS4. Although this is the most recent data and is useful to understand ethnic group patterns in attainment, this study did not adjust for socioeconomic differences between ethnic groups, which is useful to understand the true underlying associations between ethnicity and attainment.

Strand (2011) used data from the Longitudinal Study of Young People in England (LSYPE). LSYPE included an interview survey of over 15,000 young people who were aged 14 years in 2004, and had taken national tests in English, Maths, and Science. The LSYPE has the advantage of a more comprehensive measure of socioeconomic status than 'free school meal eligibility', the LSYPE measure encompasses social class, maternal education, FSM eligibility, home ownership, and family composition. Looking just at raw ethnic group differences, the mean attainment gap in national tests at age 14 between White British and several ethnic minority groups was large, where Bangladeshi, Pakistani, Black Caribbean and Black African children all attained lower test scores. Further, the gap between the highest and lowest attaining ethnic group was three times larger than the gender attainment gap, but only around one-third of the size of the social class gap (Strand, 2011b).

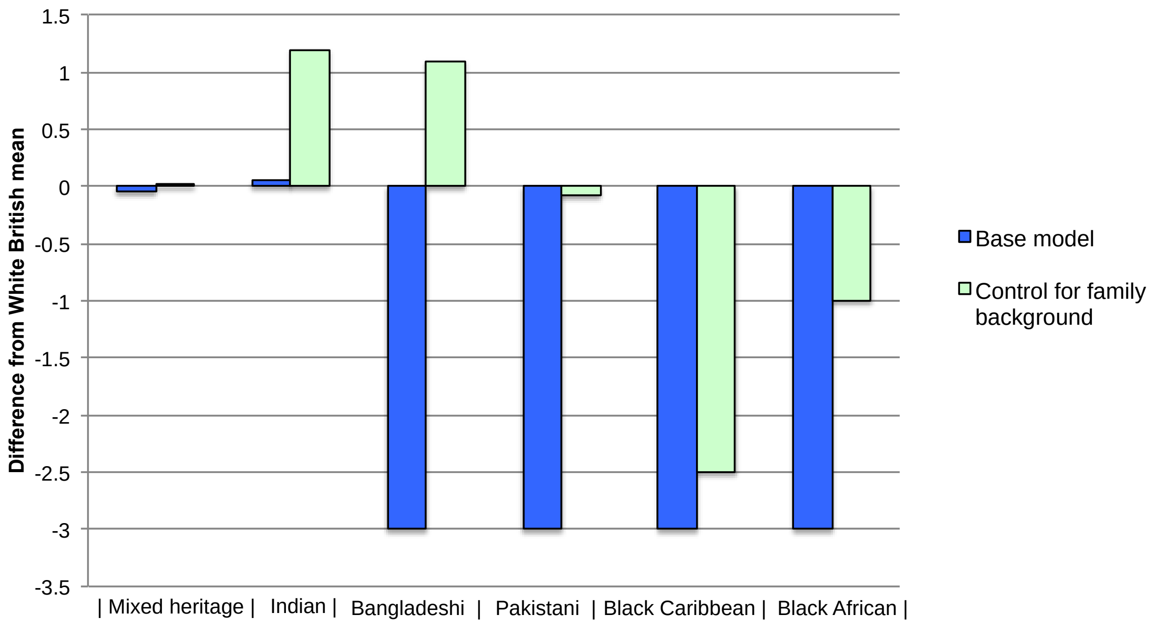


Figure 5. Regression coefficients for BAME groups relative to White British Students in five regression models of educational attainment at age 14. Source: reproduced from Strand, 2011.

Figure 5 presents regression coefficients for minority ethnic groups compared to White British pupils in the LSYPE. After controlling for family background, mixed heritage, Indian and Bangladeshi pupils score above White British pupils. High attainment for South Asian children has been attributed to supportive and motivating families who prioritise the pursuit of educational capital (Basit, 2013; Dwyer et al., 2011), which may account for Indian and Bangladeshi children's higher attainment, and the Pakistani children's more equal attainment. However, even after controlling for family background, Black Caribbean and Black African pupils still score much worse than White British pupils (Strand, 2011). In other words, socioeconomic position does not provide an adequate explanation of all ethnic group differences in attainment, as Black Caribbean and African pupils still have much worse attainment.

More recently, in a report for the Commission on Ethnic and Racial Disparities (CRED), Strand analyses the Second LSYPE (LSYPE2), a nationally representative sample of 9704 students who completed GCSE's at the end of year 11 in summer 2015. The study found that the groups with lowest achievement were White British, Black Caribbean, and Mixed White and Black Caribbean students from low socioeconomic position backgrounds. Boys from Pakistani, White Other and Any Other ethnic groups from low socioeconomic position backgrounds also had mean scores well below the grand mean, but higher than comparable White British boys (Strand, 2021).

Data like these have been cited in media to describe the "White working class" as the lowest attaining group, however, it has been argued that diverts attention from the more persistent and significant inequalities of attainment experienced by ethnic minority groups (Gillborn et al., 2021). A problem with using access to free school meals to describe the 'working class' is that the measure of free school meal eligibility actually excludes many adults who consider themselves working class – and in turn, excludes their children. This therefore means that an entire group of adults who are working class and their children are excluded from this description. Additionally, White British students are among the least likely of all ethnic groups to be eligible for free school meals in comparison to other minority ethnic groups, so the proportion of White British children with low attainment is much smaller than within the other ethnic groups.

Using attainment data from 2019-2020, it can be seen that White British pupils eligible for free school meals are not actually consistently the lowest attaining group at every timepoint (as is often reported). In fact, the following minority ethnic groups eligible for free school meals score lower than White British pupils, depending on the measure and time of attainment: Gypsy/Roma, Black Caribbean, and Dual Heritage (White/Black Caribbean). Another important point is that among the students not eligible for free school meals, the bottom four places at each attainment timepoint are never White British, but are (1) Gypsy/Roma, (2) Black Caribbean, (3) Dual Heritage (White/Black Caribbean), and (4) Pakistani students (Gillborn et al., 2021) – which is often missed due to the focus on the White "working class".

To summarise, educational inequalities exist for several ethnic groups. Strand's (2011) analysis showed that some educational inequalities can be explained by socioeconomic factors, however, educational inequalities persisted for Pakistani pupils (although at a small magnitude), Black Caribbean and Black African pupils. However, Strand's (2011) analysis did not include some of the ethnic groups found to have consistently worse attainment by Parsons (2019): Gypsy/Roma/Traveller, Mixed White and Black Caribbean, and Other Black. Further, whilst White British pupils from low socioeconomic position backgrounds have disproportionately worse attainment than expected, White pupils on average tend to have higher attainment than ethnic minority groups.

1.4 Chapter Summary

In this chapter I have defined the key concepts of interest in my thesis. Socioeconomic position refers to both the social and economic factors that influence what positions individuals or groups hold within the hierarchical structure of a society (Krieger, Williams and Moss, 1997; Galobardes et al., 2006a, 2006b). Ethnicity is identification through common history and culture – and encompasses religion, tradition and language (Chattoo & Atkin 2019, p.22). My thesis explores socioeconomic position and ethnicity, and their associations with children's working memory, which is a limited capacity system that allows the storage and manipulation of information over short time periods (Baddeley, 2010; Cowan, 2017).

I have also provided the theoretical background for studying these associations. I view any associations between socioeconomic position, ethnicity, and working memory to be primarily a result of social causation. Socioeconomic position is hypothesised to have associations with children's cognitive and educational outcomes through mechanisms of family stress, resource access, and differences in culture. Ethnic group may have associations with children's outcomes through ethnic minority children experiencing higher levels of socioeconomic disadvantage and racism, however, it is also important to consider potential protective factors for ethnic minorities.

I have summarised the profound inequalities in educational attainment that exist by socioeconomic position and ethnic group, and working memory may be one pathway by which these occur. Regardless of the measure of socioeconomic position used, the gap in educational attainment between children from the least and most disadvantaged families is large. Although the gaps between ethnic groups are smaller in magnitude, they are still of concern. Clearly, children in England suffer profound educational inequalities depending on the socioeconomic circumstances of their families, and their ethnic group. Due to the associations found between educational attainment and later health, these disadvantage and ethnic groups gaps are likely to have cumulative implications for children's future health and wellbeing.

1.5 Thesis Objectives

The key objective of this thesis is to investigate the associations between socioeconomic position and children's working memory, and between ethnicity and children's working memory. The secondary objective is to investigate potential causal factors in associations between socioeconomic position, ethnicity, and working memory.

Chapter 2. Associations Between Socioeconomic Position, Ethnicity and Children's Working Memory: A Systematic Review and Meta-analysis

This chapter provides a systematic review of the association between 1) socioeconomic position and working memory, and 2) ethnic minority status and working memory.

2.1 Introduction

Researchers disagree about the extent to which socioeconomic disadvantage affects working memory. Some researchers view a child's working memory ability as impervious to the negative effects of socioeconomic disadvantage, and conceptualise it as a cognitive ability that is independent of acquired knowledge and skills (e.g. Alloway & Copello, 2013; Engel, Santos, & Gathercole, 2008). In contrast, other studies have found that socioeconomic disadvantage is associated with significant impairments in working memory ability (e.g. Hackman et al., 2014; Lawson & Farah, 2017; Lawson, Hook, & Farah, 2018).

No study has systematically synthesised the literature investigating the association between child socioeconomic disadvantage and working memory. Lawson, Hook and Farah (2018) investigated the association between executive functions and socioeconomic status, finding a significant, but small, association across 25 studies r (r = .16 and 95% CI .12 to .21). They also explored potential moderators of the association, finding that ethnicity, mean age, and the type of socioeconomic indicator were not significant moderators. However, the strength of the association was moderated by the type of executive function measured, with 12 studies of working memory having a larger, but still small, effect size than other executive functions (r = .18 and 95% CI .13 to .22).

However, the study has significant design limitations that limit the inferences it can make about socioeconomic position and working memory. The detail regarding the search strategy is brief, and the results may not have included all available studies. The authors completed the literature search in January 2013, and research in socioeconomic disparities in executive function has increased substantially since then (e.g. Little, 2017; Arán Filippetti and Richaud, 2016). Additionally, the review only included studies reporting a Pearson's r correlation, with a continuous distribution of both socioeconomic position and executive function. Studies investigating socioeconomic disparities in working memory often divide children into "high" and "low" socioeconomic position groups, or use regression to analyse socioeconomic position as a continuous variable – excluding these kinds of studies may introduce systematic bias in the results.

The meta-analysis included all storage, processing, verbal, and visuospatial working memory tasks in one summary statistic (Lawson, Hook and Farah, 2018). However, as outlined in Chapter 1, the multicomponent model of working memory views it as responsible for both storage and processing memory abilities, in both visuospatial and phonological capacities (Baddeley, 2010). Further, it has previously been shown that the task used to assess working memory may affect its association with socioeconomic position (Tine, 2014; St. John, Kibbe and Tarullo, 2018). It therefore remains unknown whether any socioeconomic disparity in working memory will be consistent across both storage and processing tasks of working memory, or if the strength of the association may change between such tasks.

Another recent systematic review and meta-analysis found a relationship between early life stress and working memory measured in adulthood. Early life stress was defined as the occurrence of childhood trauma or maltreatment, including physical and emotional abuse, physical and emotional neglect, sexual abuse, adverse family environment, peer violence and witnessing community or collective violence prior to age 18. The meta-analysis found a small effect size relating early life stress to impaired working memory ability in adulthood (Hedges g = .22 and 95% CI .16 to .27), which was consistent across whether the task was auditory or visual, the clinical status of participants, and whether that task measured visuospatial or phonological components of working memory (Goodman, Freeman and Chalmers, 2018). This suggests that working memory may be susceptible to early life stresses (which may be overrepresented in lower socioeconomic groups). However, this review does not directly address the role of socioeconomic position or ethnicity in working memory ability.

There appear to be very few studies about the potential associations between ethnic minority status and working memory. The few studies I found prior to beginning this systematic review showed that ethnic minority children tend to have worse working memory (e.g. Hackman et al., 2015; Little, 2017). However, there has not yet been an attempt to summarise and combine the literature on ethnic minority status and working memory. Whilst Lawson et al (2018) did include a moderation analyses in their meta-analysis by ethnicity, they only considered whether the majority of the sample of the included studies was Black, White, or mixed race, and did not consider the context of different ethnicities within the countries included in the review.

I aim to update and extend this research by conducting a systematic review that aggregates information regarding the relationship between socioeconomic position, ethnicity, and different components of working memory in children aged up to 18 years across a large number of studies using as wide a range of outcome variables as possible, and report both the magnitude and the variability of these associations.

2.1.1 Systematic review objectives

To objective was to conduct a systematic review to assess the association between socioeconomic position and working memory in children, and ethnic minority status and working memory in children in children aged up to 18 years across a large number of studies using as wide a range of outcome variables as possible, and report both the magnitude and the variability of these associations. The research questions are:

1. What is the association between socioeconomic position and working memory in children?
2. What is the association between ethnic minority status and working memory in children?

2.2 Methods

The review protocol was registered on PROSPERO (CRD number: 42019134936). I used the PRISMA checklist to ensure complete and transparent reporting of methods in this review (Moher et al., 2009) (provided in Appendices A1)

2.2.1 Eligibility criteria

2.2.1.1 Rationale

I used the Population, Exposure, Outcome (PEO) framework (Pollock and Berge, 2018) to design the inclusion and exclusion criteria. The population are typically developing children aged 0-18. I used a wide age range as an association could occur between the factors at any age, and it ensured that results would be applicable to children of all ages. I only included studies that examined typically developing children, as including studies regarding children with developmental disabilities would result in far too many eligible studies and potentially much more unexplained heterogeneity in results. I therefore excluded all studies that examined only atypically developing children – defined as those with any developmental, clinical or psychiatric diagnosis.

The exposure is disadvantage, and the indicators of disadvantage are socioeconomic position (SEP) and ethnic minority status (EMS). Indicators of socioeconomic position and ethnic minority status were informed by PROGRESS (Place of residence, Race/ethnicity/culture/language, Occupation, Gender/sex, Religion, Education, Socioeconomic status, Social capital) (O'Neill et al., 2014). I included any study with one or more of these indicators, with the exception of gender, sex and religion – as these are not the disadvantage constructs of interest. Studies that compared different ethnic groups on working memory had to include an ethnic majority group and an ethnic minority group that both resided in the same country at time of testing working memory. This was to ensure that rather than comparing ethnic or cultural differences across countries, the results would compare those who experience disadvantage due to being an ethnic minority and those who experience advantage due to being an ethnic majority within the same country (e.g. White British children versus Pakistani children, living in England).

The only outcome is working memory performance. Any task that measured a child's working memory (WM) performance in a quantitative and behavioural manner was eligible. Tasks were included if they measured simple WM, complex WM, verbal WM, visuospatial WM, or some combination of these (see Section 2.2.1 for how these were defined). Although subjective assessments of working memory do exist, such assessments were not eligible for this review. The outcome of interest in this review is the objective, behavioural concept of working memory ability. Subjective assessments of working memory may not accurately represent behavioural working memory as they may include bias from assessors. As the outcome is only WM, and not any other cognitive or executive function tasks, studies that only reported a combined composite score on executive function were not eligible.

Studies were eligible for inclusion if they used any observational design (cross-sectional and longitudinal), or any intervention design if they reported baseline characteristics. The primary objective of this review is to establish if an association exists between factors, and the information that these study designs provide are able to answer questions regarding associations (Levin, 2006). Studies had to provide quantitative data on the association between SEP and WM, or EMS and WM. As studies were required to provide data on quantifiable associations, qualitative studies were not included.

2.2.1.2 Inclusion criteria and exclusion criteria

Studies were included if they met all of the following criteria: (a) they provided data on any indicator of socioeconomic disadvantage, (b) they reported disadvantage at the individual or group level, and compared individuals or groups on that measure of disadvantage, (c) they measured performance on at least one behavioural task of working memory and reported the results quantitatively, (d) they reported data for typically developing children aged between 0-18, (e) the study was reported in the English language, (f) the study was of any observational design, or baseline characteristics if an intervention, and (g) the study was published in a peer reviewed journal.

A study was excluded if: (a) study reports measures of other executive function or measures of a composite of executive function, but not working memory alone, (b) study population consists of only atypically developing children (children with any developmental, clinical or psychiatric diagnosis), (c) study population consists of participants aged 18+, or (d) systematic reviews, dissertations or qualitative studies

2.2.1.3 Changes to protocol

At the time of writing the protocol, studies were considered to be eligible for the review if they reported a PROGRESS indicator at the group level, where the researchers sampled only one specific population (e.g. children from affluent neighbourhoods). Additionally, dissertations and unpublished studies were eligible for the review. After title and abstract screening it was clear that these eligibility criteria would result in far too many eligible studies in the final review (>200). To reduce the number of eligible studies to a manageable number, inclusion criteria were changed to include (a) only peer reviewed studies, as the methods and results of these studies would be more robust than unpublished studies (and publication bias could be explored in analysis) and (b) studies that compare populations on indicators of disadvantage (e.g. children compared on neighbourhood disadvantage) as the results of these studies would be more easily synthesised in analysis. All changes to the inclusion criteria were updated on PROSPERO.

2.2.1 Conceptualisation of the outcome

The multicomponent WM model was described in Chapter 1, and I use this model to guide the separation of different tasks of working memory in this review. To distinguish between and investigate the different components of the MCWM model, I will refer to the central executive tasks as either 'complex verbal WM' or 'complex visuospatial WM' where both storage and additional processing are required. Occasionally, a task will use both verbal and visuospatial material, and in this case, I refer to it as complex composite WM. I refer to the phonological loop as simple verbal WM, and to the visuospatial sketch-pad as simple visuospatial working memory – where storage is a primary demand of a task. In this case, a task that uses both verbal and visuospatial material and only requires storage of information is referred to as simple composite WM. Finally, a task that uses a combination of simple and complex tasks is referred to as composite verbal WM, composite visuospatial WM, or composite working memory (if it uses all distinct four types). The Venn diagram below summarises the conceptualisation of the four core different types of WM, and how they overlap.

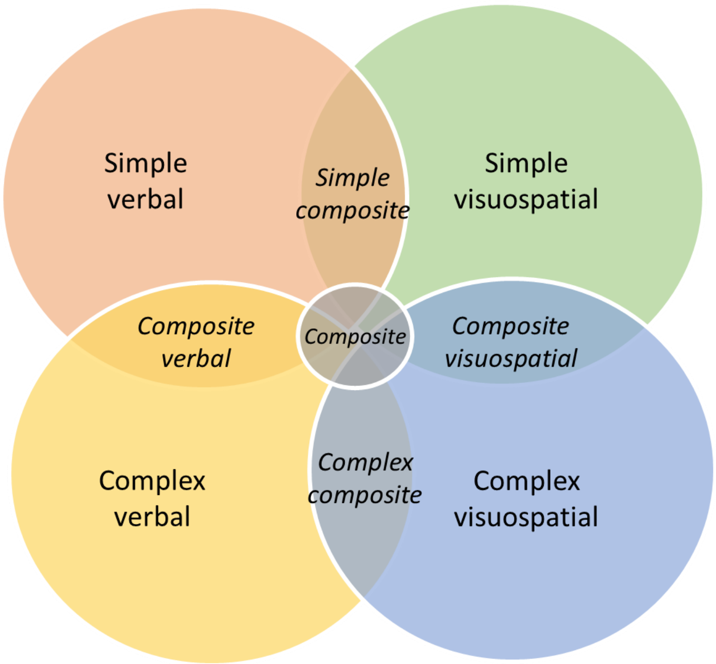


Figure 6. Description of and overlap of different working memory components guided by the MCWM

Figure 6 provides an overview of the different parts of working memory and how they are conceptualised in my systematic review. I conceptualise simple span tasks (e.g. recalling a list of items in forwards order) to measure only storage capacity and complex span tasks (e.g. recalling items in backwards order) to additionally measure processing capacity. Some tasks may combine these tasks. For example, a task may rely on either complex verbal working memory or complex visuospatial WM. If that task is combined into a composite score, I describe it as complex composite working memory and this task reflects both storage and processing capabilities of both verbal and visuospatial information. In the following table, I provide a framework for understanding the associated measurable components and working memory tasks related to these components.

Table 4. Working memory and its associated tasks

Component	Measure of	Tasks	Description
Phonological Loop	Simple verbal WM	Forwards Digit Recall (FDR)	The participant hears and repeats a series of digits in forwards order.
		Memory for Sentences *(subtest of WJ-R)*	The participant remembers and repeats simple words, phrases and sentences.
Visuospatial Sketchpad	Simple visuospatial WM	Corsi	The experimenter taps a spatial sequence on a series of nine blocks, and the participant attempts to imitate the sequence.
		Any spatial sequence task	Any task that involves the simple repetition of a spatial sequence in a similar format to above.
Central Executive	Complex verbal WM	Backwards Digit Recall (BDR)	The participant hears and repeats a series of digits in backwards order.
		Counting recall	The participant counts a number of dots in a series of presentations, and then recalls the total numbers in sequence.
		Random number generation	The participant generates random numbers at regular intervals, and cannot repeat the same number twice.
		Any 'two-back' task	The participant is presented with a series of specified stimuli, then is asked if a target stimulus is the same as one presented two stimuli previously.
		Memory for sentences (with recall)	Reading and verifying the truth of a series of sentences, and remembering the final word of each sentence for later recall.
	Complex visuospatial WM	Mr – X	Participant is presented with a picture of two Mr. X figures, and identifies whether the Mr. X with the blue hat is holding the ball in the same hand as the Mr. X with the yellow hat. The Mr. X with the blue hat may also be rotated. At the end of each trial, the child has to recall the location of each ball in Mr. X's hand in sequence, by pointing to a picture with eight compass points.
		Odd-One-Out	Nine sets of shapes appear on the screen, different from each other in colour, shape, and number. The user must pay close attention to how the shapes differ from each other, and point out the one shape that is most different from the rest.

2.2.2 Information sources

Literature databases were the primary information source; Embase, Psycinfo and MEDLINE were searched via Ovid. In addition to formal database searching, I included studies I had previously identified through my own reading. Sources of grey literature (literature that is not formally published) were not searched as many eligible records were identified through databases alone. Additionally, much grey literature would not contain the relevant required statistic to quantify associations.

2.2.2.1 Databases and search strategy

A librarian specialising in Health Sciences was consulted to construct the search strategy, which combines key terms with a search filter. A search filter was used to filter for all equity-focused studies. The filter is validated in Embase and MEDLINE (Prady et al., 2018), and has been translated for PsycInfo. The PROGRESS acronym (O'Neill et al., 2014) was used to guide the equity filter, and consequently includes the constructs of disadvantage that are of interest to this review. The search filter significantly reduces the number of titles and abstracts needed to screen by filtering relevant studies into a search. Without the search filter, the number of titles and abstracts needed to screen would have been unmanageable due to time constraints.

The equity filter is combined with terms and subject headings to identify 'working memory' abilities in 'children'. The search strategy was adapted for different databases and included all studies from database inception until 10th May 2019, and then was updated to include further studies published until 3rd June 2021. The box below describes the basic search strategy across databases, and precise information on the search strategy in different databases is provided in the appendices (see Appendices A2).

(search filter for equity studies)

AND

(subject headings) OR (“working memory”.ti,ab. OR “executive function*”.ti,ab. OR “short?term memory.ti,ab.”)

AND

(subject headings) OR (child* OR infant OR school child* OR adolescen* OR preschool* OR pre-school* OR boy* OR girl* OR young people OR teenager* OR teen* OR youth*.mp.)

The asterisk indicates truncation, to include all words that begin with the specified letters.

2.2.3 Selection process

I used Endnote X9 and web-based software Covidence to manage all references (Clarivate Analytics, 2021; Covidence, 2018). After identifying eligible studies through searching databases, I downloaded all studies into Endnote. De-duplication was carried out by varying the duplication parameters in Endnote, and I then uploaded the studies into Covidence to screen for further duplications.

I used Covidence for screening at both stages (title/abstract screening and full text screening). As a second reviewer can reduce the potential of missed eligible studies and maximise inclusion of relevant studies (Stoll et al., 2019), a second reviewer (MB) screened a random 10% of excluded studies at both screening stages. To ensure the 10% of studies was selected randomly, Endnote was used to generate a random 10% for second screening of excluded studies. MB used Covidence for screening at the first stage (title/abstract screening) and then Endnote for the second stage (full text screening). Agreement between myself and MB was considered to be acceptable if it was found to be at least 90% at both stages.

2.2.4 Risk of bias assessment

Study quality and risk of bias are distinguishable from one another. Assessment of methodological quality refers to the critical appraisal of included studies and investigation of the extent to which study authors conducted their research to the highest possible standards. A bias is a systematic error in results that can operate in either direction (an overestimation or underestimation of an effect), and can vary in magnitude (Higgins et al., 2020, 2011). The Cochrane handbook recommends a focus on risk of bias, to allow a consideration of whether results of included studies should be believed, regardless of their quality. When investigating a given study and its risk of bias, assessors should prioritise investigating how closely a study's findings may approximate the truth (Büttner et al., 2020a). The risk of bias in the results of each study contributing to an estimate of effect can then be considered as one of several factors to judge the quality of a body of evidence (Higgins et al., 2011, 2020).

Cross-sectional studies cannot assess the temporal sequence of events and whether the exposure preceded the outcome (Levin, 2006). However, cross-sectional studies are equally able to answer research questions regarding associations. This review asks about the presence of associations between disadvantage and WM, and so both cross-sectional and longitudinal studies have the power to estimate an effect size between two variables, and both are equally able to approximate a true association. The key dissimilarity is that both study designs are not equally able to establish temporal sequence – only longitudinal studies can do so (Levin, 2006).

A variety of tools exist for assessing study quality and study risk of bias. I assessed studies using two tools dependent on study design (cross-sectional or longitudinal). The tools are designed to assess both study quality and risk of bias (NHBLI, 2017; Downes et al., 2016). Since I consider risk of bias to be more important for the review results, no overall score is given for study quality. However, answers to individual questions from the tools are presented and study quality can be inferred by the reader through examining the questions. An overall score is provided for risk of bias as "high" or "low", and this was decided using the tools, and with particular attention paid to criteria relevant to this review described in Section 2.4.3.

2.2.4.1 Cohort and longitudinal studies

The National Institutes of Health (NIH) Quality Assessment Tool for Observational Cohort and Cross-Sectional Studies was used to assess study quality and risk of bias for all studies in the review with cohort or longitudinal study designs (NHBLI, 2017). Although the tool is also intended for use with cross-sectional studies, two key questions are only relevant to longitudinal designs and this may have resulted in unnecessarily worse ratings for cross-sectional studies. Studies were assessed using this tool if they provided a measurement of the exposure(s) before the outcome, or if they had repeated assessments of either. Previous systematic reviews using this scale have used numerical scales (e.g. Méndez-Bustos et al., 2019; Bayfield, Pannekoek and Tian, 2018). However, the NIH tool guidance states the tool is not intended for use with a numerical scale. Instead, critical appraisal of the studies should involve considering the risk of potential for selection bias, information bias, measurement bias, or confounding within individual studies. The guidance encourages the user to think about each question in the tool and whether the answer determines the potential for bias in a study. A degree of subjective interpretation is recommended where the user must assess each individual aspect of study design to give an overall assessment of the study. The guidance encourages studies being rated categorically, but each study must be assessed on its own based on the details that it reports.

Responses to each question include “yes” [✓], “no” [✗], “don’t know” [?] (used when information is not clear or not able to be determined) and “not reported” [NR].

2.2.4.2 Cross-sectional studies

The AXIS appraisal tool was designed to appraise study quality, in terms of both design and reporting and the risk of bias, in cross-sectional studies. The tool was also used for studies that used cross-sectional analyses of longitudinal studies. The tool was developed using Delphi methodology, and is the first critical analysis tool for assessing exclusively cross-sectional studies. The tool considers the quality of the introduction, method, results, and discussion of studies, and allows assessment of biases in both methods and/or reporting of studies (Downes et al., 2016).

Previous reviews have applied a numerical scale to assess overall quality using AXIS, summing up scores to the 20 questions to allocate study quality into distinct categories (Marzi, Demetriou and Reimers, 2018; Allen, Walter and Swann, 2019). However, the guidance for the tool describes how numerical scales can be problematic as the sums from assessment checklists are not linear. The AXIS tool does not provide or recommend a numerical scale or specific method for assessing "overall" quality of the studies. Again, a degree of subjective interpretation is recommended (Downes et al., 2016).

The responses included: "yes" [✓], "no" [✗], "don't know" [?] (used when information is not clear or not able to be determined), not applicable [N/A], and "not reported" [NR].

2.2.4.3 All studies: risk of bias assessment.

There are three key factors that I believe to result in a lower risk of bias in the context of a relationship between demographic factors and working memory performance:

a) The selection of a defined target population with reference to the population's socioeconomic position and ethnicity, with an appropriate sampling frame and selection process.

b) The measurement or consideration of screening to categorise children as 'typically developing'. This must be specified in the inclusion criteria for the study.

c) The measurement of working memory using a validated and/or referenced task.

If a study met all three of these conditions, and successfully met the majority of the questions from the relevant quality assessment tool, it was labelled as low risk of bias. A study that did not meet any of the above three conditions was labelled as high risk of bias. If a study only met one or two of the above conditions, then the context of the study and the answers to other tool questions were considered to decide if it was at low or high risk of bias.

It is important to note that a study labelled as 'high' risk of bias does not necessarily constitute a poorly conducted and fundamentally biased study, but that the information derived from that study regarding the relationship between the exposures and outcome of interest to this review may be biased due to the above reasons. Risk of bias findings are reported in the quantitative synthesis and discussion of the review. Risk of bias findings are reported by study design, including all studies with any socioeconomic position or ethnic minority status exposure. Any meta-analyses will include a risk of bias sensitivity analysis to investigate the association of bias with effect estimates (Büttner et al., 2020b).

2.2.5 Data extraction

A summary table providing study characteristics of included studies is presented (Higgins and Green, 2011). Table 1 includes all studies with information on socioeconomic position (see Section 3. 4. 2), and Table 2 includes all studies with information on ethnic minority status (see Section 3. 5. 2.). This results in some studies being presented in both tables.

Data was extracted on the relevant exposure variables. Within the socioeconomic studies, data was extracted on ethnicity where possible. If data on ethnicity was not reported, the language children spoke was instead extracted. If neither ethnicity nor language were reported, this section was marked as "NR" (Not Reported).

2.2.6 Data synthesis: Socioeconomic Position

2.2.6.1 Meta-analyses

Meta-analyses were conducted to investigate the association between socioeconomic position and different components of WM. Meta-analyses synthesise the results of several studies into a single estimate. They increase the precision in the overall estimate between the exposure and the outcome, and provide the opportunity to investigate consistency and variation between the included studies (Borenstein et al., 2011, p.4). I conducted two meta-analyses to investigate the direction, magnitude, and precision of the relationship between socioeconomic position and WM.

Since the study outcomes are considered to vary between studies, I used a random effects meta-analysis model. In contrast to a fixed effects model that assumes that a single parameter value is common to all studies, a random-effects model assumes that parameters underlying studies are different, but related (Higgins, Thompson and Spiegelhalter, 2009). Study authors investigate the effect of socioeconomic position on working memory across many different age groups and using many different socioeconomic indicators, and so the variability across studies was anticipated to be at least moderate. In a random effects model, the standard errors of the study effect estimates are adjusted to incorporate a measure of the extent of variation, otherwise known as heterogeneity (Borenstein et al., 2011). Random-effects models allow for heterogeneity by assuming that the underlying effects follow some distribution. However, this does not mean that heterogeneity is 'taken account' of, in the sense that it no longer requires exploration (Deeks, Higgins and Altman, 2019). I explored heterogeneity in the review through the use of I^2, prediction intervals, and meta-regression (see Section 2.2.6.2).

In Chapter 1 I outlined the justification for use of the multicomponent working memory model to investigate separate components of WM. I therefore conducted two meta-analyses by the type of WM: (1) simple working memory and (2) complex WM, and presented by subgroup of verbal or visuospatial WM.

2.2.6.1.1 Eligible effect sizes

Two meta-analyses were conducted by the type of working memory: (1) simple working memory and (2) complex working memory. Studies were therefore included in a meta-analysis if they reported a useable (or convertible) unadjusted effect size between socioeconomic position and working memory on ≥1 task(s) of working memory that could be conceptualised as either simple working memory, or complex working memory. I also conducted subgroup estimation within both meta-analyses, depending on whether the task modality was verbal or visuospatial. A small number of studies combined verbal and visuospatial task modalities and in order to include as many studies as possible within this analysis, I still included those studies that had a combined score, as long as they had separate measurements of simple working memory and complex working memory.

Studies were not eligible for meta-analyses if they reported an eligible effect size between socioeconomic position and working memory on ≥1 task(s) of working memory that included both simple and complex memory. These were instead included in the Harvest plot.

Standardised mean difference scores use standard deviations to standardize the mean differences to a single scale (Higgins and Green, 2011). The standardised mean difference measure of Cohen's *d* effect size is calculated using the means of two groups and the standard deviation of the sample. It is a positively biased estimator of an effect size when a sample size is small (4% larger when $n \leq 20$ or 2% larger when $n \leq 50$) (Durlak, 2009). In this review, no studies had a total sample size of ≤20, and only one study had a sample size of ≤50 (Engel et al. $n = 40$). Cohen's *d* effect size was used without the bias correction. Where studies provided mean scores in individual tasks of working memory for two different groups of socioeconomic position, Cohen's *d* effect sizes were calculated using the Stata-16 default for the model using the Meta commands.

2.2.6.1.2 Converting between effect sizes

Cohen's *d* effect sizes were calculated for all studies that provided mean scores across two groups of socioeconomic position. Not all studies provided mean scores and I therefore converted correlations to Cohen's *d* effect size where possible, using formulae provided by Borenstein et al., (2009). Converting to different effect size measures means making certain assumptions about the nature of the underlying traits or effects within the studies. However, the alternative is to simply exclude the studies that happened to use an alternate metric. Excluding particular studies would involve loss of information, and possibly the systematic loss of information, resulting in a biased sample of studies (Borenstein et al., 2011, chap.7). It was therefore important to include a larger range of studies than just those reporting mean scores for two groups of socioeconomic position, so I converted different effect sizes to a common metric. Pearson's *r* correlation is a measure of the strength of the association between two variables that varies between -1 (a perfect negative correlation) to +1 (a perfect positive correlation) (Cohen, 1988). I extracted bivariate correlations where possible and computed effect sizes to Cohen's *d* using formulae using formulae provided by Borenstein et al., (2009) (see Appendices A3).

I considered methods available for converting other effect sizes to Cohen's *d*. Although methods do exist for combining regression coefficients in meta-analysis, the methods are limited as all studies should include the same covariates in order to compare the association between outcomes and exposures (Fernández-Castilla et al., 2019). Studies that use regression analysis tend to include a range of different covariates in their analysis, and were therefore not included in meta-analysis. Other methods do exist for converting a variety effect sizes to Cohen's *d*, for instance, using online calculators (Wilson, n.d.). However, many of the review studies did not include enough relevant information to compute the effect sizes, and precision would be lost through further conversion of potentially unreliable effect estimates (e.g. *p* values to Cohen's *d*). Where effect sizes were not included in the meta-analysis due to these reasons, studies were instead synthesised in a Harvest plot (see Figure 8).

2.2.6.1.3 Sensitivity analysis: dependent effect estimates

The majority of studies reported two or more effect sizes that were eligible for the meta-analyses (70%), e.g. socioeconomic position and working memory correlations for the same individuals at different ages or time points (e.g. Lensing and Elsner, 2018). The effect estimates cannot all be included separately in the dataset to be analysed, as a univariate meta-analysis would assume the observations are independent, resulting in incorrect weights with biased significance tests and confidence intervals (Hoyt and Del Re, 2018). Averaging the effect sizes to give one effect size per study may result in a loss of potentially important information, improper sampling variance, or a higher probability of type-2 errors (Van den Noortgate et al., 2014; Moeyaert et al., 2017; Hoyt and Del Re, 2018).

I first estimated the meta-analysis by averaging the effect sizes to give one effect size per study. As a sensitivity analysis, I re-estimated the meta-analyses using the robust variance estimation method, which accounts for statistically dependent effect sizes (Tanner-Smith and Tipton, 2014), and has been used by previously published reviews with similar dependency issues to estimate both a pooled effect size and test moderating characteristics (e.g. Peng et al., 2016). However, robust variance estimation only focuses on accurately estimating pooled effect sizes, using simplistic method-of-moments estimators to produce heterogeneity parameters. Robust variance estimation models do not provide precise variance parameter estimates nor test null hypotheses regarding heterogeneity parameters, and are not suitable methods if knowledge of the heterogeneity of the data are desired (Tanner-Smith, Tipton and Polanin, 2016).

As I wanted information regarding the heterogeneity of the data, but had concerns regarding the dependency in effect estimates, I used the two methods and compared their results in a sensitivity analysis. Pooled estimates were produced using by averaging the effect sizes to give one effect per study, this allows both an estimation of the overall effect size and an assessment of the statistical heterogeneity in the data. The Stata-16 command *Meta* was used to estimate an averaged pooled estimate, produce a forest plot, calculate a prediction interval, and estimate publication bias via funnel plots. Another pooled estimate was produced using robust variance estimation, applying the user written *ROBUMETA* command (Hedberg, 2014; Tanner-Smith, Tipton and Polanin, 2016).. The command was used to estimate an unconditional mean effect size and test whether it is significantly significant.

2.2.6.2 Heterogeneity

There are three distinguishable types of heterogeneity: clinical heterogeneity (variability in the participants, interventions, and outcomes studied), methodological heterogeneity (variability in study designs, outcome measurement tools, and risk of bias), and statistical heterogeneity – the consequence of clinical and methodological heterogeneity. Statistical heterogeneity is the variability in the effects that manifests as the observed effects being more different from each other than we would expect due to random error (Deeks, Higgins and Altman, 2019, chap.10). Heterogeneity is usually assumed to be present across studies in the social sciences, as such studies are likely to address different populations, exposures, and outcomes (Higgins, Thompson and Spiegelhalter, 2009).

I anticipated at least moderate statistical heterogeneity in the meta-analyses due to the broad inclusion criteria inducing clinical heterogeneity (including a large age range of participants and a variety of socioeconomic indicators) and the inherent methodological heterogeneity present in observational studies (differences in study design and risk of bias). When a meta-analysis has very high heterogeneity, a pooled estimate and its 95% confidence intervals do not indicate the real range of estimated effects (IntHout et al., 2016). Thus, heterogeneity was investigated using the two following test statistics:

- The I^2 statistic is a formal statistical test for the presence of heterogeneity. A rough guide to interpreting the statistic is: 0% to 40% (might not be important), 30% to 60% (may represent moderate heterogeneity), 50% to 90% (may represent substantial heterogeneity), and 75% to 100% (considerable heterogeneity) (Higgins and Green, 2011). However, the meaning of I^2 is difficult to interpret (Inthout et al., 2016).
- The 95% prediction interval was calculated and presented for overall effect sizes for simple and complex WM. Prediction intervals present the heterogeneity in the same metric as the original effect size measure. They illustrate the range of true effects which can be expected in future settings, and the clinical meaning of these intervals is much more straightforward than other heterogeneity measures (Inthout et al., 2016).

Heterogeneity was also investigated via meta-regression analyses. Meta-regression allows the effect of both continuous and categorical characteristics on the estimated effect size to be investigated. It estimates whether the association of interest (socioeconomic position and working memory) is associated with an investigated characteristic, where a significant *p* value indicates evidence that it is a significant moderator (Deeks, Higgins and Altman, 2021).

I tested moderation of the association between socioeconomic position and working memory with three characteristics as pre-specified on PROSPERO: (a) the type of socioeconomic indicator (whether it was a composite or single indicator), (b) the risk of bias (low or high), and (c) the task modality (verbal or visuospatial). I also tested three further post-hoc moderators; (d) the type of effect size (Cohen's *d* or converted from

Pearson's *r*), (e) whether the effect size had been averaged from >1 estimate(s) or not, and (f) the mean age of the sample. I wanted to ensure the effect sizes were not affected by the way they were converted or combined. I tested moderation by age as enough data was available to do so, and to investigate if this could explain the heterogeneity found. If the statistical significance test was $p<.05$, the tested variable was considered to be a significant moderator of the association between socioeconomic position and working memory.

2.2.6.3 Publication bias

Publication bias is a specific type of bias that refers to the publication or non-publication of research findings, depending on the nature and direction of the results (Boutron et al., 2019) (Boutron et al., 2019). It has been found that Randomised Control Trials (RCTs) with larger effect estimates and statistically significant results are more likely to be published, and observational studies may be at an even higher risk of publication bias than RCT's, particularly studies with small sample sizes (Thornton and Lee, 2000; Boutron et al., 2019).

To investigate the presence of publication bias, I used a funnel plot and Egger's test of bias. A funnel plot is a scatter of the effect estimates from individual studies against a measure of each study's size or precision. A symmetrical funnel plot indicates no relationship between study effect size and study precision, indicating low risk of publication bias. If the funnel plot is asymmetric, this may indicate publication bias. A funnel plot with effect estimates plotted against standard errors of effect estimates were generated in Stata. Egger's test tested if the association between study size and effect estimates is greater than to be expected by chance (Egger et al., 1997).

2.2.6.4 Harvest plot for remaining studies

Previous meta-analysis research regarding associations between socioeconomic position and working memory included only Pearson's r correlations (Lawson, Hook, and Farah, 2018). One of my objectives in this review was to include a broader range of studies to update understanding regarding the relationship between socioeconomic position and WM. I did not include studies in the meta-analysis if they used statistical methods that could not be synthesised, or composite measures of working memory that included both simple and complex WM. Excluding these studies from my review would have introduced a systematic bias into the results, so I sought to include the studies using other methods.

When studies are not suitable for meta-analysis, other data synthesis methods can be considered. One such method is the Albatross plot, which uses *p* values presented on a plot with effect size contours, demonstrating the potential range of effects (Harrison et al., 2017). However, the plot uses effect size contours on the same scale (e.g. all on Pearson's r, or all odds ratios) – and would therefore require several plots to summarise across all studies. I instead chose to use a Harvest plot, which plots the results on a matrix for each category of intervention (or exposure), weighting studies by the methodological criteria and distributing them between the competing hypotheses (Ogilvie et al., 2008). The Harvest plot synthesises studies into groups based on whether they demonstrate a positive, negative, or no relationship, and synthesises information on the different outcome measures, study designs, and study quality for each individual study. This means the reader can both judge where the majority of studies lie in relation to competing hypotheses, and judge where the highest quality studies are. Although the Harvest plot cannot infer the magnitude of associations, I considered it suitable for my review as it allowed complex information to be synthesised across a number of characteristics.

I synthesised the results of the remaining studies using a 'Harvest plot', alongside a summary table and narrative synthesis of the results. I plotted each type of exposure (each different socioeconomic indicator) and the competing hypotheses (whether a statistically significant positive or negative relationship was found to WM, or no relationship). Since some studies include numerous socioeconomic indicators, studies that report multiple effect sizes are represented in the plot more than once. The plot bar colours indicate the type of working memory outcome included (verbal, visuospatial, or a combination of both), and the plot bar lengths indicate whether the study was at low or high risk of bias. Each bar is labelled with the study ID, and a double asterisk indicates a cohort or longitudinal study. The results are presented across simple working memory and complex WM. As many of the 'Harvest plot' studies were not included in the meta-analysis since they used a combination of simple and complex WM, there is a plot for studies which used a 'composite' of simple and complex WM. As an aside, the summary table included key study characteristics that were presented in the meta-analyses, to ensure continuity across the different synthesis methods. The summary table contained the estimation method that study used, as this usually explained why the study was not included in the meta-analysis.

2.2.7 Data synthesis methods across all types and number of effect sizes

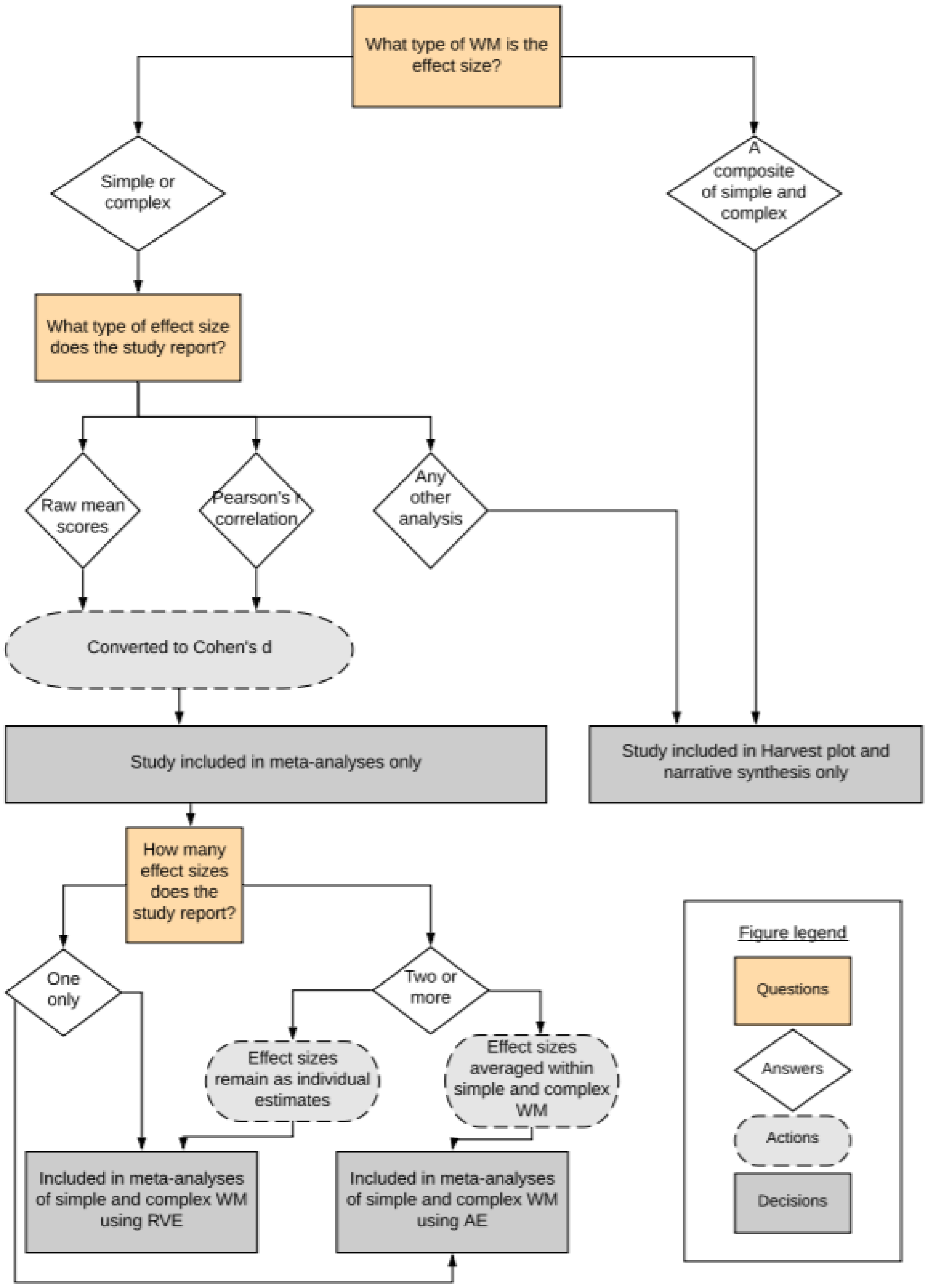


Figure 7. Flow diagram for pathways to inclusion in data synthesis methods

Abbreviations: Robust Variance Estimation (RVE), Averaging of Effect size (AE).

As there are numerous reasons described that would determine how a study was synthesised in the review, Figure 7 shows the flow of studies into different synthesising methods across meta-analyses or Harvest plot. Studies were included in the Harvest plot if they used a composite measure of WM, or if they used any analysis other than raw mean scores or Pearson's *r* correlation. Within the studies that are meta-analysed, the figure describes all study effect estimates were included in both the robust variance estimation analysis, and the analysis where effect sizes were averaged.

2.2.8 Data synthesis: Ethnicity

2.2.8.1 Forest plots

It was not feasible to conduct a meta-analysis of the association between ethnicity and working memory for several reasons. Few studies provided either mean scores that could be used to calculate an effect size, or a Pearson's *r* correlation that could be converted to a common effect size. The studies that provided information to be used in a meta-analysis included a variety of different ethnic minority and majority groups, and it may not have been appropriate to estimate a pooled statistic from such heterogeneous groups. Finally, few of the studies with this appropriate statistical information were rated as low risk of bias. It may not have been appropriate to produce a pooled estimate from studies that are mostly rated as high risk of bias. Instead, a forest plot was created using the Stata-16 *Meta* command to visualise the mean differences across the studies, with the pooled effect size and heterogeneity statistics suppressed.

2.2.8.1.1 Eligibility for forest-plots

Studies were eligible for inclusion in the forest plot if they reported raw mean scores in working memory across two different groups of ethnicities. As there were fewer studies reporting mean working memory scores across ethnic groups than across socioeconomic groups, the inclusion criteria for eligibility in the forest plot is broader than for the meta-analyses of SEP. Studies were eligible for inclusion if they reported any type of working memory score, including (1) simple WM, (2) complex WM, or (3) a combination of both simple and complex WM.

2.2.8.1.2 Effect size: eligible effect sizes and converting between them

The eligible effect sizes are the same as the eligible effect sizes for the meta-analyses of socioeconomic position and working memory (see Section 2.2.6.1). Again, I used the Stata-16 *Meta* command to produce Cohen's *d* from the studies reporting raw mean scores, and formula from Borenstein et al. (2011) to convert any Pearson's r correlations to Cohen's *d*.

2.2.8.2 Data synthesis of other studies

There were 6 studies that did not provide eligible effect estimates to be used in the forest plot. I did not produce a Harvest plot as this was not necessary for such a small number of studies, but instead created a summary table that included key study characteristics. The summary table contained the estimation method that each study used and the result from the study. These remaining studies were described and integrated with the studies from the forest plot. The description contains the key findings and characteristics of studies, and is structured by the risk of bias of individual studies, and by study designs.

2.3 **Results**

2.3.1 Study selection

The study selection process is reported according to the PRISMA STATEMENT (http://www.prisma-statement.org/) diagram.

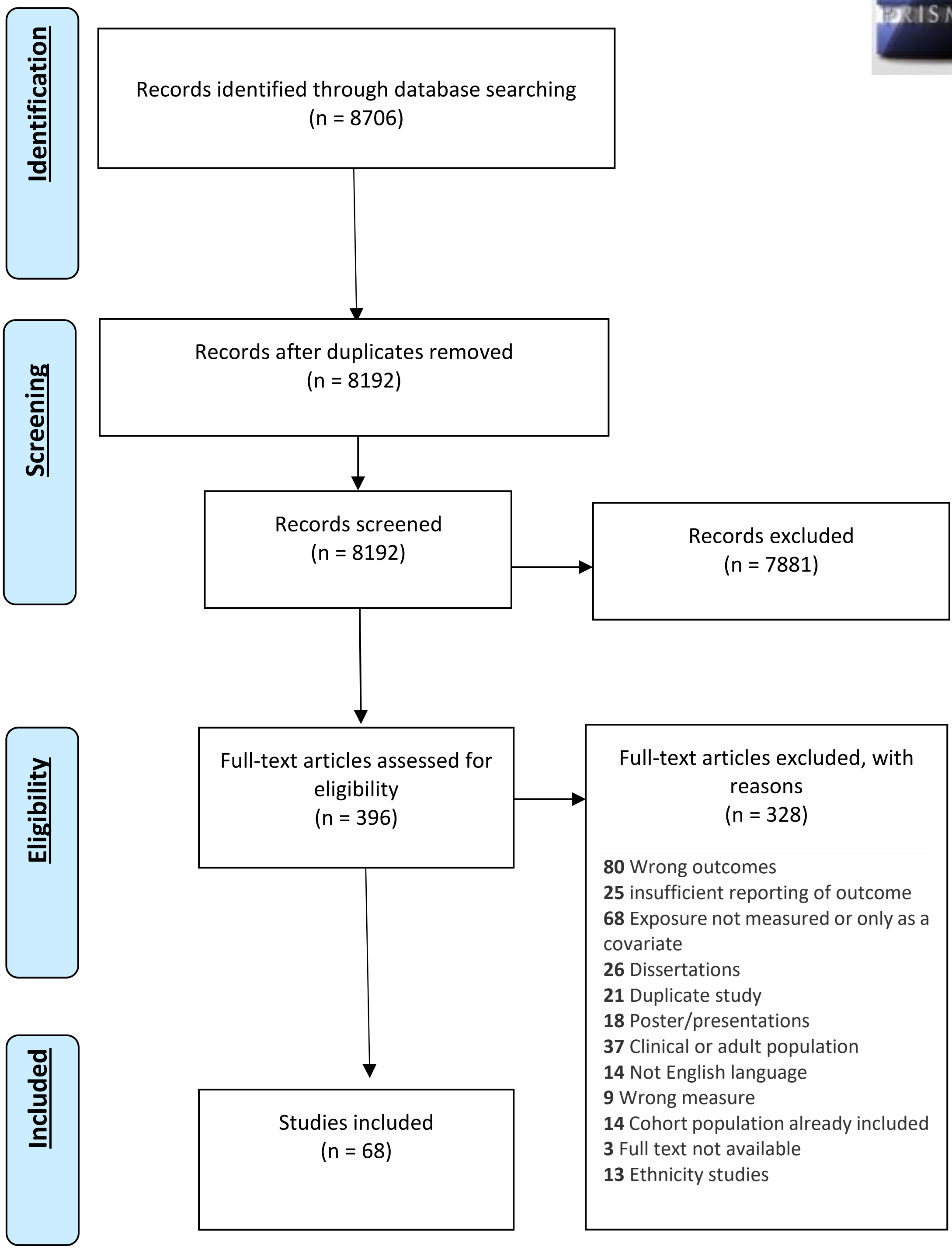


Figure 8. PRISMA diagram

The PRISMA diagram in Figure 8 describes the selection of the 64 studies eligible for the final review across both indicators of socioeconomic position and ethnic minority status. Of these, 54 contain information on only socioeconomic position, 4 on only ethnicity, and 10 studies contain information on both (and are therefore included across both reviews).

A full list of references included in the final review is provided in the appendices oh my thesis (Appendices A4). Two studies used the same population (the Early Childhood Longitudinal Study), but report different analyses for socioeconomic position and ethnicity (Little, 2017a; Wang and Fitzpatrick, 2019). Wang et al (2019) reported a correlation that is used in the SEP-WM meta-analysis, whereas Little (2017) reported regression coefficients that could not be used in meta-analysis. Little (2017) is used in the ethnicity section of the review, as Wang et al. (2019) did not report any information on ethnicity and WM.

Agreement with the second reviewer (MB) was found to be high at both screening stages, with 99% at abstract screening and 95% at full text screening. Agreement was also high at the data extraction stage (90%) and the risk of bias stage (95%)

2.3.2 Socioeconomic Position

2.3.2.1 Study selection

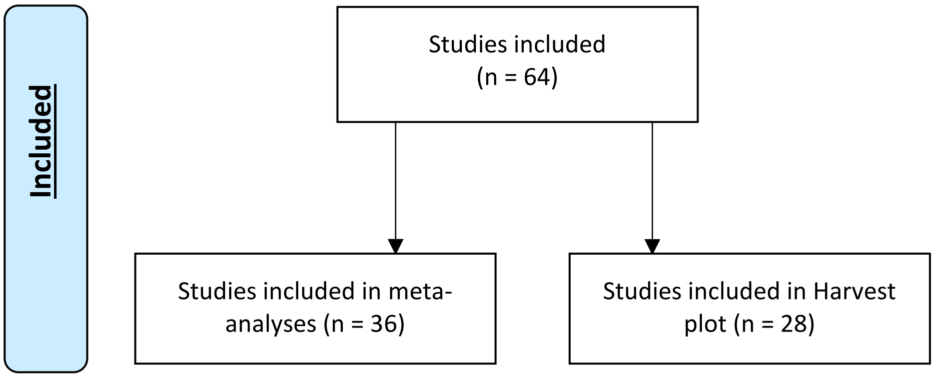


Figure 9. Studies included in the review regarding the association between socioeconomic position and working memory

Figure 9 shows the eligible studies for investigating the relationship between socioeconomic position and working memory (n = 64). There were 36 studies eligible for meta-analysis. There were 28 studies not eligible for meta-analysis due to the reasons described above, and these studies were instead included in the Harvest plot.

2.3.2.2 Study characteristics

Table 5. Extracted study characteristics for socioeconomic position and working memory

	Study details		Participant details			Exposure measure	Outcome measure		Risk of bias
	Author name	**Study location**	**Total n *(% male)***	**Age range *(M±SD)***	**Ethnicity/race/ language**	**Socioeconomic Position Indicator *(n in each group)***	**Working Memory task *(reference)***	**Effect size**	
					Studies included in meta-analyses				
1	Albert et al., 2020**	Southeast USA	203 (50%)	8-13 years (8.6±0.6) (9.6±0.6) (10.6±0.7) (13.2±0.4)	32.5% European American, 33.5% African American, 34% Latin American	(i) Parental educational attainment (ii) Family income at age 9 and 10	1. Verbal working memory (Thompson-Schill et al., 2002) 2. Spatial working memory – Corsi task (Chein and Morrison, 2010)	Converted from Pearson's r	LOW
2	Alloway et al. 2014	England	264 (48%)	51 – 68 months (NR)	100% British	A Classification of Residential Neighbourhoods (ACORN) *(low SEP n = 123, high SEP n = 141)*	1. BDR 2. Counting recall 3. Word recall (WMTBC, 2001)	Cohen's d	HIGH
3	Arán-Filippetti, 2013	Santa Fe, Argentina	248 (NR)	8 – 12 years (NR)	100% Spanish speaking	Socioeconomic coefficient of schools *(low SEP n = 124, high SEP n = 124)*	1. FDR 2. BDR 3. Letter number sequencing (WISC-IV)	Cohen's d	LOW
4	Babayiğit, 2014	England	168 (26%)	NR (115.38±3.57 months)	45% White British, 1 % White-Irish, 1% White Traveller Irish, 1 White Gypsy Roma, 2% Black-Caribbean, 15% Black-African, 11% Asian-Pakistani, 7% Asian-Bangladeshi, 4% Black-any other, 3% Asian-any other,	Free School Meals *(low SEP n = 53, high SEP n = 115)*	1. Listening recall (WMTB-C, 2001)	Converted from Pearson's r	HIGH

	Study details		Participant details			Exposure measure	Outcome measure		Risk of bias
	Author name	**Study location**	**Total n *(% male)***	**Age range *(M±SD)***	**Ethnicity/race/ language**	**Socioeconomic Position Indicator *(n in each group)***	**Working Memory task *(reference)***	**Effect size**	
					1% Chinese, and 9% White-any other background				
5	Bowey, 1995	Brisbane, Australia	48 (NR)	5 (65.11±4.44 months)	100% Native English speakers	Australian Standard Classification of Occupations (ASCO) *(low SEP n = 25, high SEP n = 23)*	1. Digit span (WISC) 2. Nonword repetition	Cohen's d	HIGH
6	Carlson and Meltzoff, 2008	Unknown	50 (52%)	58 – 83 months (72.3±5.33)	76% Monolingual English speakers, 24% bilingual Spanish/English speakers	(i) Maternal education (ii) Paternal education (iii) Annual family income	1. Visually cued recall	Converted from Pearson's r	LOW
7	Catale et al, 2012	Belgium	64 (30%)	6 – 7 years and 10 – 11 years (NR)	100% European native French speakers	Parental education *(low SEP n = 32, high SEP n = 32)*	1. Digit span 2. working memory task (Test Battery for Attentional Performance, Zimmermann and Fimm, 1994)	Cohen's d	LOW
8	Chung et al., 2017	Hong Kong	199 (50%)	44 – 67 months (58.25±3.76)	100% Chinese	Parental education, parental occupation and income-to-needs ratio [Composite] *(low SEP n = 97, high SEP n = 102)*	1. FDR 2. BDR (WISC-III)	Cohen's d	LOW
9	Corso et al. 2016	Southern Brazil	110 (51%)	9 – 12 years (135.85±12.46 months)	100% Brazilian	Brazillian Associação Brasileira de Empresas de Pesquisa (ABEP) (possession of goods, purchase of services, parental education) [Composite]	1. Pseudo word span 2. FDR 3. BDR (Child Brief Neuropsychological Assessment Battery, 2011)	Converted from Pearson's r	LOW
10	Deer et al. 2020**	UK Avon Longitudinal Study of Parents and Children (ALSPAC)	Approximately 7006 (53%)	0-5 years (NR), 8 years (NR) and 10 years (NR)	96% White	(i) Family income at ages 0-5 (ii) Parental education at age 8	1. Counting Span task at age 10 (Case, Kurland, & Goldberg, 1982)	Converted from Pearson's r	LOW

	Study details		Participant details			Exposure measure	Outcome measure		Risk of bias
	Author name	Study location	Total n *(% male)*	Age range *(M±SD)*	Ethnicity/race/ language	Socioeconomic Position Indicator *(n in each group)*	Working Memory task *(reference)*	Effect size	
11	Engel de Abreu et al. 2014	Sao Paulo City, Brazil	355 (49%)	6 – 8 years (89.11±7.84 months)	45% White, 11% Afro-Brazilian, 42% multiracial	Public and private schools *(low SEP n = 182, high SEP n = 173)*	1. Digit recall 2. Counting recall 3. Dot matrix 4. Odd-one-out (AWMA, 2007)	Cohen's d	LOW
12	Engel et al. 2008	Sao Paulo City, Brazil	40 (45%)	6 – 7 years (83.4±4.33)	100% Brazilian	Income, parental occupation, and parental education [Composite] *(low SEP n = 20, high SEP n = 20)*	1. Counting recall 2. BDR 3. FDR 4. Psuedoword repetition	Cohen's d	LOW
13	Finch and Obradović, 2017	San Francisco Bay, USA	102 (48%)	4 – 6 years (5.61±0.56)	36% White, 26% Hispanic/Latino, 20% Asian, 4% Black, 14% multiracial/other.	Family income, parental education, subjective social status, financial stress [Composite]	1. BDR	Converted from Pearson's r	LOW
14	Lawson and Farah, 2017	USA	336 (48%)	6 – 15 years (10.13±2.94 at first time point]	81% White, 8% African American/Black, 1% Asian, 2% Multiracial, 7% unknown ethnicity.	(i) Family income (ii) Parental education	1. Corsi (CANTAB) 2. Spatial working memory (CANTAB) 3. Digit span – FDR & BDR (WISC-III)	Converted from Pearson's r	LOW
15	Lensing and Elsner, 2018 **	Brandenburg, Germany	1596 (47%)	6 – 7 years (7.35±0.41) 8 – 9 years (8.90±0.52)	NR	Maternal education	1. BDR (WISC) {at three time points}	Converted from Pearson's r	LOW
16	Lima et al. 2020	Brazil	569 (52%)	7-12 years (9.51±1.52)	NR	(i) Maternal education (ii) Family income	1. Corsi Block Tapping Task – forwards 2. Corsi Block Tapping Task – backwards (Kessels et al. 2000)	Converted from Pearson's r	LOW
17	Lipina et al. 2013	Buenos Aires, Argentina	250 (46%)	NR (4.87±0.59)	100% Argentine	Unsatisfied Basic Needs with at least one of: (1) inappropriate housing, (2) absence of waste systems in household, (3)	1. Corsi blocks (Pickering, 2001)	Cohen's d	HIGH

	Study details		Participant details			Exposure measure	Outcome measure		Risk of bias
	Author name	**Study location**	**Total n *(% male)***	**Age range *(M±SD)***	**Ethnicity/race/ language**	**Socioeconomic Position Indicator *(n in each group)***	**Working Memory task *(reference)***	**Effect size**	
						overcrowding, (4) school-aged children not in education, (5) head of household with incomplete primary school *(low SEP n = 92, high SEP n = 146)*			
18	Madhushanthi et al., 2018	Galle, Sri Lanka	200 (0%)	11 – 14 (12.21±1.15)	84% Sinhalese, 16% unknown	(i) Maternal education (ii) Parental education (iii) Parental occupation (iiii) Family income [& composite for group analysis] *(low SEP n = 112, high SEP n = 88)*	1. Digit span (WISC-IV) 2. Arithmetic (WISC-IV) 3. Visuospatial (WISC-IV)	Cohen's d	LOW
19	Malda et al. 2010	South Africa	501 (51%)	Grades 3 - 4 (9.37±1.05)	32% White Urban Afrikaans, 36% Black urban Tswana, 32% Black rural Tswana	Children were asked six questions as an indication of SES: (1) do you have your own room? (£) how many TVs are there in your house (3) is there a microwave in your house? (4) how many cellphones does your family have? (5) how many cars does your family have? (6) do you have reading books at home? [Composite]	1. Short term memory 2. working memory test (WMTB-C, 2001) {adapted for two different cultures}	Converted from Pearson's r	HIGH
20	Markovits and Brunet, 2012	Montreal, Canada	205 (49%)	Grade 1 (6 years 4 months) Grade 2 (7 years 5 months)	NR	Lower: two low SEP public school in poor districts *(n = 92)* Higher: one high SEP public school in suburbs of Montreal *(n = 113)*	1. Digit span	Cohen's d	HIGH
21	Metaferia et al. 2020	Ethiopa	102 (56%)	50-74 months (62.08±7.66)	NR	Parent education and income [Composite]	1. Mr Peanut task (Kemps et al., 2000; Morra, 1994)	Converted from Pearson's r	HIGH
22	Ming et al. 2021	Southern and Northern China	888 (57%)	9-13 years (10.68±1.07)	NR	Family income, parental education, parental occupation [Composite]	1. Visual patterns test (Sala et al, 1999)	Converted from Pearson's r	HIGH

	Study details		Participant details			Exposure measure	Outcome measure		Risk of bias
	Author name	**Study location**	**Total n *(% male)***	**Age range *(M±SD)***	**Ethnicity/race/ language**	**Socioeconomic Position Indicator *(n in each group)***	**Working Memory task *(reference)***	**Effect size**	
23	Nesbitt et al. 2013 **	NR	206 (51%)	6, 12, 30, and 36 months at 4 data collections	43% European American, 57% African American	(i) Income to needs (ii) Maternal education (Aggregated from 6 – 36 months visits)	1. BDR (McCarthy Scales of Children's Abilities, 1972) (measured during kindergarten age)	Converted from Pearson's r	LOW
24	Noble et al. 2007	New York City	168 (48%)	First grade (NR)	34% African-American, 7% Asian, 23% Latino, 23% White, 14% Mixed/other	Parental education, income-to-needs, parental occupation [Composite]	1. Spatial working memory (Klingberg et al. 2002) 2. Delayed nonmatch to sample (Marks et al. 2001) {composite and individual tests}	Converted from Pearson's r	LOW
25	Noble et al. 2005	Philidelphia	60 (50%)	NR (5 years 10 months ±NR)	100% African American	Parental education, parental occupation, income-to-needs *(Low SEP n = 30, high SEP n = 30)*	1. Spatial working memory (Hughes, 1998)	Cohen's d	LOW
26	Philbrook et al. 2017**	Southeastern United States	282 (52%)	9 – 11 years (9.44±0.71, at the first wave)	65% European American, 35% African American	Income-to-needs ratio	1. working memory test (WJ-III)	Converted from Pearson's r	LOW
27	Pina et al. 2014 **	Mucia, Southeastern Spain	102 (45%)	9 – 13 years (10 years ± 11 months)	74% Spanish speakers born in Spain, 8% born outside Spain by non Spanish parents, 18% unknown	Parental education	1. Corsi forward (Kessels et al 2001, 2008) 2. Corsi Backward (Kessels et al 2001, 2008) 3. FDR 4. BDR	Converted from Pearson's r	LOW
28	Riva et al. 2017	Italy	646 (female: male ratio = .9)	6 – 11 years (8.22±1.17)	100% Italian	Parental occupation (Hollingshead, 1975)	1. FDR 2. BDR	Converted from Pearson's r	LOW
29	Rosen et al. 2020**	Seattle, USA	101 (50%)	60-75 months (5.55±0.37)	67.3% White, 14.8% Black, 2.9% American Indian or Alaska Native, 12.8% Asian, 0.9% Native Hawaiian or Pacific Islander, 0.9% Other; 8.9% Hispanic or Latino	(i) Income to needs (ii) Parental education	1. BDR	Converted from Pearson's r	LOW

	Study details		Participant details			Exposure measure	Outcome measure		Risk of bias
	Author name	**Study location**	**Total n *(% male)***	**Age range *(M±SD)***	**Ethnicity/race/ language**	**Socioeconomic Position Indicator *(n in each group)***	**Working Memory task *(reference)***	**Effect size**	
30	St John et al. 2019	USA	121 (42%)	4 – 5 years old (5.02±0.29)	43% White, 12% Black, 11% Hispanic, 10% Asian, 22% Multiracial	Maternal and paternal education level, household income, household composition, and maternal and paternal occupation. [Composite]	1. Change detection task – accuracy at two set sizes 2. Change detection task – reaction time at two set sizes (Luck and Vogel, 1997)	Converted from Pearson's r	LOW
31	Stumper et al. 2020**	USA Adolescent Cognition and Emotion (ACE) project	243 (47%)	12-16 (13.01±.79) (14.09±.81)	47.3% White/Caucasian, 49.0% Black/African American, 3.7% Biracial/other Individuals who identified as members of other racial or ethnic groups were excluded.	(i) Family income (ii) Maternal education	1. FDR 2. BDR (WISC-IV; Wechsler, 2003)	Converted from Pearson's r	LOW
32	Suor et al. 2017	Northeastern USA	185 (53%)	3.5 – 5 years old (NR)	59% European American, 19% African American, 3% Latino, 15% Biracial, 1% Asian, 3% Native American/Alaskan	(i) Maternal education at age 3.5 (ii) Income-to-needs (iii) Neighbourhood characteristics (iiii) Family SES composite	1. Backword word span at age 5 (Carlson, Moses and Breton, 2005) 2. PathSpan application (Hume, 2012) {Individual and composites} {WM at age 5}	Converted from Pearson's r	LOW
33	Wang and Fitzpatrick ,. 2019**	USA Early Childhood Longitudinal Study-Kindergarten class	14,000 (51%)	4-8 years (NR)	50% White, non-Hispanic, 13% Black/African American, non-Hispanic, 24% Hispanic, 7% Asian, non-Hispanic, 1% Native Hawaiian/Pacific Islander, non-Hispanic, 1% American Indian/Alaska native, non-Hispanic, 4% Two or more races, non-Hispanic	Family income and parental education [Composite]	1. BDR	Converted from Pearson's r	LOW
34	Waters et al 2021	USA National Institute of Child Health and	990 (52%)	4-5 years (4.64±0.09)	86% White, 14% Black	(i) Income to needs (ii) Parent education	1. Memory for sentences (Woodcock-Johnson Revised; Woodcock and Johnson, 1989)	Converted from Pearson's r	LOW

	Study details		Participant details			Exposure measure	Outcome measure		Risk of bias
	Author name	**Study location**	**Total n *(% male)***	**Age range *(M±SD)***	**Ethnicity/race/ language**	**Socioeconomic Position Indicator *(n in each group)***	**Working Memory task *(reference)***	**Effect size**	
		Development Study of Early Child Care and Youth Development (NICHD SECCYD)							
35	Wei et al. 2020	Shanghai, China	173 (51%)	(67.25±3.67 months)	NR, Native Mandarin speakers	Parent education, parent monthly income [Composite]	1. BDR (WISC-R; Wechsler, 1974)	Converted from Pearson's r	LOW
36	Wiebe et al. 2008	NR	243 (44)	2 – 6 years old (3 years 11 months±12 months)	70% White, 18% African American, 4% Asian American, 0.4 Native American, 1.7% Hispanic, 6% Multiracial	Maternal education in years	1. Delayed alternation (Espy et al. 1999) 2. Six boxes 3. Digit span (Elliott, 1990)	Converted from Pearson's r	LOW
					Studies included in Harvest plot				
1	Aran-Filippetti & Richaud De Minzi, 2012	Santa Fe, Argentina	254 (50%)	7 – 12 (9.66±1.29)	100% Argentinian	Class of neighbourhoods and socioeconomic coefficient of schools [Composite] *(low SEP n = 129, high SEP n = 125)*	1. Digit span 2. Letter-number sequencing (WM Index of WISC-IV) [Composite]	*P* value (stepwise regression)	LOW
2	Brito et al., 2021	New York City, USA	92 (61%)	18 months (18.51±0.66)	NR, range of both monolingual and bilingual speakers	Maternal education, income, and income to needs [Composite]	1. Hide the pots (Bernier, Carlson & Whipple, 2010)	*P value (ANOVA)*	LOW
3	Cockcroft, 2016	South Africa	120 (51%)	6 – 8 years (6.73±.63)	55% Monolingual English speakers, 45% bilingual English and African speakers	Living Standards Measure (South African Audience Research Foundation, 2001 – number of people in household, type of dwelling, housing tenure, area). Also occupational status and highest educational level.	1. Digit recall 2. Non-word recall 3. Counting recall 4. BDR (AWMA, 2007)	*P* value (two-way Mancova)	LOW

	Study details		Participant details			Exposure measure	Outcome measure		Risk of bias
	Author name	**Study location**	**Total n *(% male)***	**Age range *(M±SD)***	**Ethnicity/race/ language**	**Socioeconomic Position Indicator *(n in each group)***	**Working Memory task *(reference)***	**Effect size**	
						[Composite]			
4	Daubert and Ramani, 2020	Mid-Atlantic USA	74 (47%)	4-5 years (4.11±NR)	58% Caucasian/White, 23% African American or Black, 11% Asian or Pacific Islander, 7% bi or multiracial, 1% American Indian or Alaska Native	Parent education and household income [Composite]	2. Frog matrices task (Morales et al., 2013)	*P* value (Regression)	LOW
5	Dicataldo and Roch, 2020	Padua, Northeast Italy	115 (54%)	44-75 months (61.9±6.8)	NR, range of both monolingual and bilingual speakers	Parental education and annual family income [Composite]	1. FDR 2. BDR (WISC) [Composite]	*P* value (Pearson's r correlation)	HIGH
6	Dilworth-Bart, 2012	Mid-west USA	49 (53%)	54 – 66 months (NR)	22% African American/Black, 2% Asian/Pacific islander, 61% White, 14% multi-racial	Maternal education and household income [Composite]	1. Verbal WM 2. Nonverbal WM [Composite] (SB5; Roid, 2003)	*P* value (Pearson's r correlation)	HIGH
7	Farah et al. 2006	Philadelphia	60 (43%)	10 – 13 years (11.7±1.0)	100% African American	Parental occupation (Hollingshead), parental education, and low SEP mothers on state and medical assistance [Composite]	1. Spatial working memory (CANTAB, 1997) 2. Two-back	*P* value (Mancova)	LOW
8	Fernald et al., 2011	Madagascar	1232 (48%)	3 – 6 (NR)	NR	Maternal education and household wealth [Composite] *(groups of maternal education n: none = 286, primary = 692, secondary and above = 254)*	1. working memory subtest (SB5) 2. Memory of phrases (Woodcock and Munoz, 1996)	*P* value (linear regression)	HIGH
9	Flouri et al., 2019**	UK Millennium Cohort Study (MCS)	4756 51%)	0 – 11 years	74% White, 26% NR	(i) Maternal education (ii) Family poverty (household income below poverty line) (iii) Neighbourhood deprivation	1. Spatial working memory at age 11 (CANTAB; Robbins et al., 1994) – simple but check	*P* value (multilevel regression model)	LOW
10	Guerra et al. 2020	Rio Grande do Norte, Brazil	230	7-12 years	100% Brazillian	Public and private schools (low SEP n = 116, high SEP n = 114)	1. Visuospatial updating 2. Verbal updating	*P* value (ANOVA)	LOW

	Study details		Participant details				Exposure measure	Outcome measure		Risk of bias
	Author name	**Study location**	**Total n *(% male)***	**Age range *(M±SD)***	**Ethnicity/race/ language**		**Socioeconomic Position Indicator *(n in each group)***	**Working Memory task *(reference)***	**Effect size**	
								(Child Executive Function Battery; Roy et al., 2020)		
11	Hou et al. 2020	Anhui, China	142	9-10 years (10.01±2.62)	NR		(i) Paternal education (ii) Maternal education (iii) Monthly family income	1. FDR and BDR 2. Letter number sequencing (WISC-IV)	*P value (correlations)*	LOW
12	Hackman et al. 2014 **	NR	316 (46%)	10 – 13 years & four years later (14.05±0.9)	61% White, 26% African American, 10% Asian/Pacific Islander, .3% Native American, 3% Mixed, 8% Hispanic/Latino		(i) Parental education (ii) neighbourhood disadvantage	1. BDR (WISC-IV) 2. Corsi 3. Spatial WM 4. Object two-back [Composite]	*P* value (Multilevel model)	LOW
13	Hackman et al. 2015 **	USA	1009 (50%)	1 – 54 months (NR)	83% White, 11% African-American, 1% Asian/Pacific Islander, 0.2% American Indian, 4% Other, 5% Hispanic/Latino.		(i) Income to needs average from 1, 6, 15, 24, and 26 months (ii) Maternal education at 1 month	1. Memory for sentences (WJ-R COG; Woodcock, 1990) [measured at 54 months]	*P* value (Multilevel model)	LOW
14	He and Yin, 2016	Shaanxi, China	157 (59%)	8 – 12 years (9.9±1.31)	100% Chinese		Subjective family material environment (Adler et al. 2010) Parental education and occupation (Hollingshead) [Composite]	1. FDR 2. BDR (WISC-III) [Composite]	*P* value (Partial correlations)	LOW
15	Jacobsen et al. 2017	Porto Alegre, Brazil	274 (45%)	6 – 12 years (8.92±1.90)	NR		Brazilian Economic Classification (parental education and living conditions)	Random Number Generation (Towse and Neil, 1998)	*P* value (Linear regression)	HIGH
16	Kobrosly et al. 2011 **	Seychelles	463 (48%)	6 months – 17 years (NR)	100% Seychellois		(i) Hollingshead Social Status Index (maternal occupation and education) at 6 months (ii) 107 months (iii) 17 years	1. Delayed match to sample 2. Spatial recognition memory 3. Spatial WM (CANTAB) {at 17 years old}	*P* value (Linear regression)	LOW
17	Korecky-Kroll et al., 2019	Vienna	56 (50%)	49 – 56 months (53.12±1.4)	52% monolingual German speaking, 48% bilingual Turkish and German speaking		Parental education and parental occupation [Composite]	1. Phonological working memory (SETK 3-5; Grimm, 2001)	*P* value (Kruskal Wallis test)	LOW
18	Leonard et al. 2015	USA	58 (47%)	NR (14.41±0.42)	Lower-SES group: 22% African American, 4% Asian, 54% White, 4% Native		Free or reduced school meals *(low SEP n = 23, high SEP n = 35)*	1. Counting span (Conway et al. 2005, Cowan et al. 2005)	*P* value (Anova)	LOW

	Study details		Participant details			Exposure measure	Outcome measure		Risk of bias
	Author name	**Study location**	**Total n *(% male)***	**Age range *(M±SD)***	**Ethnicity/race/ language**	**Socioeconomic Position Indicator *(n in each group)***	**Working Memory task *(reference)***	**Effect size**	
					Hawaiian or Pacific Islander, 26% multiple races, 35% not Hispanic, 65% Hispanic, 35% did not report race. Higher-SES group: 6% African American, 14% Asian, 54% White, 3% Native Hawaiian or Pacific Islander, 17% multiple races, 6% did not report race; 91% not Hispanic, 3% Hispanic, 6% did not report ethnicity				
19	Maguire and Schneider, 2019	NR	90 (40%)	8-15 years (10.9±2.14)	NR, 100% fluent English speakers and 37% Spanish-English bilingual speakers	Maternal education	1. Digit span (Blackburn & Benton, 1957) (NR if forwards or backwards)	*P* value (Linear regression)	HIGH
20	Miconi et al. 2019	Northeast Italy	488 (NR but balanced)	11 – 13 years (12.11±0.80)	24% Moroccan immigrants, 25% Romanian immigrants, 51% non-immigrant Italians	Family Affluence Scale (Currie et al., 2008) Material affluence reported by adolescents themselves	1. FDR 2. BDR [Composite]	*P* value (Bivariate correlations)	LOW
21	Murtaza et al. 2019	Negeri Sembilan, Malaysia	269 (51%)	2-6 years (4.03±1.21)	Indigenous Orang Asli	(i) Maternal education (ii) Paternal education (iii) Maternal income (iiii) Paternal income	1. Picture memory 2. Zoo location (WMI, WPPSY-IV) [Composite]	*P* value (Linear regression)	LOW
22	Passareli-Carrazzoni et al. 2018	Sao Paulo state, Brazil	96 (52%)	9 – 10 years (9.5±0.5)	NR	(i) Family composition (one or two parents) (ii) Monthly family income (iii) Maternal schooling in years	1. Digit span 2. Arithmetic 3. Letter-number-sequencing [Composite]	*P* value (Linear regression)	LOW
23	Piccolo et al. 2019	USA	108 (58%)	9 – 18 years (14.10±1.76)	NR	(i) Yearly family income (ii) Parental educational attainment	1. List-sorting working memory test (NR)	*P* value (Linear regression)	HIGH
24	Rhoades, 2012 **	Pennsylvania	1155 (approx. 50%)	2, 7, 24, and 36 months	60% White, 40% African American	LCA to create risk classes in different ethnic groups based on household income, unmarried,	1. working memory task (NR)	*P* value (Linear regression)	LOW

	Study details		Participant details			Exposure measure	Outcome measure		Risk of bias
	Author name	Study location	Total n *(% male)*	Age range *(M±SD)*	Ethnicity/race/ language	Socioeconomic Position Indicator *(n in each group)*	Working Memory task *(reference)*	Effect size	
				old at each visit		partner status, teen mother, no high school diploma, mood problems, smking during pregnancy, high stress, low social support, and crowded house			
25	Rowe et al. 2016	California	501 (48%)	6 month, 1, 2, 3.5, 5, 7, 9 and 10.5 years old at each visit	96% Latina, 4% other ethnicity	(i) Household poverty status as a binary variable (ii) Neighbourhood poverty status in quartiles) (At the 10.5 year visit)	1. working memory subscale (WISC-IV) (at 10.5 year visit)	*P* value (Linear regression)	LOW
26	Sarsour et al. 2011	San-Francisco	60 (31%)	8 – 12 years (9.9±0.96)	100% Brazilian	The MacArthur Research Network on SES and Health questionnaire, family income-to0needs ratio, parental occupation via Hollingshead (1975), family wealth, and maternal education [Composite]	1. Pseudo word span 2. FDR 3. BDR [Composite] (Child Brief Neuropsychological Assessment Battery, Salles et al. 2011)	*P* value (Correlation)	LOW
27	Tine, 2014	NR	186 (52%)	10 – 12 years (11.3±NR)	In rural schools; 96% White. Low-income urban schools: 62% ethnic minority. High income urban school: 36% ethnic minority (Ethnic minorities include American Indian, Alaskan Native, Asian, Black/African American, or Pacific Islander)	Low SEP: 1) Attended a school that serves a community with a median family income below the national median family income of $50,033. 2) Attended a school in which at least 75% of students qualify for FSM or reduced. 3) They themselves qualified for FSM. Divided into urban and rural schools *(n = 94)* High SEP: 1) Attended a school that serves a community with a median family income above the national median. 2) Less than 25% of the school were on FSM. 3) They did not qualify for FSM. Divided into urban and rural schools *(n = 92)*	1. Listening recall 2. BDR 3. Odd-one-out 4. Mr X (AWMA, 2007)	*P* value (t-test)	LOW

	Study details		Participant details			Exposure measure	Outcome measure		Risk of bias
	Author name	**Study location**	**Total n *(% male)***	**Age range *(M±SD)***	**Ethnicity/race/ language**	**Socioeconomic Position Indicator *(n in each group)***	**Working Memory task *(reference)***	**Effect size**	
27	Vandenbroucke et al. 2016	Belgium	78 (65%)	5 – 6 years old (5.88±0.29)	92.5% Monolingual Dutch speakers born in Belgium, 8% Bilingual, 5% not Belgium born	Low SEP: single parent and low-income families, with a young low-educated mother who more often smoked during pregnancy *(n = 21)* High SEP: mainly two-biological-parent high income families, with a highly educated mother who did not smoke during pregnancy *(n = 57)*	1. Verbal WM: Digit recall, word recall, listening recall, BDR 2. Visuospatial WM: dot matrix, block recall, odd-one-out and Mr-X (AWMA; Alloway, 2007)	*P* value (t-test)	LOW

Notes: 1. Age range is in years unless otherwise stated.

2. In author name: **Means study is longitudinal or cohort study, all other study designs are cross-sectional.

3. In the socioeconomic position column, (i) indicates that the study analysed an indicator of socioeconomic position on its own, rather than as a composite.

4. Abbreviations: A Classification of Residential Neighbourhoods (ACORN), Associação Brasileira de Empresas de Pesquisa (ABEP criteria, www.abep.org) Backwards Digit Recall (BDR), Forwards Digit Recall (FDR), Working Memory Test Battery for Children (WMTB-C), Wechsler Intelligence Scales for Children (WISC), Automated Working Memory Assessment (AWMA), Woodcock Johnson (WJ), Stanford Binet Intelligence Scales for Early Childhood, 5th edition (SB5), Cambridge Neuropsychological Test Automated Battery (CANTAB) and not reported (NR).

2.3.2.3 Risk of bias results

The risk of bias results are displayed below, separated by the tool used for cross-sectional or longitudinal studies. A descriptive summary is then provided to assess the overall risk of bias in studies.

2.3.2.3.1 Cross-sectional studies

Table 6. Quality assessment and risk of bias of cross-sectional socioeconomic position studies (using AXIS tool)

Authors		**AXIS tool question**																				**Risk of bias**
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	
Studies included in meta-analysis																						
1	Albert et al., 2020**	N/A – assessed with longitudinal tool																				LOW
2	Alloway et al. 2014	✔	✔	✗	✔	NR	NR	✗	✔	✔	✔	NR	✔	N/A	N/A	✔	?	✔	✔	✗	NR	HIGH
3	Arán-Filippetti, 2013	✔	✔	✗	✔	✔	✔	✗	✔	✔	✔	✔	✔	N/A	N/A	✔	✔	✔	✔	✗	✔	LOW
4	Babayiğit, 2014	✔	✔	✗	✔	NR	NR	✗	✔	✗	✔	✔	✔	N/A	N/A	✔	?	✔	✔	✗	✔	HIGH
5	Bowey, 1995	✔	✔	✗	✔	NR	NR	✔	✔	✔	✔	NR	✔	✔	✔	✔	✔	✔	✗	✗	✔	HIGH
6	Carlson and Meltzoff, 2008	✔	✔	✗	✔	✔	✔	✗	✔	✔	✔	✔	✔	N/A	N/A	✔	✔	✔	✔	✗	✔	LOW
7	Catale et al, 2012	✔	✔	✗	✔	✔	✔	✗	✔	✔	✔	✔	✔	N/A	N/A	✔	✔	✔	✔	✗	✔	LOW
8	Chung et al., 2017	✔	✔	✗	✔	✔	NR	✗	✔	✔	✔	✔	✔	N/A	N/A	✔	✔	✔	✔	✗	✔	LOW
9	Corso et al. 2016	✔	✔	✗	✔	✔	✔	✗	✔	✔	✔	✔	✔	N/A	N/A	✔	✔	✔	✔	✗	✔	LOW
10	Deer et al. 2020**	N/A – assessed with longitudinal tool																				LOW
11	Engel de Abreu et al. 2014	✔	✔	✗	✔	✔	✔	✗	✔	✔	✔	NR	✔	N/A	N/A	✔	?	✔	✗	✗	✔	LOW
12	Engel et al. 2008	✔	✔	✗	✔	✔	✔	✗	✔	✔	✔	NR	✔	N/A	N/A	✔	?	✔	✔	✗	✔	LOW
13	Finch and Obradović, 2017	✔	✔	✗	✔	NR	NR	✗	✔	✔	✔	✔	✔	NR	✗	✔	✔	✔	✔	✗	NR	LOW
14	Lawson and Farah, 2017	✔	✔	✔	✔	✔	✔	✗	✔	✔	✔	✔	✔	N/A	N/A	✔	✔	✔	✔	✗	✔	LOW
15	Lensing and Elsner, 2018 **	N/A – assessed with longitudinal tool																				LOW
16	Lima et al. 2020	✔	✔	✗	✔	✔	NR	✗	✔	✔	✔	✔	✔	N/A	N/A	✔	✔	✔	✔	✗	✔	LOW
17	Lipina et al. 2013	✔	✔	✗	✔	✔	NR	✗	✔	✔	✔	✔	✔	N/A	N/A	✔	✔	✗	✗	✗	✔	HIGH

	Authors	**AXIS tool question**																				**Risk of bias**
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	
18	Madhushanthi et al., 2018	✔	✔	✗	✔	✔	✔	✗	✔	✔	✔	✗	✔	N/A	N/A	✗	?	✔	✔	✗	✔	LOW
19	Malda et al. 2010	✔	✔	✗	✔	✔	NR	✗	✔	✗	✔	NR	✔	N/A	N/A	✔	?	✔	✔	✗	✔	HIGH
20	Markovits and Brunet, 2012	✔	✔	✗	✔	?	NR	✗	✔	✔	✔	✔	✔	N/A	N/A	✔	✔	✔	✗	✗	NR	HIGH
21	Metaferia et al. 2020	✔	✔	✗	✔	✔	NR	✗	✔	✗	✔	✔	✔	N/A	N/A	✔	✔	✔	✔	✗	✔	HIGH
22	Ming et al. 2021	✔	✔	✗	✔	✔	NR	✗	✔	✔	✔	✔	✔	N/A	N/A	✔	✔	✔	✔	✗	✔	HIGH
23	Nesbitt et al. 2013 **	N/A – assessed with longitudinal tool																				LOW
24	Noble et al. 2007	✔	✔	✗	✔	✔	✔	✗	✔	✔	✔	NR	✔	N/A	N/A	✔	?	✔	✗	✗	✔	LOW
25	Noble et al. 2005	✔	✔	✗	✔	✔	✔	✗	✔	✗	✔	NR	✔	N/A	N/A	✔	?	✔	✔	✗	✔	LOW
26	Philbrook et al. 2017**	N/A – assessed with longitudinal tool																				LOW
27	Pina et al. 2014 **	N/A – assessed with longitudinal tool																				LOW
28	Riva et al. 2017	✔	✔	✗	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✗	✔	LOW
29	Rosen et al. 2020**	N/A – assessed with longitudinal tool																				LOW
30	St John et al. 2019	✔	✔	✗	✔	NR	✔	✗	✔	✔	✔	✔	✔	N/A	N/A	✔	✔	✔	✔	✗	✔	LOW
31	Stumper et al. 2020**	N/A – assessed with longitudinal tool																				LOW
32	Suor et al. 2017	✔	✔	✗	✔	✔	NR	✗	✔	✔	✔	✔	✔	✗	✔	✔	✔	✔	✔	✗	NR	LOW
33	Wang and Fitzpatrick,. 2019**	N/A – assessed with longitudinal tool																				LOW
34	Waters et al. 2021	N/A – assessed with longitudinal tool																				LOW
35	Wei et al. 2020	✔	✔	✗	✔	✔	NR	✗	✔	✔	✔	✔	✔	N/A	N/A	✔	✔	✔	✔	✗	✔	LOW
36	Wiebe et al. 2008	✔	✔	✗	✔	✔	NR	✗	✔	✔	✔	✔	✔	N/A	N/A	✔	✔	✔	✗	✗	NR	LOW
Studies included in Harvest plot																						
1	Aran-Filippetti & Richaud De Minzi, 2012	✔	✔	✗	✔	✔	✔	✗	✔	✔	✔	✔	✔	N/A	N/A	✔	✔	✔	✗	✗	✔	LOW
2	Brito et al., 2021	✔	✔	✗	✔	✔	✔	✗	✔	✔	✔	✔	✔	N/A	N/A	✔	✔	✔	✔	✗	✔	LOW

Authors		**AXIS tool question**																				**Risk of bias**
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	
3	Cockcroft, 2016	✔	✔	✗	✔	✔	NR	✗	✔	✔	✔	✔	✔	N/A	N/A	✔	?	✔	✔	✗	✔	LOW
4	Daubert and Ramani, 2020	✔	✔	✗	✔	✔	NR	✗	✔	✔	✔	✗	✔	N/A	N/A	✔	?	✔	✔	✗	✔	LOW
5	Dicataldo and Roch, 2020	✔	✔	✗	✔	✔	NR	✗	✔	✔	✔	✗	✔	N/A	N/A	✔	?	✔	✔	✗	✔	HIGH
6	Dilworth-Bart, 2012	✔	✔	✔	✔	✔	NR	✗	✔	✔	✔	✔	✔	?	✗	✔	✔	✔	✔	✗	NR	HIGH
7	Farah et al. 2006	✔	✔	✗	✔	?	✔	✗	✔	✔	✗	NR	✗	N/A	N/A	✔	?	✔	✗	✗	NR	LOW
8	Fernald et al., 2011	✔	✔	✗	✔	NR	NR	✗	✔	✔	✔	✔	✗	NR	✗	?	✔	✔	✔	✗	✔	HIGH
9	Flouri et al., 2019**	N/A – assessed with longitudinal tool																				LOW
10	Guerra et al. 2020	✔	✔	✗	✔	✔	✔	✗	✔	✔	✔	✔	✔	N/A	N/A	✔	✔	✔	✔	✗	✔	LOW
11	Hou et al. 2020	✔	✔	✗	✔	✔	✔	✗	✔	✔	✔	✔	✔	N/A	N/A	✔	✔	✔	✔	✗	✔	LOW
12	Hackman et al. 2014 **	N/A – assessed with longitudinal tool																				LOW
13	Hackman et al. 2015 **	N/A – assessed with longitudinal tool																				LOW
14	He and Yin, 2016	✔	✔	✗	✔	✔	✔	✗	✔	✔	✔	✔	✔	NR	✗	✔	✔	✔	✔	✗	✔	LOW
15	Jacobsen et al. 2017	✔	✔	✗	✔	✔	✔	✗	✔	✔	✔	✔	✗	N/A	N/A	?	✗	✔	✗	✗	✔	HIGH
16	Kobrosly et al. 2011 **	N/A – assessed with longitudinal tool																				LOW
17	Korecky-Kroll et al., 2019	✔	✔	✗	✔	✔	NR	✗	✔	✔	✔	✔	✔	N/A	N/A	✔	✔	✔	✗	✗	✔	LOW
18	Leonard et al. 2015	✔	✔	✗	✔	?	NR	✗	✔	✔	✔	NR	✔	N/A	N/A	✔	?	✔	✔	✗	✔	LOW
19	Maguire and Schneider, 2019	✔	✔	✗	✔	✔	NR	✗	✔	✔	✔	✔	✔	N/A	N/A	✔	✔	✔	✔	✗	✔	HIGH
20	Miconi et al. 2019	✔	✔	✗	✔	✔	NR	✗	✔	✔	✔	✔	✔	N/A	N/A	✔	✔	✔	✔	✗	✔	LOW
21	Murtaza et al. 2019	✔	✔	✗	✔	✔	✔	✗	✔	✔	✔	✔	✔	N/A	N/A	✔	✔	✔	✔	✗	✔	LOW
22	Passareli-Carrazzoni et al. 2018	✔	✔	✗	✔	✗	✔	✗	✔	✔	✔	✔	✔	N/A	N/A	✔	✔	✔	✔	✗	✔	LOW
23	Piccolo et al. 2019	✔	✔	✗	✔	?	✔	✗	✔	✗	✔	✔	✔	N/A	N/A	?	✗	✔	✔	✗	✔	HIGH
24	Rhoades, 2012 **	N/A – assessed with longitudinal tool																				LOW

	Authors	**AXIS tool question**																				**Risk of bias**
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	
25	Rowe et al. 2016	✔	✔	✗	✔	✔	✔	✗	✔	✔	✔	✔	✔	N/A	N/A	✔	✔	✔	✔	✗	✔	LOW
26	Sarsour et al. 2011	✔	✔	✗	✔	✔	✔	✗	✔	✔	✔	✔	✔	N/A	N/A	✔	✔	✔	✔	✗	NR	LOW
27	Tine, 2014	✔	✔	✗	✔	✔	✔	✗	✔	✔	✔	✗	✔	N/A	N/A	?	?	✔	✗	✗	NR	LOW
28	Vandenbroucke et al. 2016	✔	✔	✗	✔	✔	✔	✗	✔	✔	✔	✔	✔	N/A	N/A	✔	✔	✔	✔	✗	✔	LOW

Introduction
1. Were the aims/objectives of the study clear?
Methods
2. Was the study design appropriate for the stated aim(s)?
3. Was the sample size justified?
4. Was the target/reference population clearly defined? (Is it clear who the research was about?)
5. Was the sample frame taken from an appropriate population base so that it closely represented the target/reference population under investigation?
6. Was the selection process likely to select subjects/participants that were representative of the target/reference population under investigation?
7. Were measures undertaken to address and categorise non-responders?
8. Were the risk factor and outcome variables measured appropriate to the aims of the study?
9. Were the risk factor and outcome variables measured correctly using instruments/measurements that had been trialled, piloted or published previously?
10. Is it clear what was used to determined statistical significance and/or precision estimates? (e.g. p-values, confidence intervals)
11. Were the methods (including statistical methods) sufficiently described to enable them to be repeated?
Results
12. Were the basic data adequately described?
13. Does the response rate raise concerns about non-response bias?
14. If appropriate, was information about non-responders described?
15. Were the results internally consistent?
16. Were the results presented for all the analyses described in the methods?
Discussion
17. Were the authors' discussions and conclusions justified by the results?
18. Were the limitations of the study discussed?
Other
19. Were there any funding sources or conflicts of interest that may affect the authors' interpretation of the results?
20. Was ethical approval or consent of participants attained?

(Tools and questions from Downes et al., 2016)

2.3.2.3.2 Longitudinal studies

Table 7. Quality assessment and risk of bias for longitudinal socioeconomic position studies (NIH tool)

id	Authors	NIH tool question														Risk of bias
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	
Meta-analysed studies																
1	Albert et al. 2020	✓	✓	✓	✓	✗	✗	✓	✓	✓	✓	✓	NR	NR	✗	LOW
10	Deer et al. 2020	✓	✓	✓	✗	✗	✗	✓	✓	✓	✓	✓	NR	✗	✓	LOW
15	Lensing and Elsner, 2018	✓	✓	✓	NR	✗	NR	NR	✓	✓	✗	✓	NR	✓	✓	LOW
23	Nesbitt, 2013	✓	✓	✓	✓	✗	✓	✓	✓	✓	✓	✓	NR	✗	✓	LOW
26	Philbrook et al., 2017	✓	✓	✓	✓	✗	✓	✓	✓	✓	✗	✓	NR	✓	✓	LOW
27	Pina, 2019	✓	✓	✗	✓	✗	✓	✓	✓	✓	✗	✓	NR	✗	✓	LOW
29	Rosen et al. 2020	✓	✓	✓	✓	✗	✓	✓	✓	✓	✗	✓	NR	NR	✗	LOW
31	Stumper et al. 2020	✓	✓	✓	✓	✗	✓	✓	✓	✓	✗	✓	NR	NR	✓	LOW
33	Wang and Fitzpatrick 2019	✓	✓	✓	✓	✗	NR	NR	✓	✓	✗	✓	NR	N/A	✓	LOW
34	Waters et al 2021	✓	✓	✓	✓	✗	✓	✓	✓	✓	✓	✓	NR	✓	✓	LOW
Studies included in Harvest plot																
9	Flouri et al 2019	✓	✓	✓	✓	✗	✓	✓	✓	✓	✓	✓	NR	✗	✓	LOW
14	Hackman et al., 2014	✓	✗	NR	NR	✗	✓	✓	✓	✓	✗	✓	NR	NR	✓	LOW
15	Hackman et al., 2015	✓	✓	✓	✓	✗	✓	✓	✓	✓	✓	✓	NR	NR	✓	LOW
16	Kobrosly, 2011	✓	✓	✓	✓	✗	✓	✓	✓	✓	✓	✓	NR	NR	✓	LOW
24	Rhoades, 2012	✓	✓	✓	✓	✗	✓	✓	✓	✓	✗	✗	NR	✓	✓	LOW

1. Was the research question or objective in this paper clearly stated?
2. Was the study population clearly specified and defined?
3. Was the participation rate of eligible persons at least 50%?

4. Were all the subjects selected or recruited from the same or similar populations (including the same time period)? Were inclusion and exclusion criteria for being in the study prespecified and applied uniformly to all participants?
5. Was a sample size justification, power description, or variance and effect estimates provided?
6. For the analyses in this paper, were the exposure(s) of interest measured prior to the outcome(s) being measured?
7. Was the timeframe sufficient so that one could reasonably expect to see an association between exposure and outcome if it existed?
8. For exposures that can vary in amount or level, did the study examine different levels of the exposure as related to the outcome (e.g., categories of exposure, or exposure measured as continuous variable)?
9. Were the exposure measures (independent variables) clearly defined, valid, reliable, and implemented consistently across all study participants?
10. Was the exposure(s) assessed more than once over time?
11. Were the outcome measures (dependent variables) clearly defined, valid, reliable, and implemented consistently across all study participants?
12. Were the outcome assessors blinded to the exposure status of participants?
13. Was loss to follow-up after baseline 20% or less?
14. Were key potential confounding variables measured and adjusted statistically for their impact on the relationship between exposure(s) and outcome(s)?

(Assessment tool and questions reproduced from NHBLI, 2014)

2.3.2.3.3 Descriptive risk of bias results

Of the 64 studies reporting socioeconomic position and working memory, 14 were rated as high risk of bias (22%), and all of these were cross-sectional studies.

Cross-sectional studies

There were 49 cross-sectional studies assessed using the AXIS tool. Here, I highlight key questions from the tool and summarise the responses across the studies. All of the studies had clear aims/objectives and appropriate study designs with appropriate measures for their study (100%). Fewer studies reported an appropriate sample frame (77%), an appropriate selection process (54%), and methodological detail that would allow the study to be repeated (73%). The vast majority of studies used validated measures for their risk and outcome variables (90%).

Of these 49 cross-sectional studies, 14 studies (28%) were rated as high risk of bias. Studies were usually rated as high risk of bias due to not clearly specifying their population in enough detail, particularly with regards to whether the population were classed as typically developing or their ethnic group. Occasionally, studies used a tool of working memory that was not validated, and these were usually classed as high risk of bias.

Longitudinal studies

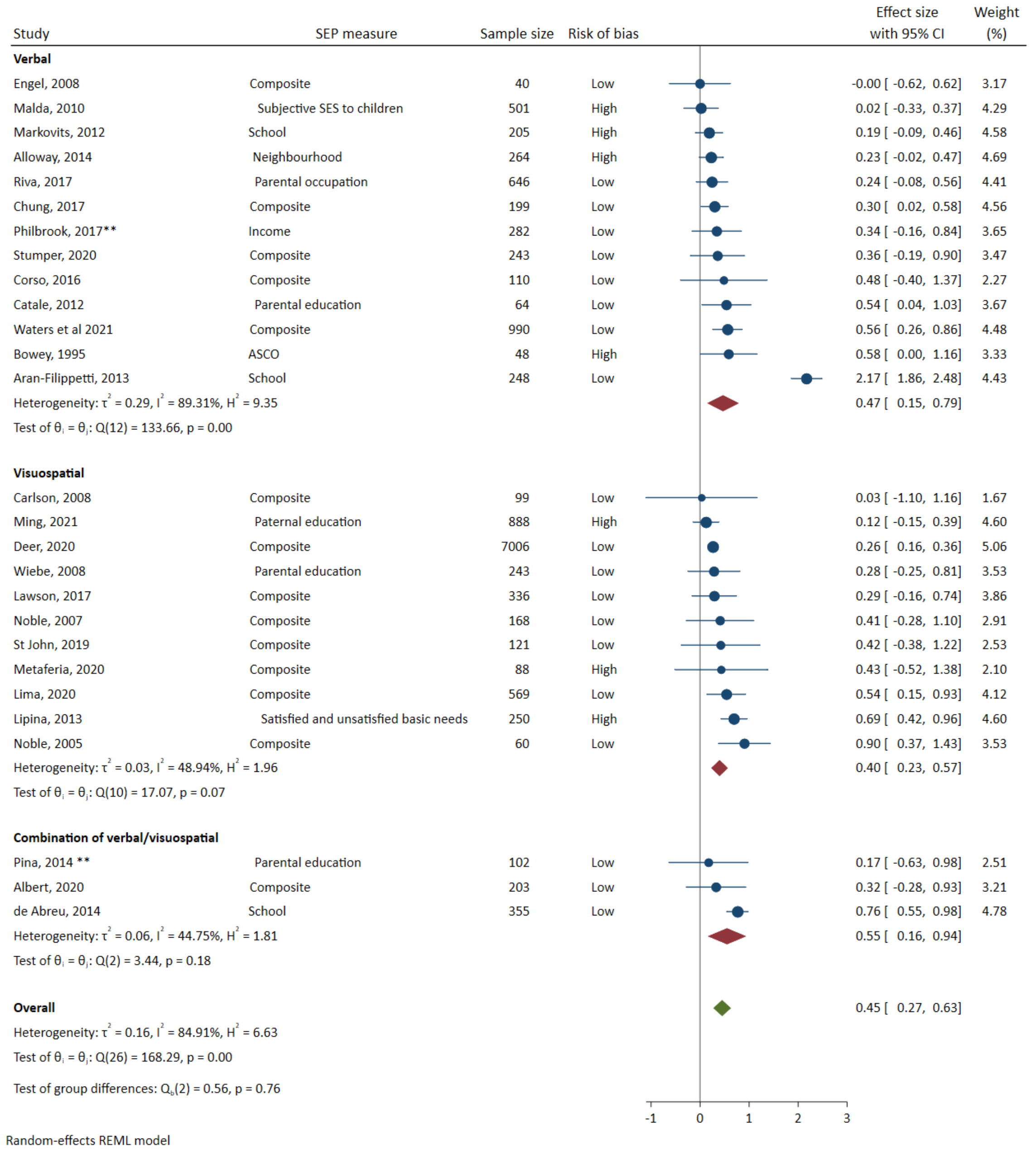
There were 15 studies assessed using the NIH longitudinal tool, all of which were rated as low risk of bias (100%). Here, I highlight key questions from the tool and summarise the responses across the studies. All studies had clear aims/objectives and used validated exposure variables (100%). Fewer studies had participation rates of at least 50% (87%), and reported that the exposure was measured prior to the outcome (73%). Few studies measured the exposure more than once over time (46%), highlighting a key area for future research.

Of these 15 longitudinal studies, none were rated as high risk of bias. This is because all studies clearly specified their population with regards to typical development and ethnic group, and they all used validated tools to measure working memory.

2.3.2.4 Meta-analyses

2.3.2.4.1 Summary of effects.

There were 25,249 individual participants from 36 individual studies included across both meta-analyses. Results are presented firstly for the meta-analysis of simple working memory and then the meta-analysis of complex working memory. Within each meta-analysis, the subgroup analysis is presented by modality (verbal vs visuospatial).

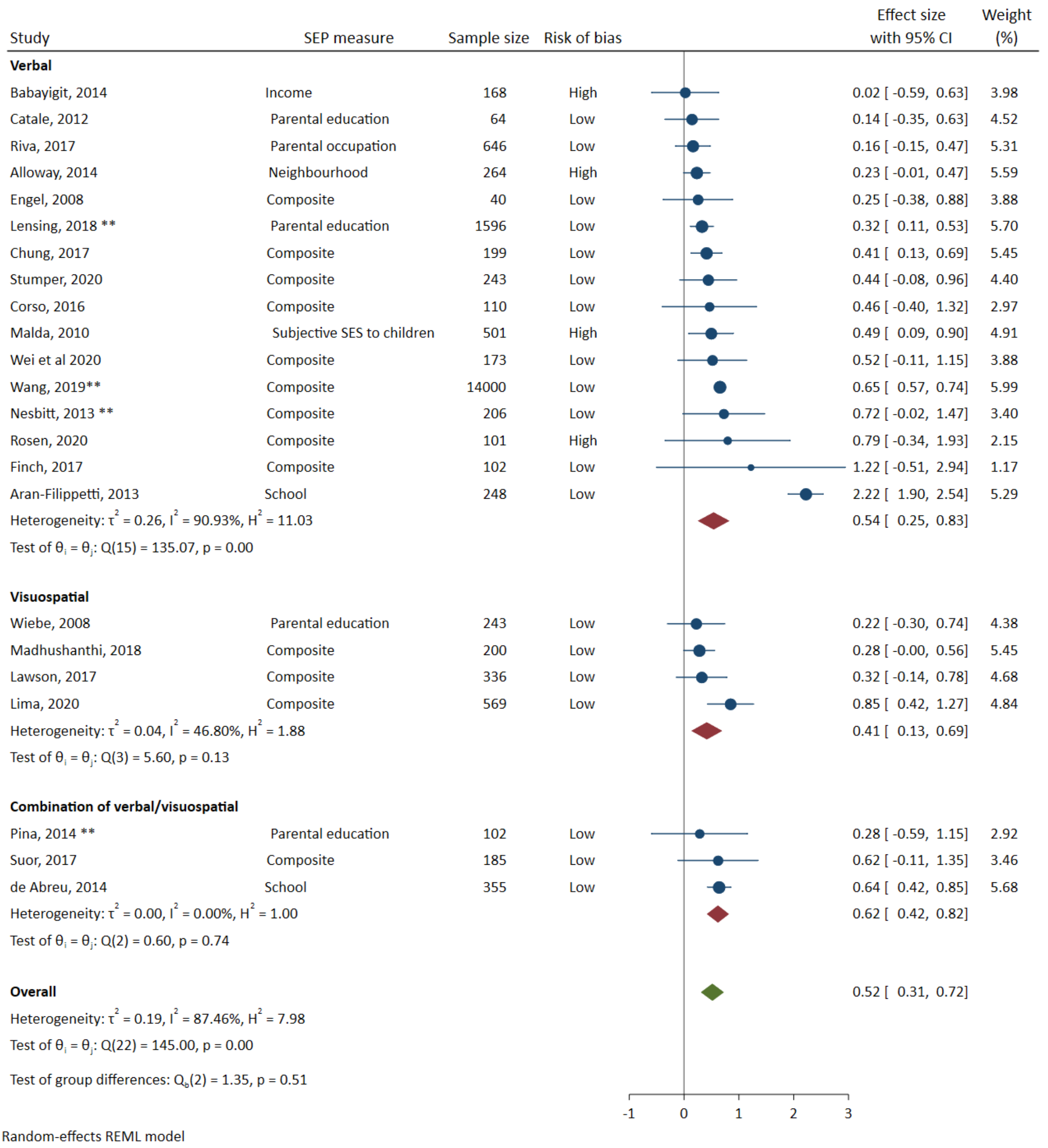


<u>Figure 10. Meta-analysis of the association between socioeconomic position and simple working memory (sorted by effect size).</u>

*Note: A double asterisk ** indicates a cohort or longitudinal study.*

Figure 10 shows the meta-analysis of simple working memory, which included 27 studies with 14,328 participants (including 7006 from one study). The effect size and 95% CI was 0.45 (0.27 to 0.63). In the task modality subgroup analysis, the verbal estimate and its 95% CI was 0.47 (0.15 to 0.79), the visuospatial estimate 0.40 (0.23 to 0.57), and the combination of verbal and visuospatial estimate was 0.55 (0.16 to 0.94).

Complex working memory.



<u>Figure 11. Meta-analysis of the association between socioeconomic position and complex working memory (sorted by effect size).</u>

*Note: A double asterisk ** indicates a cohort or longitudinal study.*

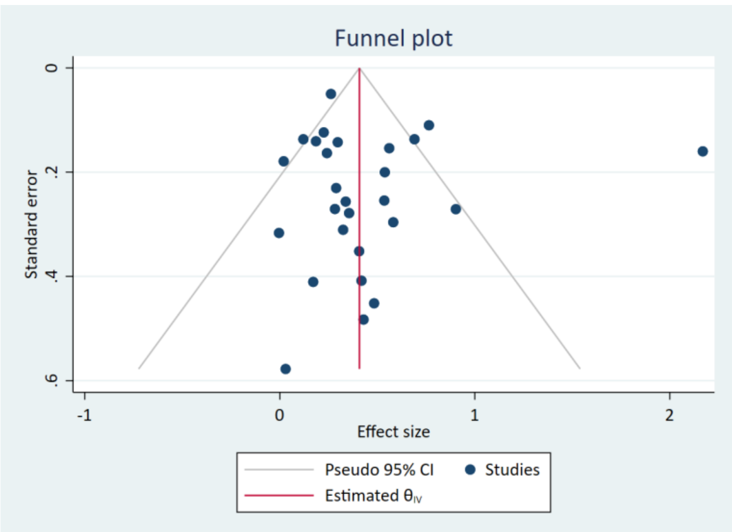
Figure 11 shows the complex working memory meta-analysis, which included 23 studies with 20,651 participants (including 14,000 from one study). The effect size and 95% CI was 0.52 (0.31 to 0.72). In the subgroup analysis of task modality, the verbal estimate was 0.54 (0.25 to 0.83), the visuospatial estimate 0.41 (0.13 to 0.69), and the combination of verbal and visuospatial estimate 0.62 (0.42 to 0.82).

2.3.2.4.2 Heterogeneity.

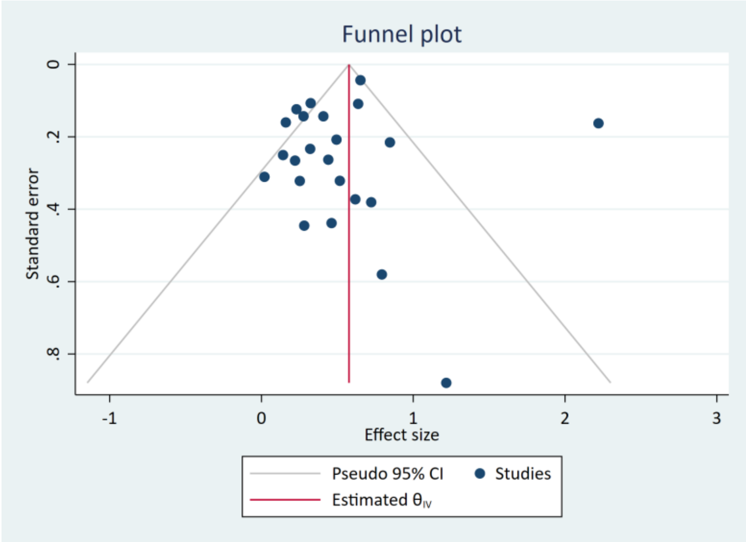
Heterogeneity was high overall. I^2 was 85% overall in simple working memory, with substantially higher heterogeneity in simple verbal working memory (89%) than simple visuospatial working memory (48%). I^2 was 87% overall in complex working memory, with again substantially higher heterogeneity in complex verbal working memory (91%) than complex visuospatial working memory (47%) (likely due to the subgroup analysis including only 4 studies). Prediction intervals were wide and overlapped with the null, indicating some uncertainty about the direction and magnitude of any effect to be expected in a new study. The 95% prediction intervals were -0.399 to 1.297 for simple working memory, and -0.407 to 1.438 for complex working memory.

2.3.2.4.3 Publication bias.

I assessed publication bias for each of the two meta-analyses. The funnel plots in Figure 12a and 12b were both judged to be symmetrical and did not show an association between study size and study effect estimates. The Egger's tests were both non-significant (simple working memory p = .44, complex working memory p = .93), again indicating low risk of publication bias.



(a) Funnel plot for meta-analysis of simple working memory



(b) Funnel plot for meta-analysis of complex working memory

Figure 12a and 12b. Funnel plots for simple and complex working memory meta-analyses

2.3.2.4.4 Sensitivity analysis.

The robust variance estimation (RVE) analysis of simple working memory included 27 studies with 50 individual effect sizes. The simple working memory effect size and 95% CI was 0.44 (0.24 to 0.64). The RVE analysis of complex working memory included 23 studies with 39 individual effect sizes. The complex working memory effect size and 95% CI was 0.53 (0.30 to 0.75). As these estimates are extremely similar to when effect sizes were averaged within studies and this indicates that averaging the effect sizes is suitable for this study, here I have presented only the forest plots for the averaged effect sizes and the discussion focuses on the results when the effect sizes were averaged.

Removing one study (Arán-Filippetti, 2013) with substantially larger effect sizes than others in both meta-analyses (d = 2.17 in simple working memory, and d = 2.22 in complex working memory) reduced the effect sizes by approximately 0.1 (simple working memory from 0.45 to 0.37 and complex working memory from 0.52 to 0.42). Removing this study also substantially reduced the heterogeneity as measured by I^2, from 87% to 48% in simple working memory, and from 88% to 43% in complex working memory. As the overall effect sizes were still within the bounds interpreted as “medium”, I retained the Aran-Filippetti (2013) study in all meta-analyses.

2.3.2.4.5 Meta regression analyses.

Table 8. Meta-regression analysis results

	Simple working memory		Complex working memory	
Regression factor	**B (95% CI)**	***p***	**B (95% CI)**	***p***
Pre-specified				
Task modality (0 = verbal, 1 = visuospatial)*	-0.07 (-0.50 to 0.35)	.47	-0.26 (-0.91 to 0.38)	.42
Risk of bias (0 = low risk, 1 = high risk)	-0.20 (-.60 to .21)	.36	-0.20 (-0.77 to 0.36)	.49
Socioeconomic indicator (0 = single, 1 = composite)	-.11 (-0.48 to 0.27)	.58	-.00 (-0.44 to 0.43)	.97
Post-hoc				
Effect size (0 = Cohen's d, 1 = Converted from Pearson's r)	-0.35 (-0.71 to -0.00)	.05	-0.18 (-0.63 to 0.26)	.41
Effect size (0 = single, 1 = averaged)	-.17 (-0.55 to 0.02)	.40	0.19 (-0.27 to 0.65)	.42
Age in years**	-.05 (-0.11 to .00)	.09	-.02 (-.07 to .03)	.43

**Three studies used combined estimates of verbal and visuospatial task modalities, and were excluded from this analysis.*
**Nine studies did not report a mean age of their sample, and were excluded from this analysis.*

Results from the meta-regression analysis are presented in Table 8. I conducted pre-specified moderation analyses by the task modality, risk of bias, and type of socioeconomic indicator; however, none of these variables significantly moderated the association between socioeconomic position and working memory. As a post-hoc analysis, age in years did not significantly moderate the association (for those studies that reported mean age in years). I also found that whether the effect size was averaged or not did not significantly moderate the association, nor did whether the effect size was converted from Pearson's *r*. However, the test was borderline significant (p = .05) for the effect size type moderation test in simple working memory.

2.3.2.5 Harvest plot

There were 28 studies included in the Harvest plot using 51 effect sizes from 12,488 individual participants. The majority of studies contributed ≥2 effect sizes (58%).

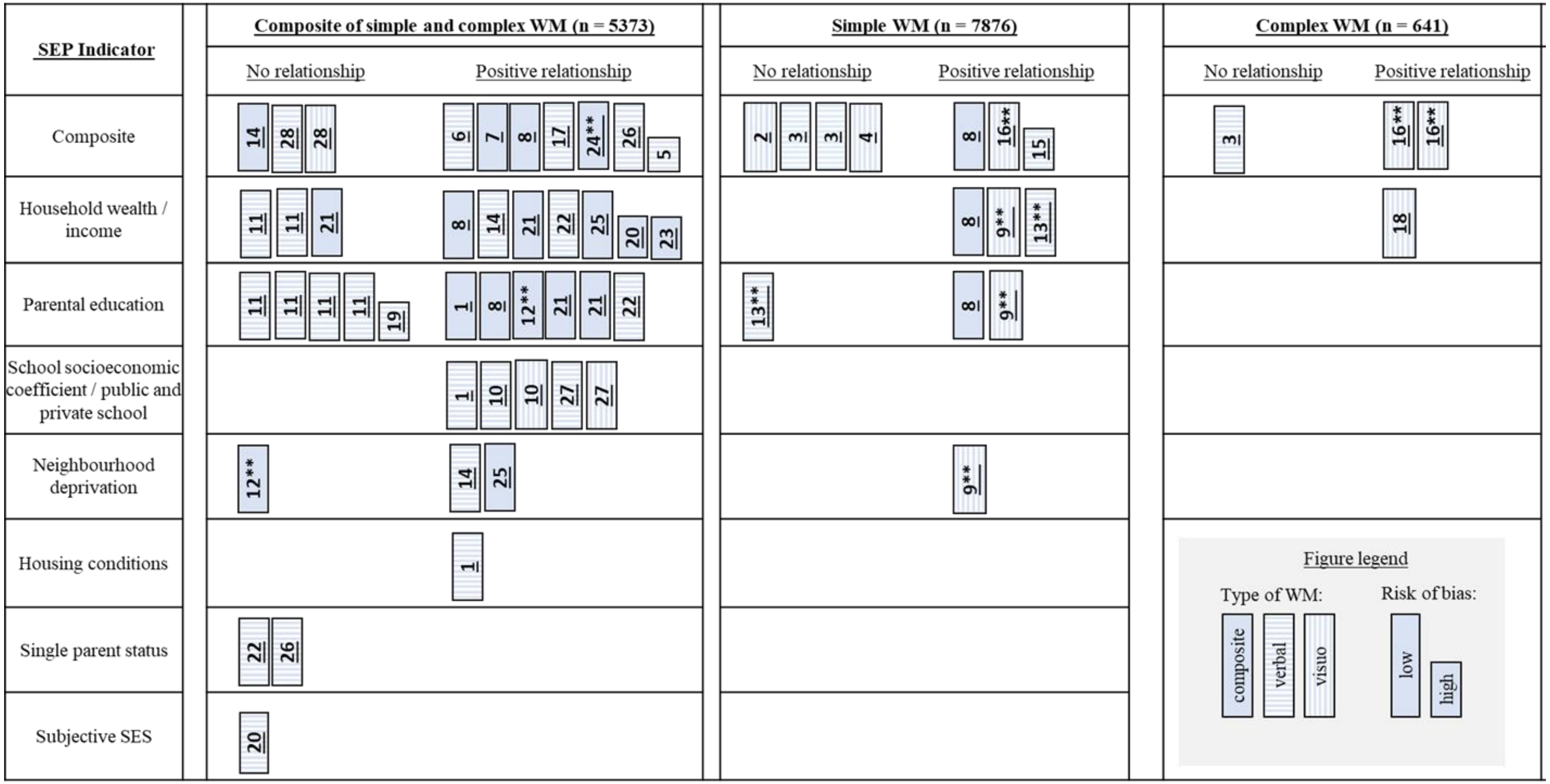


Figure 13. Harvest plot of the association between different socioeconomic position indicators with composite working memory, simple working memory, and complex working memory.

Note: Study IDs are indicated on each bar as follows: 1. Aran-Filippetti & Richard De Minzi, 2012; 2. Brito et al., 2021; 3. Cockcroft, 2016; 4. Daubert and Ramani, 2020; 5. Dicataldo and Roch, 2020; 6. Dilworth-Bart, 2012; 7. Farah et al. 2006; 8. Fernald et al., 2011; 9. Flouri et al., 2019; 10. Guerra et al., 2020; 11. Hou et al., 2020; 12. Hackman et al. 2014**; 13. Hackman et al. 2015 **; 14. He and Yin, 2016; 15. Jacobsen et al. 2017;16. Kobrosly et al. 2011; 17. Korecky-Kroll et al., 2019; 18. Leonard et al. 2015; 19. Maguire and Schneider, 2019; 20.

Miconi et al. 2019; 21. Murtaza et al., 2019; 22. Passareli-Carrazzoni et al. 2018; 23. Piccolo et al. 2019; 24. Rhoades, 2012 **; 25. Rowe et al. 2016; 26.Sarsour et al. 2011; 27. Tine, 2014; 28. Vandenbroucke et al. 2016.

The plot bar lengths indicate whether the study was at low or high risk of bias. A double asterisk ** indicates a cohort or longitudinal study.

In Figure 13, the Harvest plot shows the distribution of statistically significant associations and non-statistically significant associations across composite working memory, simple working memory, and complex working memory by socioeconomic position measure. Studies only showed a positive association (increased socioeconomic position and increased working memory), or no association, so there is no column representing negative association. The abundance of studies in the composite working memory columns relative to the simple and complex working memory columns reflects that studies with composite working memory measures were not included in the meta-analyses.

Nineteen individual studies including 5373 participants provided 43 effect sizes on composite working memory. The majority of studies found composite working memory to be significantly positively associated with composite socioeconomic indicators, household wealth and parental education, and most of these studies were rated as low risk of bias. Two studies rated as low risk of bias found no association between composite socioeconomic position and working memory, and two studies rated as low risk of bias found single parent status to not be associated with verbal working memory. Eight individual studies including 7826 participants provided 14 effect sizes for simple working memory. Simple working memory was found to be associated with composite socioeconomic position indicators, household wealth, and parental education, and most of these studies were rated as low risk of bias. Only three studies found no association between socioeconomic position and simple working memory. Three individual studies including 641 participants provided four effect sizes for complex working memory. Complex working memory was found to be associated with composite socioeconomic position and household wealth in two different studies, one of which was rated as low risk of bias. The third study of complex working memory, rated as low risk of bias, found no association with composite socioeconomic position.

Overall, the Harvest plot indicates an association between socioeconomic position and different types of working memory across different indicators of socioeconomic position, that appear unrelated to risk of bias. Although there were some studies that found evidence against these hypotheses, the weight of evidence rated as low risk of bias was much more in favour of supporting the evidence for an association.

2.3.3 Ethnicity

2.3.3.1 Study selection

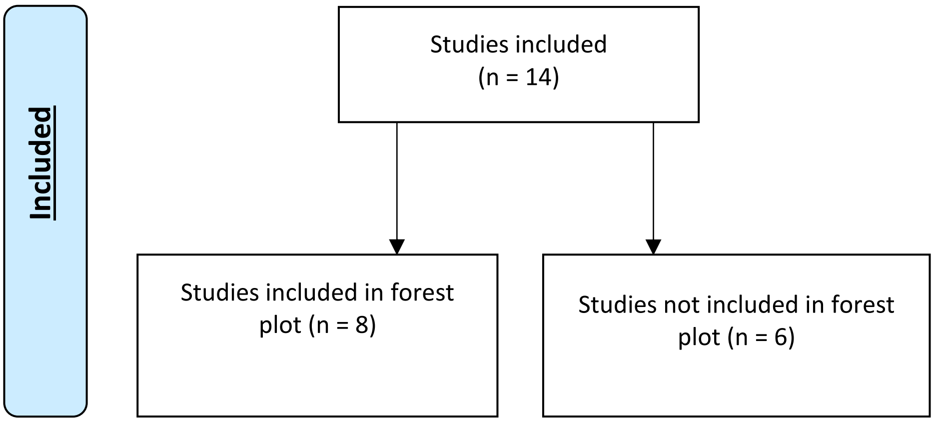


Figure 14. The number of included studies in the review that contain information on ethnic minority status and the number of eligible studies for the forest plot and narrative synthesis.

Figure 14 shows the number of included studies that investigated the relationship between ethnic minority status and working memory (n = 14). There were 7 studies included in the forest plot. Of these, 4 were simple WM, 3 were complex WM, and 1 used a composite of both types of WM. There were 6 studies that were not included in the forest plot but were narratively synthesised.

2.3.3.2 Study characteristics

Table 9. Extracted data for studies including information on ethnicity

Study details		Participant characteristics					WM task	Risk of bias
ID & author		**Location**	**Total n (% male)**	**Age range (M±SD)**	**Other characteristics**	**Ethnicity (n)**		
					Studies included in forest plot			
1	Finch, 2017 [SEP and EMS]	San Francisco Bay	102 (48%)	4 – 6 years (5.61±0.56)	Family income, parental education, subjective social status, financial stress	White (36%) Hispanic/Latino (26%) Asian (20%) Black (4%) Multiracial/other (14%)	1. BDR	LOW
2	Jaekel et al. 2019	Ruhr, North West Germany	337 (46%)	5 – 15 years	Parental education	Turkish immigrants Non-immigrant Germans	1. BDR	LOW
3	McCarver, 1972	Alabama	60 (62%)	5 years (NR)	Deprived group (N = 30): Black children attending a summer Head Start program and from extremely impoverished homes in the Negro sections of Tuscaloosa, Alabama Nondeprived (N = 30): White middle class children from a church affiliated kindergarten. Parents were mostly college professors, graduate students, and other professionals.	Black (30) White (30)	1. Digit span test	HIGH
4	Miconi et al. 2019 [SEP and EMS]	Northeast Italy	488 (NR)	11 – 13 years (12.11±0.80)	Family Affluence Scale (Currie et al., 2008) Material affluence reported by adolescents themselves	Moroccan immigrants (116) Romanian immigrants (124) Non-immigrant Italians (248)	1. FDR 2. BDR	LOW
5	Nesbitt et al. 2013 **	NR	206 (51%)	6, 12, 30 and 36 months (N/A)	(i) Income to needs (ii) Maternal education	European (89) African American (117)	1. BDR (McCarthy Scales of Children's	LOW

Study details			Participant characteristics				WM task	Risk of bias
ID & author		Location	Total n (% male)	Age range (M±SD)	Other characteristics	Ethnicity (n)		
	[SEP and EMS]						Abilities, 1972)	
6	Philbrook et al. 2017** [SEP and EMS]	Southeastern United States	282 (52%)	9 – 11 years Three time points: (9.44±.71) (10.37±.68) (11.33±.69)	Income-to-needs ratio	European American (65%) African American (35%)	1. working memory test (WJ-III) [At age 9, 10, 11]	LOW
7	Stevenson, 2016	Innercity district in Netherlands	111 (57%)	NR (8.1±5 months)	Parental education level	Indigenous Dutch (56) Ethnic minorities (55)	1. BDR (WISC-IV)	HIGH
8	Waters 2021 [SEP and EMS]	USA National Institute of Child Health and Development Study of Early Child Care and Youth Development (NICHD SECCYD)	990 (52%)	4-5 years (4.64±0.09)	(i) Income to needs (ii) Parent education	86% White, 14% Black	1. Memory for sentences (Woodcock-Johnson Revised; Woodcock and Johnson, 1989)	LOW
					Studies *not* included in forest plot			
9	Flouri et al 2019** [SEP and EMS]	UK Millennium Cohort Study (MCS)	4756 (51%)	0 – 11 years	(i) Maternal education (ii) Family poverty (household income below poverty line) (iii) Neighbourhood deprivation	74% White, 26% NR	Spatial working memory at age 11 (CANTAB; Robbins et al., 1994)	LOW

Study details				Participant characteristics			
ID & author		Location	Total n (% male)	Age range (M±SD)	Other characteristics	Ethnicity (n)	WM task	Risk of bias
10	Hackman et al. 2015 ** [SEP and EMS]	USA	1009 (50%)	1 – 54 months (NR)	(i) Income to needs average from 1, 6, 15, 24, and 26 months (ii) Maternal education at 1 month	White (844) African-American (108) Asian/Pacific Islander (15) American Indian (2) Other (40), Hispanic/Latino (55)	1. Memory for sentences (WJ-R COG; Woodcock, 1990) [measured at 54 months]	LOW
11	Little, 2017**	USA ECLS-K	18180 (NR)	Kindergarten to second grade	Parental education, occupational prestige, and household income [5 quintiles]	White, Black, Hispanic, Asian, or other	1. BDR	LOW
12	Maguire and Schneider, 2019 [SEP and EMS]	NR	90 (40%)	8-15 years (10.9±2.14)	Maternal education	NR, 100% fluent English speakers and 37% Spanish-English bilingual speakers	1. Digit span (Blackburn & Benton, 1957) (NR if forwards or backwards)	HIGH
13	Malda et al. 2010 [SEP and EMS]	South Africa	501 (51%)	Grades 3-4 (9.37)	Children were asked six questions as an indication of SES: (1) do you have your own room? (£) how many TVs are there in your house (3) is there a microwave in your house? (4) how many cellphones does your family have? (5) how many cars does your family have? (6) do you have reading books at home? [Composite]	White Urban Afrikaans (161) Black urban Tswana (181) Black rural Tswana (159)	1. Short term memory 2. working memory test (WMTB-C, 2001) [Adapted for two different cultures]	HIGH
14	Rhoades, 2012 ** [SEP and EMS]	Pennsylvania	1155 (approx. 50%)	2, 7, 24, and 36 months old at each visit	LCA to create risk classes in different ethnic groups based on household income, unmarried, partner status, teen mother, no high school diploma, mood problems, smoking during pregnancy, high stress, low social support, and crowded house	White (60%) African American (40%).	1. working memory task (no citation)	LOW

Notes: 1. Age range is in years unless otherwise stated.
2. In author name: **Means study is longitudinal or cohort study, all other study designs are cross-sectional. [SEP and EMS] means a study is also included in the socioeconomic position table.
3. Abbreviations: Backwards Digit Recall (BDR), Forwards Digit Recall (FDR), Wechsler Intelligence Scales for Children (WISC), Automated Working Memory Assessment (AWMA), Kaufman Assessment Battery for Children (K-ABC).

2.3.3.3 Risk of bias results

The risk of bias results are displayed below, separated by the tool used for cross-sectional or longitudinal studies. A descriptive summary is then provided, to assess the overall risk of bias in studies that investigate the association between ethnic minority status and WM.

2.3.3.3.1 Cross-sectional studies

Table 10. Quality and risk of bias assessment of cross-sectional studies using AXIS tool

	Authors	AXIS tool question																				Risk of bias
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	
Studies included in forest plot																						
1	Finch, 2017	✔	✔	✗	✔	NR	NR	✗	✔	✔	✔	✔	✔	NR	✗	✔	✔	✔	✔	✗	NR	LOW
2	Flouri et al. 2019**	N/A – assessed using longitudinal tool																				LOW
3	Jaekel et al. 2019	✔	✔	✔	✔	✔	✔	✗	✔	✔	✔	✔	✔	N/A	N/A	✔	✔	✔	✔	✗	✔	LOW
4	McCarver, 1972	✔	✔	✗	✔	✗	NR	✗	✗	✗	✔	NR	✔	N/A	N/A	✔	?	✗	✗	✗	NR	HIGH
5	Miconi et al., 2019	✔	✔	✗	✔	✔	NR	✗	✔	✔	✔	✔	✔	N/A	N/A	✔	✔	✔	✔	✗	✔	LOW
6	Nesbitt**	N/A – assessed using longitudinal tool																				LOW
7	Philbrook et al., 2019**	N/A – assessed using longitudinal tool																				LOW
8	Stevenson, 2016	✔	✔	✗	✔	✔	NR	✗	✔	✔	✔	NR	✔	N/A	N/A	✔	?	✔	✗	✗	✔	HIGH
Studies not included in forest plot																						
9	Waters 2021	N/A – assessed using longitudinal tool																				LOW
10	Hackman et al. 2015	N/A – assessed using longitudinal tool																				LOW
11	Little, 2017**	N/A – assessed using longitudinal tool																				LOW
12	Malda, 2010	✔	✔	✗	✔	✔	NR	✗	✔	✔	✔	NR	✔	N/A	N/A	✔	?	✔	✔	✗	✔	HIGH
13	Maguire and Schnieder, 2019	✔	✔	✗	✔	✔	NR	✗	✔	✔	✔	✔	✔	N/A	N/A	✔	✔	✔	✔	✗	✔	HIGH
14	Rhoades et al, 2012**	N/A – assessed using longitudinal tool																				LOW

Introduction
1. Were the aims/objectives of the study clear?
Methods
2. Was the study design appropriate for the stated aim(s)?
3. Was the sample size justified?
4. Was the target/reference population clearly defined? (Is it clear who the research was about?)
5. Was the sample frame taken from an appropriate population base so that it closely represented the target/reference population under investigation?
6. Was the selection process likely to select subjects/participants that were representative of the target/reference population under investigation?
7. Were measures undertaken to address and categorise non-responders?
8. Were the risk factor and outcome variables measured appropriate to the aims of the study?
9. Were the risk factor and outcome variables measured correctly using instruments/measurements that had been trialled, piloted or published previously?
10. Is it clear what was used to determined statistical significance and/or precision estimates? (e.g. p-values, confidence intervals)
11. Were the methods (including statistical methods) sufficiently described to enable them to be repeated?
Results
12. Were the basic data adequately described?
13. Does the response rate raise concerns about non-response bias?
14. If appropriate, was information about non-responders described?
15. Were the results internally consistent?
16. Were the results presented for all the analyses described in the methods?
Discussion
17. Were the authors' discussions and conclusions justified by the results?
18. Were the limitations of the study discussed?
Other
19. Were there any funding sources or conflicts of interest that may affect the authors' interpretation of the results?
20. Was ethical approval or consent of participants attained?

(Tools and questions from Downes et al., 2016)

2.3.3.3.2 Longitudinal studies

id	Authors	EMS - NIH tool question														Risk of bias
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	
Studies included in forest plot																
2	Flouri et al 2019	✓	✓	✓	✓	✗	✓	✓	✓	✓	✓	✓	NR	✗	✓	LOW
6	Nesbitt, 2013	✓	✓	✓	✓	✗	✓	✓	N/A	✓	N/A	✓	N/A	✗	✓	LOW
7	Philbrook et al., 2017	✓	✓	✓	✓	✗	✓	✓	N/A	✓	N/A	✓	N/A	✓	✓	LOW
Studies not included in forest plot																
9	Waters et al 2021	✓	✓	✓	✓	✗	✓	✓	✓	✓	✓	✓	NR	✓	✓	LOW
10	Hackman et al., 2015	✓	✓	✓	✓	✗	✓	✓	N/A	✓	N/A	✓	N/A	NR	✓	LOW
11	Little, 2017	✓	✓	✓	✓	✗	NR	NR	N/A	✓	N/A	✓	N/A	✓	✓	LOW
14	Rhoades, 2012	✓	✓	✓	✓	✗	✓	✓	N/A	✓	N/A	✗	N/A	✓	✓	LOW

1. Was the research question or objective in this paper clearly stated?
2. Was the study population clearly specified and defined?
3. Was the participation rate of eligible persons at least 50%?
4. Were all the subjects selected or recruited from the same or similar populations (including the same time period)? Were inclusion and exclusion criteria for being in the study prespecified and applied uniformly to all participants?
5. Was a sample size justification, power description, or variance and effect estimates provided?
6. For the analyses in this paper, were the exposure(s) of interest measured prior to the outcome(s) being measured?
7. Was the timeframe sufficient so that one could reasonably expect to see an association between exposure and outcome if it existed?
8. For exposures that can vary in amount or level, did the study examine different levels of the exposure as related to the outcome (e.g., categories of exposure, or exposure measured as continuous variable)?
9. Were the exposure measures (independent variables) clearly defined, valid, reliable, and implemented consistently across all study participants?
10. Was the exposure(s) assessed more than once over time?

11. Were the outcome measures (dependent variables) clearly defined, valid, reliable, and implemented consistently across all study participants?
12. Were the outcome assessors blinded to the exposure status of participants?
13. Was loss to follow-up after baseline 20% or less?
14. Were key potential confounding variables measured and adjusted statistically for their impact on the relationship between exposure(s) and outcome(s)?

(Assessment tool and questions reproduced from NHBLI, 2014)

2.3.3.3.3 Descriptive risk of bias results

There were 14 studies that assessed the relationship between ethnic minority status and WM, of which 7 used cross-sectional designs and 7 which used longitudinal designs. Overall, 4 of these were rated as low risk of bias, and 10 of these were rated as low risk of bias. Studies were rated as high risk of bias because they did not always specify the socioeconomic position of their population, did not have clear inclusion criteria, or used a measure of working memory that was not referenced or validated.

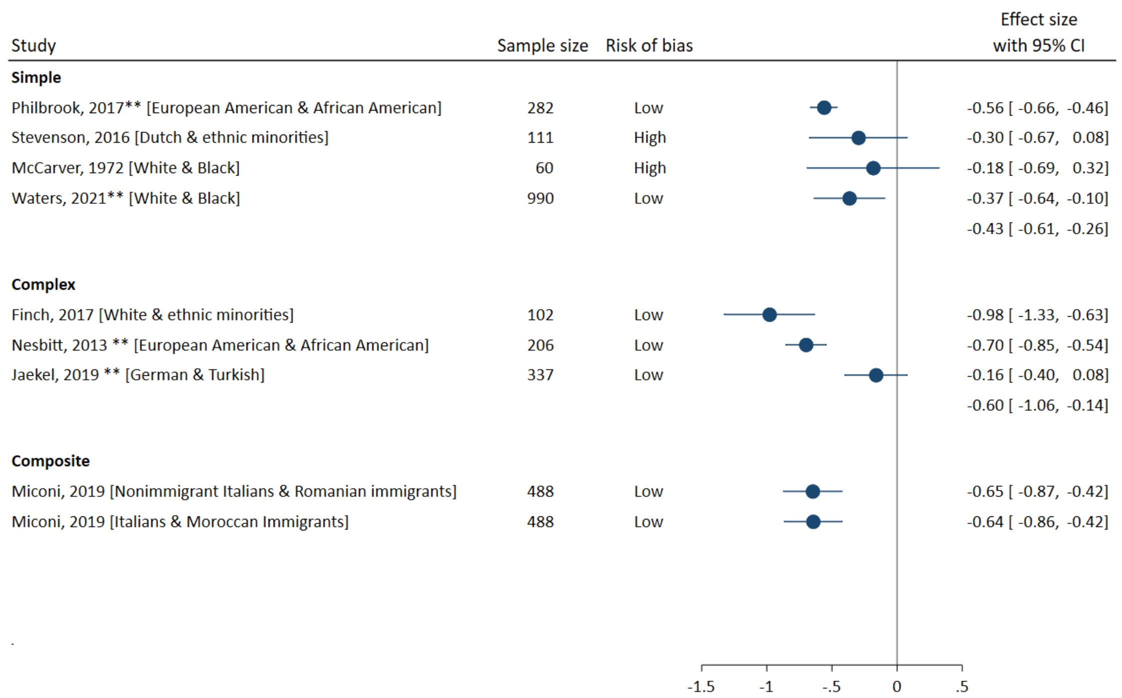
Cross-sectional studies

There were 7 studies assessed using the AXIS tool, 4 of which were rated as high risk of bias, and 3 of which was rated as low risk of bias. All studies (100%) had clear aims and objectives, and all studies (100%) used appropriate study designs for the study aims. All studies (100%) had clearly defined target populations, however, fewer study authors (71%) used appropriate sample frames and only 1 study author (14%) specified their selection process. Most study authors measured the exposure and outcome variables appropriately (85%), and one study author did not do so. This one study recruited only Black children from deprived families, and White children from middle class families (McCarver, 1972). This was considered inappropriate since it assumes class to be consistent within ethnic groups. The majority of study authors measured the risk and outcome factors appropriately using previously validated instruments (85%), and one did not (McCarver,1972).

Longitudinal studies

There were 7 studies assessed using the NIH tool, all of which were rated as low risk of bias. All studies (100%) had clear research questions, clearly specified populations, participation rates above 50%, and appropriate selection of participants. Most study authors (80%) measured the exposure prior to the outcome, and one study did not explicitly mention when the exposure was measured (Little, 2017). However, this study had repeated measurements of WM, and the exposure of ethnic minority status is unlikely to change, and the study is therefore still longitudinal. Most study authors (85%) had a sufficient timeframe between the exposure and outcome, and one had not reported this (Little, 2017). All study authors (100%) measured the exposure appropriately, and most studies (85%) measured the outcome appropriately - one study author used a measure of working memory that was not referenced or validated (Rhoades et al., 2012). This study was not rated as high risk of bias as it scored highly on all other questions and aspects of bias.

2.3.3.4 Forest-plot



<u>**Figure 15. Forest plot to show ethnic minorities versus majorities for verbal WM.**</u>

Note: effect sizes on the left favour the ethnic majority group, effect sizes on the right favour the ethnic minority group

Figure 15 plots the 9 individual effect size estimates from 8 different studies regarding the association between ethnic minority status and working memory ability. The studies only investigated verbal WM, and the plot includes estimates for simple verbal WM, complex verbal WM, and a composite of both simple and complex verbal WM. The forest plot shows that within each individual study, ethnic minority status groups had consistently lower scores across different tasks of WM. The potential magnitude of the relationships vary in effect size from small (-.16, 95% CI -.4 to .08) to large (-.98, 95% CI -1.33 to -.63). There are five studies where the 95% CI's do not cross the 0 line and the hypothesis of an association between ethnic minority status and working memory is therefore supported. In contrast, there are 3 studies where the 95% CIs do cross the 0 line - which suggests the association between ethnic minority status and working memory is not significant. There are 2 studies rated as high risk of bias, and 6 studies rated as low risk of bias. On visual inspection of the forest plot, there are no clear differences in the magnitude of associations between studies rated as low or high risk of bias. There are 4 longitudinal or cohort studies (as indicated by the asterisks), and 4 cross-sectional studies.

Five of the studies were in the USA, finding that ethnic minority status children described as African American (Nesbitt et al. 2013; Philbrook et al, 2017), black (McCarver, 1972; Waters, 2021) and a mixed group of ethnic minorities (Finch, 2017) all scored lower than ethnic majority White children on working memory. Three of the studies were in Europe, finding that a mixed group of ethnic minority status children have lower scores than native Dutch children in the Netherlands (Stevenson, 2016), Romanian and Moroccan immigrant children had lower scores than Italian-born children in Italy (Miconi et al. 2019) and Turkish immigrant children had lower scores than German children in Germany (Jaekel, 2019).

Although all studies in Figure 15 did measure socioeconomic position in their sample, not all studies reported the socioeconomic position of their samples stratified by ethnicity. Studies that did report socioeconomic position for different ethnic groups found that socioeconomic position was on average higher in the ethnic majority groups (Stevenson. 2016; Jaekel et al. 2019; Miconi et al. 2019). It cannot be known if the differences in working memory scores between the two ethnic groups is largely due to lower levels of socioeconomic position in ethnic minority status groups, as raw mean scores between the two ethnic groups will not take this into account.

2.3.3.5 Description of other studies

First, I present a table summarising the key characteristics of studies that are not presented in the forest plot. Then, I describe the studies and synthesise the findings across studies.

Table 11. Key characteristics for studies not in forest plot

Study author	Sample size and location	Ethnic majority and ethnic minority status group(s)	Risk of bias	Estimator method	Result *B* [95% CI or *p* if NR]
Flouri et al 2019**	4756 (51%) UK, Millennium Cohort Study (MCS)	74% White, 26% NR	Low	Regression	-1.48 [-4.95 to -1.35]
Hackman et al., (2015)**	1009 (50%) USA	White (844) and African-American (108), Asian/Pacific Islander (15), American Indian (2) Other (40), Hispanic/Latino (55)	Low	Regression	African American: -4.24 [*p* <.01] Hispanic Latino: -5.48 [*p* <.05]
Little (2017)**	18,180 (NR) USA	White and Black, Hispanic, Asian, or other	Low	Regression	*See note*
Rhoades et al. (2011)**	1155 (50%), Pennsylvania	White (60%) and African American (40%).	Low	Latent Class Analysis	*See note*
Malda et al. (2010)	501 (50%) South Africa	White Urban Afrikaans (161) and Black urban Tswana (181), Black rural Tswana (159)	High	MANOVA	*See note*
Maguire and Schneider, 2019	90 (50%) NR	NR, 100% fluent English speakers and 37% Spanish-English bilingual speakers	High	Regression	Ethnicity: -.29 [*p* >.05] Race: .01 [*p* > .05]

Note: three studies reported more than one coefficient (e.g. multiple timepoints, multiple outcomes) or did not report a coefficient, but another test method. The results from these studies are described below.

Six studies were not included in the forest plot. There are four studies that are longitudinal and rated as low risk of bias. Hackman et al., (2015) found that in 1009 children in the NICHD Study of Early Childcare, early low income-to-needs ratio and low maternal education predicted lower simple verbal working memory scores at 54 months. In a regression analysis with both socioeconomic position and ethnicity as predictors, African-American and Hispanic/Latino children scored significantly lower than White children on WM. Little (2017) found socioeconomic and ethnic differences in the ECLS-K study with 18,180 young children. In a regression analysis with both socioeconomic position and ethnicity as predictors, White children scored higher on complex verbal working memory than Black and Hispanic children at all four time points, and higher than Asian children at three time points. The socioeconomic gaps in working memory were larger in magnitude than the ethnicity gaps, and the gaps narrowed across the four time points. In the UK, a large study found that White children in the UK had better spatial working memory than a mix of ethnic minority groups (Flouri et al, 2019). None of these studies discuss any potential reasons for ethnic minority status groups scoring worse on the working memory tests, as it was not the focus of these studies.

A problem with these studies is that they may be subject to residual confounding (Hackman et al. 2014; Little, 2017; Flouri et al., 2019). Little (2017) adjusted for parental education, occupational prestige, and household income, Flouri (2019) adjusted for maternal education, poverty, and neighbourhood deprivation, and Hackman et al. (2014) adjusted for neighbourhood disadvantage and parental education. However, ethnic minority status groups are unlikely to have equal social positions in all other aspects than the socioeconomic position indicator that the studies adjusted for (Kaufman et al., 1997). The association between ethnic minority status and working memory could therefore be due to "residual confounding".

A further issue is that all of these studies report regression coefficients for the conditional effect of both ethnicity and socioeconomic position on working memory ability, and they do not adjust for socioeconomic position as a mediator. As described earlier, socioeconomic position is a mediator since it may be caused by ethnicity (and obviously socioeconomic position cannot cause ethnicity). The estimated effect of ethnicity on working memory may therefore be distorted by mediator-outcome bias (Cole et al., 2010; Pearl and Mackenzie, 2018). Consequently, it cannot be known if the regression coefficients provided in these studies are reliable estimates of the relationships between ethnic minority status and working memory.

Rhoades et al (2011) use latent class analysis and mediation models to establish links between socioeconomic risk and EF skills, and find them to be at least partially explained by associated variations in parenting behaviours. This is the only study to explore working memory scores on a visuospatial working memory task, using a combination of both simple and complex WM. White children scored similarly whether their mothers were in the 'married, low risk' group, or the 'married, stressed, and depressed', 'poor and married', or 'poor and unmarried' risk groups. In contrast, African American children significantly differed in working memory scores depending on their mothers group allocation, with children in the 'married, low risk' group scoring best, and children in the 'poor, unmarried, and no partner, multi-problem' group scoring worst. The results suggest that socioeconomic risks to working memory may matter more for African American children. This study provides a more reliable estimate of the relationships between ethnic minority status and WM, as it is not subject to this collider bias due to stratifying different classes of socioeconomic risks by two different ethnic groups (Rhoades et al. 2011).

There are two cross-sectional studies rated as high risk of bias. One study found that neither ethnicity nor race had a significant association with verbal working memory (Maguire and Schneider, 2019). However, this study was missing key details: the study location, specific ethnicities, how 'ethnicity' and 'race' were defined as different, and whether the digit recall task was forwards or backwards. Thus, not many conclusions can be made from this study.

The next cross-sectional study is also rated at high risk of bias, but has some interesting results regarding culture and working memory (Malda et al. 2010). In South Africa, White Afrikaan and ethnic minority status Black Tswana children in middle childhood from urban and rural homes completed working memory tests adapted for their two different cultures (Afrikaan culture or Tswana culture). The study authors found differences in raw mean scores on simple and complex verbal WM, with Black Tswana children generally scoring worse. However, this result changes after adjustment for socioeconomic position and interpreting the different cultural adaptations of working memory tests. In simple verbal WM, both White Afrikaan children and urban Black Tswana children score highest on the Afrikaan culture test version, and urban Tswana children score highest on the Tswana culture version. For complex verbal WM, White Afrikaan children score highest on the Afrikaan culture version, and rural Black Tswana children score highest on the Tswana culture version. After accounting for differences in socioeconomic position and tests being adapted for culture, the Black Tswana ethnic minority status children do not appear to have lower working memory scores than the White Afrikaan ethnic majority children.

2.4 Discussion

2.4.1 Socioeconomic position and working memory

This is the first systematic review of the association between socioeconomic position and children's working memory abilities, with a very large sample of individual participants across two data synthesis methods (n = 37,737). In a meta-analysis of 27 studies with 14,328 participants, higher socioeconomic position was associated with overall higher simple working memory ability with a medium effect size. In a meta-analysis of 23 studies with 20,651 participants, higher socioeconomic position was associated with overall higher complex working memory, also with a medium effect size. Furthermore, socioeconomic position was significantly associated with both verbal and visuospatial tasks within both simple and complex working memory. I also synthesized 28 studies including 12,488 participants with more diverse measures of effect using a Harvest plot, finding that most predictors of socioeconomic position were associated with working memory. The findings are consistent with literature that views socioeconomic disadvantage to be associated with impairments in working memory (Hackman et al., 2014; Lawson and Farah, 2017), and therefore does not support the view that working memory is unrelated to socioeconomic disadvantage (Engel, Santos and Gathercole, 2008; Alloway and Copello, 2013).

The magnitude of the association was similar across both the simple and complex working memory meta-analyses (d = 0.45 and d = 0.52 for simple and complex working memory, respectively). This indicates that child socioeconomic disadvantage is associated with not only difficulties in the simple storage of information, but also with the ability to process and manipulate information. This does not support the argument that simple working memory may be more sensitive to the effects of socioeconomic disadvantage than complex working memory due to being more reliant on knowledge structures (Alloway and Copello, 2013).

I also investigated whether the magnitude of the association differed by modality (verbal and visuospatial), finding a similar magnitude of associations within the simple working memory meta-analysis (d = 0.47 and d = 0.40 for verbal and visuospatial, respectively) and the complex working memory meta-analysis (d = .54 and d = 0.41 for verbal and visuospatial working memory, respectively). I tested this formally through meta-regression, and found that task modality did not moderate the association between socioeconomic position and working memory. Still, visuospatial working memory tended to have smaller effect sizes, and this is likely because the subgroup analyses of the visuospatial studies contained fewer effect sizes – perhaps due to difficulties with assessing visuospatial working memory in children.

As I described in Chapter 1, modular working memory theories, such as the multicomponent model (Baddeley, Hitch and Allen, 2021; Baddeley, 2010), propose separate components for different functions within working memory. In contrast, unitary approaches such as the attentional control model (Engle and Kane, 2004) and Cowan's embedded processes model (Cowan, Morey and Naveh-Benjamin, 2021; Cowan, 2008) do not support dissociable components. The results showed a similar level of association between socioeconomic position and different components of working memory. This could be seen as evidence to support a more unitary approach to working memory, or it may also be that the separate components of working memory are affected by socioeconomic position to a similar extent. Either way, this is a strength of the review as the results can be considered within the context of both types of working memory theory.

2.4.1.1 Heterogeneity

The meta-analysis indicated significant heterogeneity across the studies, with prediction intervals crossing the null line. However, the prediction intervals included a high upper boundary and the average effect size in both studies was medium, indicating that a significant average effect is likely to exist in future settings (IntHout et al., 2016). High heterogeneity can be due to clinical or methodological diversity, and in most cases, it is likely due to both (Deeks, Higgins and Altman, 2019). It was difficult to ascertain the source of heterogeneity in this review as I synthesised a large number of studies, varying in both methodological and participant characteristics. The finding of high heterogeneity can be interpreted as an indication that the association between socioeconomic position and working memory is highly likely to vary across different settings and participants. Further, the prediction intervals overlapped with the null, indicating some uncertainty about the direction and magnitude, and therefore uncertainty regarding the generalizability of the effect to future studies.

I investigated some sources of the high heterogeneity through exploration of potential moderating characteristics using meta-regression (Borenstein et al., 2011). The risk of bias of individual studies did not moderate the association, where studies at high risk of bias had similar associations as those with low risk of bias. This may be because only a small proportion of meta-analyzed studies were assessed to be at high risk of bias (20%). I found that child age did not moderate the association; this finding is consistent with the aforementioned meta-analysis regarding socioeconomic position and executive function (Lawson, Hook and Farah, 2018). This indicates that socioeconomic disadvantage is detrimental to children's working memory regardless of child age, and does not accumulate throughout childhood. Still, as the majority of studies in this review were cross-sectional in design, this finding warrants further validation with longitudinal studies measuring the absence of cumulative effects of socioeconomic disadvantage on children's working memory.

Finally, the type of socioeconomic indicator did not moderate the association; this was again consistent with the aforementioned meta-analysis regarding socioeconomic position and child executive function (Lawson, Hook and Farah, 2018). This shows that single indicators of socioeconomic position are as sensitive as composite indicators are for detecting negative associations with child working memory. However, I was only able to compare the difference between single and composite indicators of socioeconomic position, as there was not enough data to explore differences across single indicators. This finding therefore warrants further exploration across single indicators of socioeconomic position and working memory, as this may give more insight into any causal mechanisms between disadvantage and working memory.

I also explored the influence of the data synthesis methods on the effect sizes through meta-regression. I found that the association was not moderated by whether the effect size had been averaged or not (and this was further confirmed with the RVE sensitivity analysis). Finally, there was some evidence to suggest the association between socioeconomic position and simple working memory was moderated by whether effect sizes had been converted from Pearson's *r,* with smaller effect sizes for those that had been converted (B = -0.35, p = .05). However, this finding did not hold for complex working memory. Nonetheless, studies that had been converted from Pearson's r may therefore have had weaker associations than those that used mean scores across two groups, and this is unsurprising since studies representing a continuum of socioeconomic position would have weaker associations than those comparing two extreme groups of socioeconomic position. This finding may therefore suggest the true association between two extreme groups of socioeconomic position and working memory is even larger than I have estimated here.

2.4.1.2 Future research suggestions

This systematic review has highlighted several knowledge gaps that I address with the remaining studies in my PhD. Although it is clear that the association between socioeconomic position and working memory is 'medium', the practical meaning of the medium strength association between socioeconomic position and working memory remains unknown. It would be useful to contextualise these socioeconomic gaps in comparison to differences in working memory by age, in order to fully understand the implications of this association.

I did not systematically investigate causal or contextual factors that may mediate the association between socioeconomic position and working memory as this was not the focus of the review. Therefore, further investigation using longitudinal studies would enable an exploration of the complex interplay between different factors and the links to working memory. As mentioned in the introduction, two key potential mediating causal factors between socioeconomic disadvantage and child development are the home learning environment and chronic stress (Duncan, Magnuson and Votruba-Drzal, 2017; Votruba-Drzal, 2006; Lupien et al., 2001). Socioeconomic disadvantage may impair parents' ability to provide home enrichment resources and activities (use of toys, books, and learning experiences), which has been found to be associated with children's working memory (Hackman et al., 2014). Additionally, allostatic load, a biological marker of cumulative chronic stress, has been found to mediate the associations between childhood poverty and adult working memory ability (Evans and Schamberg, 2009), and this is consistent with a systematic review that found an association between early life stress and working memory (Goodman, Freeman and Chalmers, 2018). These are therefore two factors for future research to consider within the context of working memory.

One potential moderating characteristic of the association between socioeconomic position and working memory is ethnicity. It was not possible to explore ethnicity as a moderator as nearly half of the studies in this review included two or more ethnic groups, with both ethnic majority and minority children. Minority ethnic groups tend to experience higher levels of disadvantage (Chattoo and Atkin, 2019), and it has previously been found that socioeconomic disadvantage is associated with worse working memory in ethnic minority children, whilst ethnic majority children at different levels of socioeconomic risks have similar working memory ability (Rhoades et al., 2011). The disadvantage faced by ethnic minority groups may therefore exacerbate the negative association between socioeconomic position and working memory, something that could be explored more fully in future research.

2.4.2 Ethnicity and working memory

I identified 14 studies containing statistical information regarding the association between ethnic minority status and working memory. The forest plot used 8 studies with 9 individual effect sizes to plot the difference between ethnic minority and majority groups on different types of verbal WM. The individual effect sizes suggest that ethnic minority groups tended to score worse, with the association varying from small to large in magnitude. There were 6 studies that were not included in the forest plot, and these studies generally found that ethnic minority status groups score lower on working memory than the ethnic majority groups, even after adjusting for socioeconomic differences. However, it cannot be determined whether these apparent associations were due to residual confounding or due to the statistical distortion of mediator-outcome bias, meaning the true association between ethnic minority status and working memory remains unknown.

Overall, the number of studies regarding the relationship between ethnicity and working memory was limited. Although the included studies individually indicated that ethnic minority status children do have worse working memory than their ethnic majority peers, the study effect sizes could not be synthesised in a pooled estimate, and consequently, no pooled estimate or any heterogeneity statistics are available for these data. It was therefore not possible to ascertain whether an association exists between ethnic minority status and working memory.

2.4.2.1 Future research suggestions

Since this systematic review was unable to make conclusions about ethnicity and working memory, future research should attempt to ascertain whether ethnic minority children have worse working memory than ethnic majority children. In particular, there was only one study in the review providing data on the association between ethnic minority status and visuospatial working memory. Future studies should therefore include visuospatial tasks if looking at ethnic differences in working memory. The meta-analysis showed that socioeconomic disadvantage was consistently associated with all types of working memory, so it seems likely that any association between ethnic minority status and working memory will be consistent across both verbal and visuospatial working memory, however, this is yet to be investigated.

Whilst investigating the differences across ethnic majority and ethnic minority children's working memory, studies should also explore potential causal factors that may cause differences in ethnic minority working memory. The most obvious potential causal factor is socioeconomic disadvantage, as ethnic minority children may have worse working memory due to higher levels of socioeconomic disadvantage. However, this is unlikely to explain all of the differences between ethnic groups, as there are many other factors to consider.

Cultural differences are a plausible mechanism for explaining differences in working memory. Many published psychology studies, including many that have been used in investigating working memory, use samples that are White, Educated, Industrialized, Rich, and Democratic (WEIRD) (Nielsen et al., 2017). Assuming that research results with WEIRD samples will generalise to non-WEIRD samples is common practice (Rogoff, Dahl and Callanan, 2018), however, the models and theories regarding working memory may be culturally specific to WEIRD populations, and assumptions made using such populations should not be attributed as universal to all populations (Nielsen et al., 2017).

Future research should consider the role of cultural differences in any association between ethnic minority status and working memory, with particular knowledge regarding the ethnic groups they are comparing. Indeed, I identified one study where cultural adaptation of a working memory test accounted for differences in working memory scores between ethnic groups (Malda et al., 2010). Although "culture" encompasses a complex phenomenon that will be almost impossible to capture and study completely and accurately, researchers can first focus their attention on particular aspects of culture that can be accurately measured and analysed.

One cultural factor that may cause true differences in working memory and can easily be explored is first language status. Children who are not first language speakers in the language that the working memory test is being administered in are likely to score worse, as they may not be as familiar with its instructions and structure. Another factor that may cause differences in working memory is whether a child is a 1st or 2nd generation immigrant. A child born in the country they currently reside in is more likely to be culturally acclimatised than a child who was born elsewhere. This may also relate to language status, where a child born in the country they currently reside in may be more likely to have fluency in that country's main language.

Finally, as home enrichment and maternal sensitivity were identified to be potential mediating factors between socioeconomic position and working memory, these could also be potentially important factors in the relationship between ethnic minority status and working memory. Different cultural practices may induce differences in the home environment and maternal sensitivity, so these could be factors for future research to include in mediation analysis between ethnic minority status and working memory.

Furthermore, the scope of the evidence regarding the association between ethnic minority status and working memory across different countries is limited, with the majority coming from the USA. The experience of a child belonging to an ethnic minority group will vary depending on the country the child is residing in, and the political and societal context of that country. Further, comparing all combined ethnic minority groups in contrast to an ethnic majority group (as several of the studies in this review did) is not an effective approach. Each ethnic minority group within the same country will have different experiences of disadvantage and culture. A more effective approach will compare different categories of ethnic minority groups to be as specific as possible, and contrast their working memory in comparison to the ethnic majority group.

2.4.3 Strengths and limitations

This systematic review included a broad range of studies using a variety of methods to assess the association between disadvantage and working memory. The use of a comprehensive search strategy utilising the equity filter based on PROGRESS (Prady et al., 2018) allowed identification a large number of studies (>7000 at the initial stage). Unlike previous reviews on this topic, inclusion was not constrained to any particular estimation method, but included all studies with any quantitative measure of association between socioeconomic position and working memory. The use of the Harvest plot allowed inclusion of studies using any estimation method and reduces the likelihood of bias in the findings. This systematic review is the first to analyse the association between socioeconomic position, ethnicity, and working memory, and explores the association by the different components of working memory. The separation of the results into the different components of working memory allows the results to be applicable to both modular and unitary working memory models, as the summary effect sizes for each component can be considered to reflect those different components of working memory, or they can be combined to consider working memory as one construct.

A limitation is that as the majority of studies used cross-sectional designs, I am not able to establish causality from the associations reported in this review. Further, I converted effect size measures to a common metric, and thus the conversion into Cohen's *d* therefore means that the meta-analyses analysed socioeconomic position as a dichotomous variable with two groups of socioeconomic position – which is not how socioeconomic position is actually distributed. However, the alternative would have been to exclude the studies that happened to use an alternate metric - potentially resulting in a biased sample of studies (Borenstein et al., 2011).

2.5 Chapter Summary

This chapter has systematically and comprehensively synthesised the literature regarding the association between socioeconomic position and working memory, and ethnicity and working memory. It has highlighted the need for understanding the true magnitude of these associations, and potential causal factors underlying these associations. In particular, it has highlighted a lack of understanding on the association between ethnic minority status and working memory. In Section B, I address some of these research gaps through analyses of data from a cohort study.

Section B: Cohort Study Data Analysis

This section contains the methods and findings for the cohort study data analysis across four chapters:

- Chapter 3 describes the research context and the included variables across all studies.
- Chapter 4 describes the methods, findings, and discussion for Study 1: Working Memory by personal demographic characteristics.
- Chapter 5 describes the methods, findings, and discussion for Study 2: The structural associations between socioeconomic position, the home learning environment, and working memory
- Chapter 6 describes the methods, findings, and discussion for Study 3: Potential positive factors for ethnic minority working memory

Chapter 3. Research Context and Conceptualisation for Cohort Data Analysis

This chapter outlines the research context, data sources and ethical considerations for analysing the cohort study data. It also describes the theoretical assumptions about the relationships between the variables through use of a Directed Acyclic Graph (DAG), and specifies how and where they are analysed. In the final section, the source and nature of each variable included in the analyses are described.

3.1 Research Context: Born in Bradford

The data source is the longitudinal cohort study, Born in Bradford (BiB). The BiB cohort recruited pregnant mothers between March 2007 and December 2010 at the Bradford Royal Infirmary. All babies born to these mothers were eligible to participate and more than 80% of women invited agreed to participate (Raynor et al., 2008). The cohort comprises of 12,453 mothers, 13,776 pregnancies and 3,448 fathers. BiB's primary aims were to describe health and ill-health and identify relationships between potential causal factors and health outcomes (Wright et al., 2013).

Bradford is a city in northern England with a population of 534,800 people - the UK's seventh most populated city. Out of 318 local authority districts, Bradford is the 13th most deprived on the Index of Multiple Deprivation, and the 41st most deprived on the Index of Deprivation Affecting Children (IDACI) (GOV.UK, 2019a). Bradford has the 11th highest proportion of neighbourhoods in the most deprived 10 per cent of neighbourhoods nationally on the IMD (2019) (GOV.UK, 2019a).

The Office for National Statistics 2017 census reveals that the largest proportion of Bradford's population (63.9%) identify themselves as White British, and the city has the largest proportion in England of people of Pakistani ethnic origin (20.3%) (Bradford Council, 2017). As outlined in Chapter 1, 56% of pupils in Bradford schools are from ethnic minority groups – and over 70% in that group are Asian (Department for Education, 2018). At recruitment, the BiB sample represented the general demography of Bradford. The two largest ethnic groups in the sample are White British (40%) and Pakistani (45%) (Wright et al., 2013; Fairley et al., 2014).

The proportion of ethnic minority residents living in Bradford varies between neighbourhoods. Some integration between the White British and Pakistani populations is established by the presence of Pakistani students in Bradford's Further and Higher Education institutions. Integration is also present where the Pakistani community are involved in local politics and professions (Fairley et al., 2014; Small, 2012). However, segregation is present in patterns of residential locations, where some streets and local neighbourhoods are nearly exclusively made up of people of Pakistani origin and others are dominated by White British families. In compulsory schooling, some schools have large majorities of pupils of Pakistani origin and nearby schools have almost none (Greenhalf 1993, in Small, 2012).

3.1.1 Data Collection Timepoints

BiB collects data throughout the life course on various demographic measures and health outcomes. The figure below summarises the data collection points that are required for my analyses.

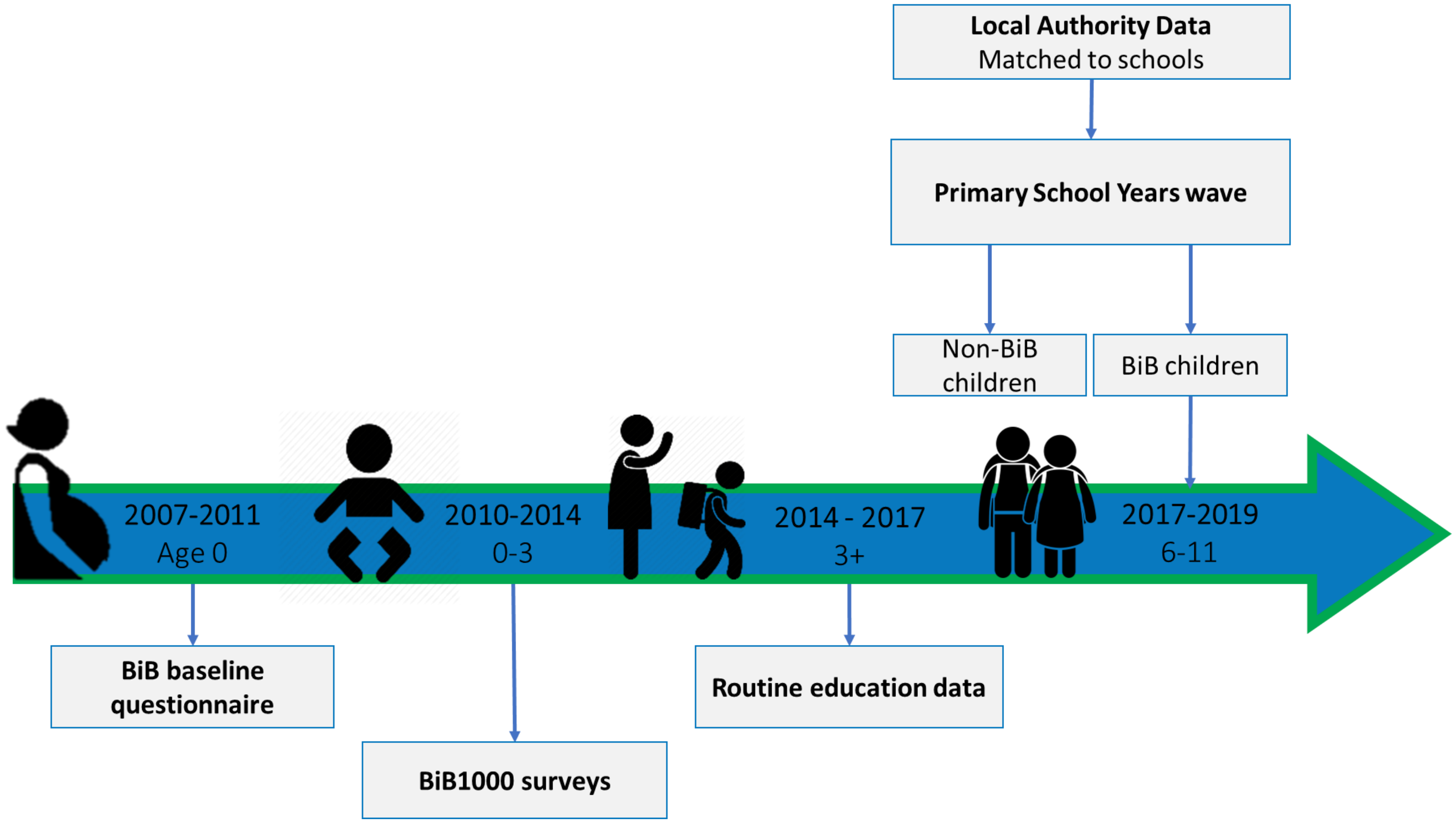


Figure 16. The data sources required for analyses

Figure 16 summarises the required data sources from BiB. Although BiB collects much more data on a variety of measures, the figure presents only the data required for my thesis. Mothers completed the BiB baseline questionnaire when they were recruited to the cohort during pregnancy and reported information on family demographics and several indicators of socioeconomic position. When children were aged 6 months, the BiB1000 cohort invited 1763 mothers to take part in BiB1000 surveys, where responses to a broad range of sociodemographic, clinical, and developmental questions were collected. Surveys were administered every 6 months, from when the child was aged 6 months until they were aged 36 months. As the surveys at the 24-month and 36-month timepoints include questions regarding the frequency of home learning activities, these were used in Study 2 to measure the home learning environment. Routine education data is obtained from the Local Authority and updates key child characteristics every year that the child attends school (e.g. Ethnicity, Special Educational Needs and Disability classification and whether the child is learning English as an Additional Language) (Born in Bradford, 2020b).

A large-scale data collection period was conducted between 2016 and 2019, including assessments of child physical activity, wellbeing and cognition. The data collection period is hereafter referred to as the 'Primary School Years' wave. Schools in the Bradford district were invited to take part based on whether they had previously taken part in a large-scale data collection period when BiB children were aged 4-5, and then schools with higher numbers of children in the BiB study were also invited. Data were collected in three academic school years (3-6, covering ages 7-11 years) in 90 primary schools that have high number of BiB children attending them (Bird et al., 2019). Researchers tested whole classes of children at a time, including both children who were and were not part of the BiB study. With regards to the cognitive and sensorimotor data, this most recent wave contains data from whole classes of children (n = 15,820), some of whom are participating in the BiB cohort (n = 9604). The cognition assessments included three measures of working memory, which are the outcomes of interest to all studies in my PhD (Hill et al., 2021b).

Through obtaining names of the schools in the Primary School Years wave, I linked data from local authority databases with school and area relevant information obtained during years 2018-2019 (GOV.UK, 2019c). Of interest to my research were the publicly available information for each school regarding the ethnic proportions within schools and the area deprivation of a school's location.

3.2 Ethical Considerations

3.1.2 Data Collection

BiB is overseen by a Scientific Steering Group and Executive Group, and BiB studies are reviewed and approved by the independent NHS Research Ethics Committee (Born in Bradford, 2020a). For the Primary School Years wave, ethnical approval was obtained from the NHS Health Research Authority Yorkshire and the Humber (Bradford Leeds) Research Ethics Committee (reference: 16/YH/0062). Consent was first obtained from schools, and schools provided information sheets and consent forms to parents, who were provided with the option to 'opt-out' of consent (Bird et al., 2019).

The use of BiB data is therefore covered by its own ethics procedures and I did not seek further additional ethical approval for this study consisting of secondary analysis of anonymous data.

3.1.3 Data Protection

All BiB data received by collaborators has been pseudonymised and uses identification numbers instead of names. BiB informs its participants that they will not be identified by the results or any reports that they publish (Born in Bradford, 2020c). Identification may be a risk if studies use small sample sizes. Individuals are at a low risk of becoming re-identified in this study as the sample sizes were likely to be large, however, if any cell counts contained <5 participants, they were suppressed and not presented.

3.1.4 Data Management

I applied to access BiB data and this was approved on 05/09/2019 (reference number SP358). I requested and received data regarding socioeconomic position, educational context, the home learning environment, and working memory (see Appendices B1). I signed a collaboration and information sharing agreement between myself and the Bradford Teaching Hospitals NHS Trust (see Appendices B2). The signed collaboration and information sharing agreement between myself and the Bradford Teaching Hospitals NHS Trust specifies that data will only be retained for as long as necessary to complete the study. The agreement also states that the investigator must not transfer the data to a third party without the third party entering into a separate information sharing agreement with BiB. In compliance with this, I will not share the data with any third parties. Finally, the agreement states that the investigator must return datasets with any new derived variables.

The University of York's Data Management Policy was followed (University of York). To comply with this, I took the following steps:

- To ensure data are retrievable and available when needed, received data were stored on my personal University of York drive accessible only via a password.
- To ensure it is secure and safe, the raw data and any new datasets generated from the raw data were protected with a different password.
- Compliance with ethical and legal issues outlined by University of York Library (2020)
- A descriptive meta-data document was created containing contextual information required to make data meaningful and to aid its interpretation both now and in the future. It will contain decisions made regarding data analysis, including generating new variables, dropping cases, and any deviations from the analysis plan.
- The descriptive meta-data document will be available to BiB when the data is returned at the end of the project or when requested (if sooner).

3.3 Identification of Covariates

In order to investigate the research questions, other covariates that might influence the relationship should be identified. Covariate variables are those that are not the exposure of interest, but their inclusion in a model reduces bias in estimates of the relations between exposure and outcome variables (Shrier and Platt, 2008). Theoretical context allows us to designate some variables as exposure variables, and some as covariates. Identifying potential biasing covariates and purposefully including them in models to control for factors that may bias coefficients is desirable (Bollen and Bauldry, 2011).

A covariate can be one that is not casually associated with the exposure, but improves the precision of the estimate in the outcome. Further, a covariate can be a confounder, mediator, or a moderator. A confounding variable has an independent causal relationship to both the outcome and the exposure (Frank, 2000). To be conceptualised as a true confounder variable, a variable must be all three of the following: (1) associated with the exposure, (2) a risk factor for the outcome, and (3) not on the causal pathway between the exposure and outcome (Jewell, 2003). In this context, if 'C' is a confounder, it will influence both working memory and socioeconomic position (SEP⟵C⟶working memory). If data on confounders have been measured, they can either be included in and adjusted for in statistical analysis, or the results can be stratified by the confounder (Jager et al., 2008). Failing to take account of confounding variables could bias the estimation of the relationships between exposure variables socioeconomic position and ethnicity, and the outcome (working memory). It could also bias the estimation of any relationships between mediators and the working memory (Williams et al., 2018).

A moderator affects the direction and/or strength of the relationship between an exposure and outcome variable – describing *when* and *for whom* an association occurs. Moderation is also known as interaction, where an interaction can change either the magnitude or the direction of an association (Vetter and Mascha, 2017). Whilst a moderator can be thought as the changer of a relationship in a system, a mediator can be thought of as a carrier of information along the causal chain of effects. A mediator therefore explains *how* or *why* relationships between exposures and outcomes occur. A mediator means that: (1) variations in the exposure significantly account for variations in the mediator and (2) variations in the mediator significantly account for variations in the outcome (Baron and Kenny, 1986). This is also known as an indirect effect (Wu and Zumbo, 2008). Inappropriately controlling for mediators can result in a null-biased estimate of the effect between the exposure and outcome (Schisterman and Cole, 2009; Richiardi, Bellocco and Zugna, 2013).

Directed acyclic graphs (DAGs) provide graphical summaries of theorised causal relationships, where an arrow connecting two variables indicates assumed causation, and variables with no direct causal association are left unconnected (Greenland, Pearl and Robins, 1999; Shrier and Platt, 2008). DAGs are a simple and transparent way prior to observational data analysis to identify and develop knowledge, theories, and assumptions about the causal relationships between variables (Greenland, Pearl and Robins, 1999). DAGs are particularly useful to identify potential confounders and mediators in relationships between exposures and outcomes, as appropriate adjustment for these is important for reducing bias in the estimation of a relationship (Williams et al., 2018; Schisterman, Cole and Platt, 2009; Richiardi, Bellocco and Zugna, 2013). A variable may simultaneously be a confounder, mediator, or exposure variable in separate research questions using the same data. What matters to the precision of an analysis is the analytical strategies in the separate research questions (Williams et al., 2018).

However, DAGs have some limitations. A DAG can only be as good as the theory that is used to create it. If we are not aware of confounding variables, a spurious relationship could appear between the exposures and outcomes (Williams et al., 2018). If we inappropriately condition on a true mediating variable (because it is believed to be a confounding variable), we could bias an association between an exposure and outcome (Richiardi, Bellocco and Zugna, 2013). A DAG should therefore include both measured and unmeasured variables (Dunn et al., 2015; Williams et al., 2018). This assists researchers in including measured variables in an analysis in an appropriate way, and assists understanding of potentially spurious relationships by identifying unmeasured variables (Dunn et al., 2015). Additionally, although it is acknowledged that almost all DAGs will be an oversimplification of the true causal relationships amongst the variables, they can still assist researchers in identifying covariates to reduce bias in analysis (Williams et al., 2018; Shrier and Platt, 2008).

I created a DAG regarding the relationships between ethnicity, SEP, and working memory, including only variables that lie on the causal path between Ethnicity⟶working memory or SEP ⟶working memory. I have specified those that were possible to be investigated using BiB data, but also specified where unmeasured variables may lie.

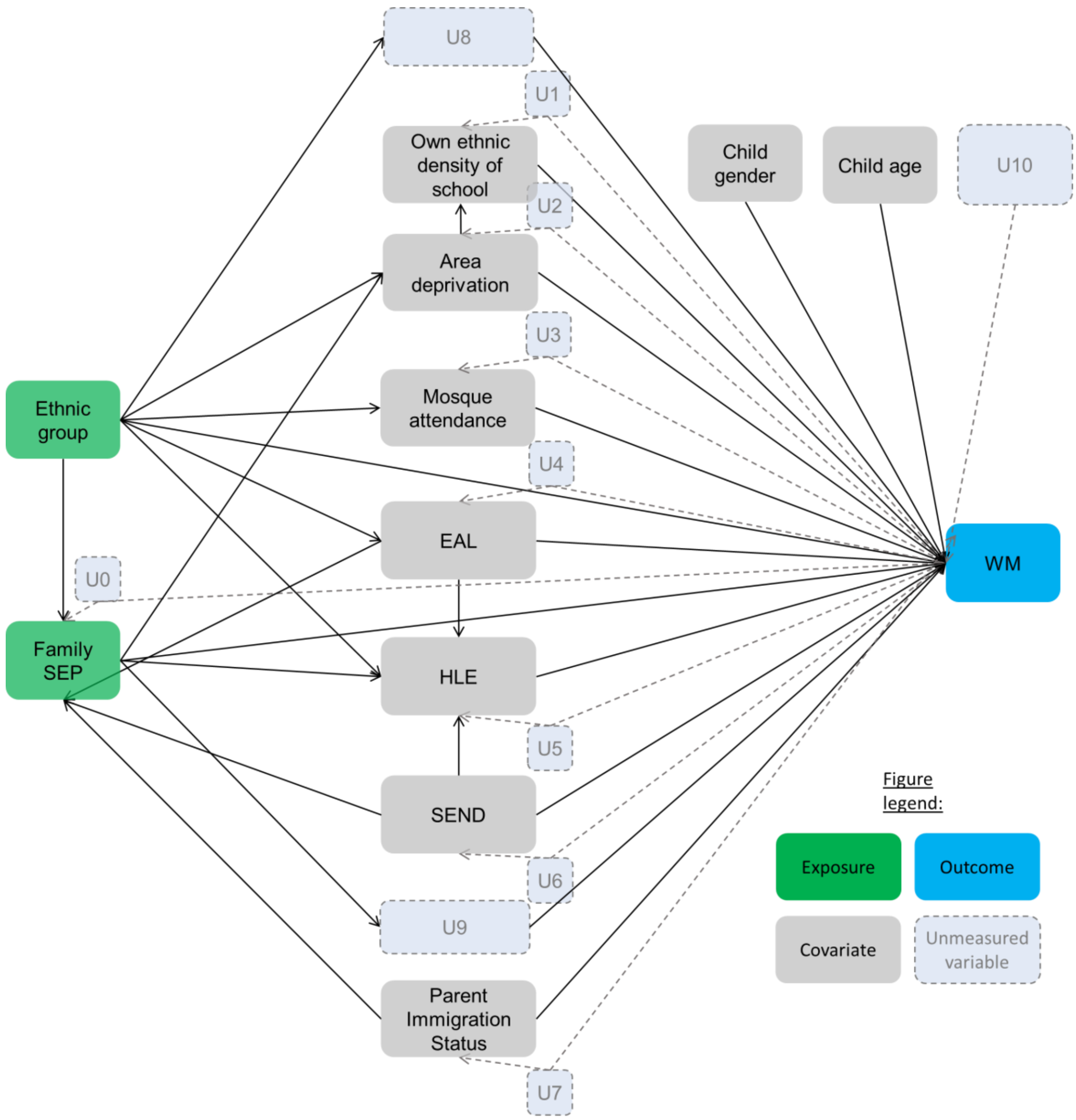


Figure 17. Directed Acyclic Graph of the causal theory between the exposures and working memory

[Abbreviations: Socioeconomic Position (SEP), Special Educational Needs or Disability (SEND) English as an Additional Language (EAL), Home Learning Environment (HLE), and Working Memory (working memory)]

The Directed Acyclic Graph (DAG) in Figure 17 presents my theory and causal assumptions about the potential relationships between ethnicity, socioeconomic position, and working memory. It includes variables that are both measured in BiB, and identifies where potential unmeasured and confounding variables may lie (U0 – U10). U0 to U7 identify where relationships may be confounded, U8 and U9 identify that associations between socioeconomic position/ethnicity and working memory may be mediated through unmeasured variables, and U10 identifies that unmeasured variables are likely to have direct associations with working memory. Identification that such variables may exist assists understanding of potentially spurious relationships and unexplained variance (Dunn et al., 2015).

The DAG does not specify whether the social determinants on the causal pathways between Ethnicity and SEP⟶working memory are either moderators or mediators, as a DAG with multiple arrows pointing at a single variable implicitly allows for interactions between the causal variables (Pearl and Mackenzie, 2018). Instead, I conceptualise variables as either mediators or moderators in the analysis plans in the following chapters. In Figure 17, ethnic group is conceptualised as an exogenous variable (it is not influenced by any other variables inside the DAG), and socioeconomic position is conceptualised as endogenous (it is influenced by a variable inside the DAG – ethnicity).

In the following sections, I describe how and where each variable is included within each study.

3.4 Inclusion of Covariates

Table 12. Summary of variables included across analysis sections

Data source	Variable	Study 1: Linear Regression	Study 2: Structural Equation Model	Study 3: Multileve l Model
Primary School Years wave	Working Memory	✓	✓	✓
	Ethnicity	✓	✓	✓
	Gender	✓	✓	✗
	Age	✓	✓	✓
	Mosque/Madrassah attendance	✗	✗	✓
Born in Bradford cohort	Socioeconomic Position	✓	✓	✗
	Parent Immigration Status	✓	✓	✗
	The Home Learning Environment	✗	✓	✗
	English as an Additional Language	✓	✓	✗
	Special Educational Needs	✓	✗	✗
Local Authority school data	Own ethnic density	✗	✗	✓
	Area Deprivation	✗	✗	✓

Table 12 specifies all of the variables included across the three studies. It also includes the data source of the variable. The first five variables were obtained via the Primary School Years data collection wave, the next six variables were obtained via BiB, and the final two were linked via local authority data to schools. The following sections specify how these variables are conceptualised and measured across studies.

3.1.5 Working Memory

The outcome of interest is children's working memory scores. The BiB Primary School Years wave administered a battery of executive function tasks, including three tasks of working memory. Trained research assistants administered all assessments. The child participated in the tasks on a tablet laptop, and used headphones to hear the sequences (Bird et al., 2019; Hill et al., 2021a). In all studies, I use the percentage of correctly recalled items as the outcome and model this as continuous. The three tasks are described in the following sections.

3.1.5.1 Forwards Digit Recall

In the Forwards Digit Recall (FDR) task, children were presented with a sequence of numbers through headphones and subsequently asked to recall these numbers in the order they were audibly presented, by touching the appropriate boxes on the screen in order (see Figure 18). Nine boxes were ordered sequentially from 1 to 9 on the screen. The tasks progressed from sequence length three to six, with four trials for each sequence length, with a total of 16 trials.

As described in Chapter 1, the multicomponent working memory model views it is having distinct and separable systems. As the task includes the forwards recall of verbal information, it as a measure of simple verbal working memory.

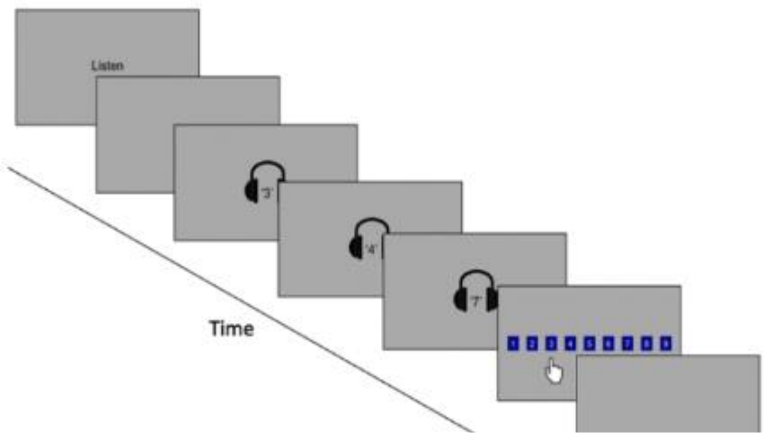


Figure 18. Schematic illustration of the FDR task (Hill et al., 2021)

3.1.5.2 Backwards Digit Recall

Backwards Digit Recall (BDR) was similar to FDR, but children were asked to recall the numbers in reverse order. As this task is more difficult than FDR, sequence length started at two digits and increased to sequence length five, with four trials at each length. As this task has additional processing demands, it is a measure of complex verbal working memory.

3.1.5.3 Corsi block tapping (Corsi)

Children were presented with nine randomly arranged blue squares, in which a random and unique sequence of boxes flashed yellow. The task was for the child to remember the order and once the sequence was finished, to tap the blue boxes in the order in which the yellow boxes flashed (see Figure 19). Sequence length increased as the task progressed, from three squares to six squares, with four standardised sequences presented for each sequence length, equalling a total of 16 trials. As the task includes the forwards order but with visuospatial processing, it is a measure of simple visuospatial working memory.

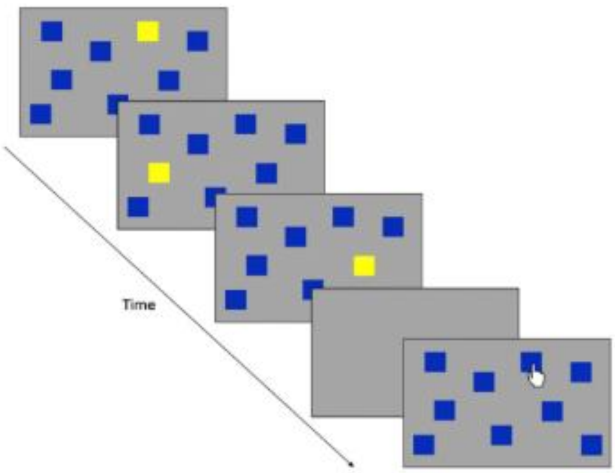


Figure 19. Schematic illustration of the Corsi task (Hill et al., 2021)

3.1.6 Ethnicity

The two most populous ethnic groups in the BiB cohort, and also in Bradford, are White British and Pakistani (Wright et al., 2013). The largest proportion of Bradford's population (63.9%) identify themselves as White British, and the city has the largest proportion in England of people of Pakistani ethnic origin (20.3%) (Bradford Council, 2017). Schools in Bradford have high numbers of ethnic minorities, with 56% of their pupils coming from minority groups – and over 70% in that group are Asian (GOV.UK, 2019c). As described in Chapter 1, I conceptualise the White British group as the ethnic majority group, and all other ethnicities as ethnic minority groups. Although there are actually a higher number of Pakistani mothers in the BiB sample than White British mothers, the Pakistani mothers and their children are still a minority group within the context of the UK.

In Study 1, I include all ethnic groups available to provide a descriptive overview of children's working memory across ethnic groups. However, including all 9 categories of the ethnic groups would have overcomplicated the interpretation of further analyses, and may have compromised statistical power due to small counts within the smaller minority groups, so I excluded the smaller ethnic minority groups in further analyses. In Study 2, I only include White British and Pakistani ethnic groups, and explore associations across the two ethnic groups using a multi-group model. In Study 3, I include only White British and Pakistani participants in the ethnic density analysis (as these groups have the most meaningful variations in own ethnic density), and South Asian participants in the Mosque analysis (as these groups report high Mosque attendance).

Data regarding child ethnicity is reported by parents on registration with a school. In the Primary School Years wave, the tested schools provided class lists containing ethnicity data. In the BiB cohort, ethnicity data were additionally obtained from the local authority (which schools submit to as part of their regular census). Although both ethnicity records originate from the parents reports of child ethnicity, they have been classified at different times and to different schemes and this led to some minor differences in coding of ethnic groups, and some minor discrepancies and missingness of data. The ethnicity information from school records obtained as part of the Primary School Years study contained 192 categories. For the purpose of analysis of the full Primary School Years data, these were regrouped into ten: Pakistani, Bangladeshi, Indian, Black/Black British, White British, Mixed, Gypsy/Irish Traveller, Other White, Other, and Unknown. In the BiB cohort, the categorisation of ethnicity includes: Bangladeshi, Indian, Pakistani, Chinese/Other Asian, African, Black Caribbean/Black British, Mixed, White Other, and Other ethnic groups.

For the analyses of the full Primary School Years sample, the school class lists were used and if data were missing, it was supplemented from the BiB cohort where possible. For the analyses of the BiB-only children, the ethnicity data from the local authority is used and if data were missing, it was supplemented from the PSY school lists where possible. If any discrepancies arose where children had different codes in each dataset, the ethnicity coding for the primary dataset was used (Primary School Years wave or BiB cohort only).

3.1.7 Gender

Although meta-analyses have indicated a small but significant male advantage in overall visuospatial working memory ability (d = 0.155, 95% confidence interval = 0.087-0.223) (Voyer, Voyer and Saint-Aubin, 2017), the true standing of these differences has been disputed (Grissom and Reyes, 2019). Grisson and Reyes (2019) argue that gender differences are more likely due to variability in strategies used during testing as well as how different challenges, either within the task or as part of the environment, affect performance. Still, I include child gender as a covariate as it may improve the precision of the estimate between the exposures and working memory.

Child gender is obtained through access to children's educational records, and is recorded as a binary variable (male or female). Child gender was included in Study 1 to describe differences by gender and included in Study 2 to improve the precision of the estimates. However, I did not include it in Study 3 as the previous analyses showed it to have very little influence on working memory.

3.1.8 Age

Child age is a covariate that is likely to increase the precision in estimates of the relationships, since child working memory ability improves with age (León, Cimadevilla and Tascón, 2014; Hill et al., 2021b; Alloway et al., 2004). Age is obtained through the Primary School Years wave, and is recorded as age in year and age in months at time of testing. As its inclusion in the analyses will increase the precision of the estimated relationship between the exposures and outcome, child age is included in Studies 1-3.

3.1.9 Mosque and/or Madrassah Attendance

As part of the Primary School Years wave, children were asked about their attendance to a variety of after school and/or extracurricular activities. One of these activities is Mosque and/or Madrassah attendance (where the response was yes or no). If children replied yes, they also indicated how often they attended Mosque and/or Madrassah (less than once per week, some days, or most days). The response to the first question was included in analyses in Study 3.

Other activities included asking about whether children attend sports clubs, Church or Sunday school, music lessons and dance lessons. I explored working memory scores in response to these other activities to descriptively compare the scores in comparison to Mosque attendance in Study 3.

3.1.10 Socioeconomic Position (BiB only)

Socioeconomic Position is the key exposure of interest in my thesis. In Study 1, I include three measures of SEP. In Study 2, I include a 5-category latent class socioeconomic position measure. In Study 3, I do not include any measures of socioeconomic position as this analysis used data from the Primary School Years whole classes including non-BiB children for whom there is no information about family SEP. The measures included in Study 1 and 2 are described next.

3.1.10.1 Latent Class Analysis of Socioeconomic Position

A measure that is consistent with the definition of socioeconomic position in Chapter 1 will combine information about material assets and prestige-based components, determining the position that a family holds within society. I use a 5-category Latent Class Analysis (LCA) of the socioeconomic measures of the BiB cohort that has already been conducted (Fairley et al., 2014). LCA is a statistical analysis technique that groups variables or observations into distinct clusters, based on the assumption that there are underlying "latent classes" within the data (Porta, 2014). The latent classes are determined by a set of behaviours or characteristics, so individuals within each class will have similar response patterns to observed indicator variables (Lanza and Cooper, 2016). The classes are formed so that there is as much similarity within a class as possible, whilst also ensuring as many differences between the classes as possible (Lanza & Cooper, 2016).

The LCA socioeconomic position variable is available in the BiB data dictionary and classifies mother's socioeconomic position into 5 distinct categories using 19 variables relating to employment, education, benefits, and material deprivation. The variables were questions asked in the baseline questionnaire when mothers were pregnant. The profiles and sample sizes within each class are:

- "Least socioeconomically deprived and most educated" (20% n = 2231)
- "Employed and not materially deprived" (19%, n = 2248)
- "Employed and no access to money" (16%, n = 1722)
- "Benefits and not materially deprived" (29%, n = 3325)
- "Most economically deprived" (16%, n = 1800).

I include this socioeconomic position measure in both Study 1 and Study 2.

3.1.10.2 Ethnic-specific Latent Class Analysis of Socioeconomic Position

To examine differences by ethnicity, it is important to adjust for socioeconomic position appropriately, however, the extent to which traditional measures of socioeconomic position are valid in different ethnic groups is contested (e.g., educational attainment (Kelaher et al., 2009)). In response to this problem, ethnic-specific measures of socioeconomic position have been developed for BiB (Fairley et al., 2014).

Fairley et al. (2014) found that components of socioeconomic position aggregated separately in the White British and Pakistani groups of women. Using LCA stratified by ethnicity, there were marked differences in the classes by the woman's employment status and education. The White British classes included:

- "Employed, educated, not materially deprived" (44%, n = 2038)
- "Employed, moderate education, materially deprived" (14%, n = 614)
- "Low education, benefits, not materially deprived" (23%, n = 992)
- "Low education, benefits, subjectively poor and materially deprived" (18%, n = 836).

Whereas the Pakistani classes included:

- “Educated, low benefits, not materially deprived” (22%, n = 1113)
- “Women employed, moderate education, benefits, not materially deprived” (17%, n = 935)
- “Women not employed, low education, benefits, not materially deprived” (33%, n = 1642)
- “Women not employed, moderate education, benefits, subjectively poor and materially deprived (28%, n = 1427).

Within the White British group two classes can be described as materially deprived, whereas within the Pakistani group only one class were materially deprived. This ethnic-specific socioeconomic position measure is included in Study 1 only.

3.1.10.3 Self-reported financial situation

The response rate to questions regarding income has been reported to be low and biased. In particular, people of lower social status are reluctant to share this information in a survey (Kelaher et al., 2009). Uphoff, Pickett and Wright (2016) found the strongest evidence of a social gradient in health for Pakistani women in the BiB cohort with the self-reported measure of financial situation in relation to mental health. Self-reported financial situation was assessed during the BiB baseline questionnaire, where participants were asked how well the mother and husband were coping financially. The responses include: 1 (living comfortably), 2 (doing alright), 3 (just about getting by), 4 (quite difficult), 5 (very difficult), and 6 (does not wish to answer).

I therefore included this measure of socioeconomic position in Study 1. This variable was not included in Study 2 since broad socioeconomic position was the exposure of interest, and was not included in Study 3 as it was not measured in the non-BiB Primary School Years wave.

3.1.11 Parent Immigration Status (BiB only)

Immigration status was queried in the BiB baseline questionnaire, where mothers responded whether they were born in the UK or born outside of the UK. As parents' immigration status might be important to ethnic minority children's development through cultural differences associated with recent immigration (García et al., 1996), I included this in Study 1 and Study 2. It could also be a confounder of the association between socioeconomic position and working memory, as recently immigrated ethnic minorities may have lower socioeconomic position (Schnepf, 2006). It could not be included in Study 3 as this information was only available for children participating in the BiB cohort.

3.1.12 The Home Learning Environment (HLE) (BiB only)

The HLE was found to be a significant mediating variable between socioeconomic position and working memory in a study identified in my systematic review (Hackman et al., 2014), and is frequently found to be a significant contributor in studies regarding socioeconomic position and child development (e.g. Kelly *et al.*, 2011). The hypothesis that ethnicity could be associated with working memory due to cultural differences can also be explored through differences in the home environment (HLE). Cultural variations in parenting practices are well documented, and these may translate into differences in children's learning environments at home (Bornstein, 2009, 2012).

A general definition and common operationalisation of the HLE does not yet exist (Niklas et al., 2016). Some studies measuring HLE may focus on different constructs within the HLE such as home literacy, home numeracy or a more general overall learning environment (Melhuish, 2010; Niklas and Schneider, 2013). I aimed to focus on a general overall learning environment, and constructed a measure that assesses engagement with a variety of different learning activities.

Previously, HLE has been measured through parental interviews regarding the frequency that children engaged in the following 14 activities: playing with friends at home; playing with friends elsewhere; visiting relatives or friends; shopping with parent; watching TV; eating meals with the family; going to the library; playing with letters/numbers; painting or drawing; being read to; learning activities with the alphabet, numbers/shapes, and songs/poems/nursery rhymes; as well as having a regular bedtime. In a sample of 141 preschool centres including data for 2603 children and families at 3 and 5 years old and 2354 children and families at 3, 5, and 7 years, this measure of HLE had a larger influence than socioeconomic position on children's educational attainment (Melhuish et al., 2008). In a different study that used a composite score of similar questions at ages 3 and 5, the contribution of the HLE to socioeconomic inequalities in child health and development was investigated in the Millennium Cohort Study. In this sample of 15,383 3-year-old children and 12,042 5-year-old children, it was found that adjusting for the HLE explained income gaps in socioemotional difficulties (Kelly et al., 2011).

The HLE measure used in these studies has since been further developed by Melhuish (2010). Melhuish (2010) used the Growing Up in Scotland longitudinal survey, a longitudinal study of 5217 Scottish children from aged 10 months, to assess a questionnaire including 51 HLE activities (including some of those described above). The 51 questions were assessed in regards to their associations with children's cognitive development (Naming Vocabulary and Picture Similarities), and with children being 'under' or 'over' achieving in school. In total, eight activity items were chosen to form a HLE index. The questions regarded the following items: reading, library visits, physical activities, playing with letters, the alphabet, counting, songs/nursery rhymes, and drawing (Melhuish, 2010).

As described in Section 3. 1. 1, BiB1000 is one of several primary research follow-ups of the BiB children in which a broad range of sociodemographic, developmental and clinical measures were taken longitudinally. BiB1000 asks a variety of questions at the 24 month and 36 month follow-ups about different home activities, how often the activities take place, and how long they take place for. Since previous research has found child outcomes to be sensitive to questions regarding the frequency of activities (rather than the length of time in the activity) (Melhuish et al., 2008; Melhuish, 2010; Kelly et al., 2011), I also assessed HLE using frequency questions. Additionally, the non-response rate to the frequency of activities was much lower than the non-response rate to the length of time engaged in the activities in the BiB 1000 questionnaire.

Five of the included activities in the BiB1000 questionnaire are similar to those in the previously tested HLE index (Melhuish, 2010). The other four activities are not represented in the HLE index - playing with toys, playing on the computer, playing actively in the house, and playing actively in the garden. A further difference in the BiB1000 questionnaire is the framing of questions regarding the engagement with different activities. The HLE index frames questions by asking parents about their engagement in HLE activities with the child, e.g. “does anyone at home ever read to your child?”, whereas the BiB1000 questionnaire does not emphasise the parent’s engagement. The BiB1000 questionnaire frames questions by asking primarily about the child’s engagement with activities, e.g. “how often/how long would you say your child has spent doing the following activities at home?”.

Table 13. Questionnaire items regarding the HLE (Born in Bradford, 2020a)

1. In the last month, how many days each week and for how long each day would you say your child has spent doing the following activities at home? (Please mark either Less than once a week OR how often?)		
	How often	
	Number of days each week	Less than once a week
(a) Colouring/drawing/craft	………	☐
(b) Sitting playing with toys (e.g. dolls/puzzles educational play)	………	☐
(c) Watching TV/DVDs	………	☐
(d) Playing on the computer (not physically active games such as Nintendo Wii)	………	☐
(e) Sitting listening/singing to music	………	☐
(f) Reading/being read to	………	☐
(g) Playing actively inside the house (dancing, crawling, running, sit and ride toys, push toys, physically active computer games such as Nintendo Wii)	………	☐
(h) Playing actively in the garden/yard	………	☐
(i) Engaging in physical activity/active play that makes them sweat or breathe harder	………	☐

Table 13 displays the questions asked regarding HLE. The HLE variable response is coded as: 1 = 1 day per week, 2 = 2 days per week, 3 = 3 days per week, 4 = 4 days per week, 5 = 5 days per week, 6 = 6 days per week, 7 = 7 days per week, and 8 = <once per week. The ‘8’ response will be recoded as 0.

HLE is included as a mediator in Study 2, where exploratory and confirmatory factor analyses are used to find a measurement model of HLE. It is not included in Study 3 as it is not measured in the Primary School Years non-BiB children.

3.1.13 English as an Additional Language (EAL) (BiB only)

Children learning English as an Additional Language (EAL) are more likely to belong to ethnic minority groups (a small minority of children learning EAL may still belong to an ethnic majority group in the UK e.g. White British children whose first language is Welsh, Cornish, or Gaelic). One hypothesis that developed in the systematic review is that children with EAL status may also have worse working memory test scores, as working memory tasks and their instructions are developed in the English language. However, children with EAL are a varied group, with English language skills spanning the full continuum of proficiency (Strand, Malmberg and Hall, 2015). A highly active research area is the study of childhood bilingualism as a cognitive advantage, which has found bilingualism to be advantageous even in low-income minority children (Bialystok and Martin, 2004; Bialystok, 2016; Bialystok and Viswanathan, 2009). Whether EAL status is detrimental or beneficial to working memory ability, it is still identified as a potential covariate in the relationship between socioeconomic position, ethnicity, and working memory. Additionally, EAL may be causally related to both socioeconomic position and working memory, and the HLE and working memory, making it a confounder of this relationship.

However, the validity of the specification of EAL may vary. Language information is collected when children start school, however, they are only classed as EAL or monolingual (ie. no information is available on which language is spoken first and how proficient the children are in these languages). Further, through email communication with researchers in Bradford I have learnt that when aiming to test children recorded as monolingual, they later found out the children do speak another language (L Gunning 2020, personal communication, 13th August). Still, I included the EAL variable as it was only likely to improve estimations of relationships, and unlikely to bias any associations. Further, since it is likely related to parent immigration status, I supposed that the inclusion of both of these as covariates *together* may improve precision of estimation of associations.

EAL is a binary variable where a child is either classed as learning English as an Additional Language (EAL), or is classed as being a First Language English (FLE) speaker. EAL is included in Study 1 and as a covariate in Study 2. As it is only available for children in the BiB cohort, it is not included in Study 3.

3.1.14 Special Educational Needs and Disability (SEND) (BiB only)

Children with Special Educational Needs and/or Disabilities (SEND) are overrepresented in lower socioeconomic position groups (Education Endowment Foundation, 2018), and children with SEND have been found to have worse working memory (Peng and Fuchs, 2016). SEND status is identified as a potential covariate in the relationship between socioeconomic position and working memory.

SEND status is obtained through educational records and is a categorical variable. The SEND indicator classes children as (1) not SEND, (2) SEND, or (3) Education and Health Care Plan (EHCP). EHCP plans are provided for children whose special educational needs require more help than would normally be provided in school. All EHCP were recategorized and included in SEND, making it a binary variable including (1) not SEND and (2) SEND or EHCP.

SEND is included in Study 1 as a descriptive variable. However, SEND is unlikely to explain a large portion of the variation in working memory as only a small proportion of children have SEND. I therefore did not include SEND in Study 2, but stratified by SEND to include only typically developing children in order to remove its potential confounding influence on associations.

3.1.15 Own Ethnic Density

Own ethnic density and school area deprivation were obtained via local authority records for Study 3. As ethnic density could be measured for the school attended by the child and is linked to the whole Primary School Years wave, it was possible to explore this in a much larger sample than the BiB only children. Own ethnic density is the density of ones own ethnic group in the same area (e.g. neighbourhood or school) (Pickett and Wilkinson, 2008). It was obtained by matching a school's pupil characteristics data through Government records from 2019 (GOV.UK, 2019c).

3.1.16 Area Deprivation

Area deprivation is a potential confounder of the relationship between ethnic density and working memory, as area deprivation has been found to be associated with higher minority ethnic density (Uphoff et al., 2016). Area deprivation is measured as the IMD decile of the schools Lower Super Output Area (LSOA). Although area deprivation can also be obtained for the area containing each BiB child's home, this would not be available for the non-BiB PSY wave. Area deprivation is obtained by matching the school LSOA to IMD deciles (GOV.UK, 2019a). The IMD decile ranges from 1-10, where 1 is the most deprived and 10 is the least deprived. There are seven distinct domains of deprivation which are combined and weighted to form the IMD (Ministry of Housing, 2019). These are:

- income (22.5%) – measures the proportion of the population experiencing deprivation due to income
- employment (22.5%) – measures the proportion of the working age population in an area involuntarily excluded from the labour market
- health deprivation and disability (13.5%) – measures the risk of premature death and the impairment of quality of life through poor physical mental health

- education and skills training (13.5%) – measures the lack of attainment and skills in the local population
- crime (9.3%) – measures the risk of personal and material victimisation at local level
- barriers to housing and services (9.3%) – measures the physical and financial accessibility of housing and local services
- living environment (9.3%) – measures the quality of both the indoor and outdoor local environment

3.2 Chapter Summary

This chapter has summarised the relevant information regarding the Born in Bradford data and variables included in the following analyses chapters. On the following page, Table 14 provides an overview of each study title, methods used, and the research questions for each study.

Table 14. Research questions and method across the three studies

Study title and method used	**Research question**
Chapter 4. Study 1: Working Memory by personal demographic characteristics Descriptive statistics and Linear Regression Model	1. How are working memory scores patterned by personal demographic characteristics (socioeconomic position, ethnicity, gender, age, English as an Additional Language, Special Educational Needs and parent immigration status)? 2. In comparison to age differences, what are the magnitude of the socioeconomic and ethnic differences in working memory? 3. How are working memory scores patterned by socioeconomic position within White British and Pakistani ethnic groups?
Chapter 5. Study 2: The structural associations between socioeconomic position, the home learning environment, and working memory Structural Equation Model	4. Does increased socioeconomic disadvantage at birth predict lower working memory scores? 5. Does the home learning environment partially mediate the relationship between socioeconomic position and working memory? 6. Does ethnicity moderate the association between socioeconomic position, the home learning environment, and working memory?
Chapter 6. Study 3: Potential protective factors for ethnic minority working memory Multilevel Model	7. Is own ethnic density associated with working memory ability? 8. Is Mosque/Madrassah attendance associated with working memory ability?

Chapter 4. Study 1: Working Memory by Personal Demographic Characteristics

This chapter outlines the introduction, methods, results, and discussion for a study of working memory by several different personal demographic characteristics.

4.1 Introduction

The systematic review (Chapter 2) found a strong association between socioeconomic position and working memory, however, several research gaps remained. The practical meaning and magnitude of these socioeconomic differences remains unknown. Furthermore, the systematic review was not able to make substantive conclusions regarding ethnic minority status and working memory due to methodological constraints in the synthesis of the studies. In particular, no research is yet available that explores numerous measures of working memory across ethnic majority and several groups of ethnic minority children.

To address these research gaps, I take a novel approach to conceptualising the magnitude of socioeconomic and ethnic differences by comparing them to differences by age in months. The key aim of this study was to provide a description of the sample, and a basic overview of the magnitude of socioeconomic and ethnic differences in children's working memory. As the graph in Figure 17 highlights potential covariates in the associations between socioeconomic position, ethnicity, and working memory, this study describes working memory scores by these covariates (gender, English as an Additional Language, Parent Immigration Status, Special Educational Needs and Age).

The remainder of this chapter specifies the methods, results, and discussion for the following research questions:

1. How are working memory scores patterned by personal demographic characteristics (Socioeconomic Position, Ethnicity, Gender, English as an Additional Language, Parent Immigration Status, Special Educational Needs and Age)?
2. In comparison to age differences, what are the magnitude of the socioeconomic and ethnic differences in working memory?
3. How are working memory scores patterned by socioeconomic position within White British and Pakistani ethnic groups?

4.2 Methods

I first describe the broad methods which apply to the whole chapter, and then specific methods for each of the three research questions.

4.2.1 Data Source

The Primary School Years cohort is used in this study, including both the BiB cohort and non-BiB children. Whilst the BiB cohort sample has more detailed information on potential covariates, the Primary School Years cohort is much larger and includes information on age and ethnicity. This study utilises both data sources to obtain detailed information on large sample sizes in children's working memory.

4.2.2 Included Variables

Table 15. Included variables across the Primary School Years wave and BiB only children

Variable	Primary School Years (n = ~15,000)	BiB-only children (n= ~6000)
Working memory (outcome)	✓	✓
Ethnicity	✓	✓
Gender	✓	✓
Age	✓	✓
SEP Latent Class Analysis	✗	✓
Self-reported financial situation	✗	✓
English as an Additional Language	✗	✓
Special Educational Needs and Disability	✗	✓
Parent immigration status	✗	✓

Table 15 summarises the availability of specified variables across the two cohorts. The wider Primary School Years wave has a larger sample and access to data on child ethnicity, child gender, and child age. The BiB only sample is a subset of the Primary School Years sample, and is linked to further data on socioeconomic position, self-reported financial situation, English as an Additional Language (EAL), parent immigrations status, and Special Educational Needs and Disability (SEND). All of the variables specified in Table 15 are included in the descriptive section.

Descriptive statistics will be displayed for both: (1) the whole Primary School Years wave and for (2) just BiB children where it was possible to do so. This was done in order to examine for possible selection bias effects of participation in the BiB cohort.

4.2.3 Sample Characteristics

The sample sizes for children that took part in any working memory task(s) across both cohorts will be described. Sample sizes across both cohorts will be displayed for the following: ethnic groups, child gender and child age in years. Sample sizes for the BiB only cohort will be described for the following: socioeconomic position, self-reported financial situation, English as an Additional Language (EAL), parent immigrations status, and Special Educational Needs and Disability (SEND).

4.2.4 Research Question 1: How are working memory scores patterned by personal demographic characteristics?

4.2.4.1 Inclusion Criteria

The participants were included if they met the following inclusion criteria:

- Child took part in the Primary School Years wave
- Child completed ≥1 working memory task(s)

4.2.4.2 Distribution of the Outcome

Mean, standard deviation and range are described for each working memory task (FDR, Corsi, BDR). Histograms for each working memory task are presented to visualise the frequency distribution of the working memory scores, and the minimum, maximum, and interquartile ranges will be described for each task. These were compared across both cohorts (BiB only and the Primary School Years wave).

4.2.4.3 Description of Working Memory by Personal Demographic Characteristics

Mean working memory scores and standard deviations are described by Socioeconomic Position, Ethnicity, Gender, English as an Additional Language, Special Educational Needs and Age. For socioeconomic position, working memory scores are described by the latent class analysis groupings of socioeconomic position, and by self-reported financial situation. For ethnicity, working memory scores are described by all available ethnic groups across both BiB and non-BiB children.

No analyses were done in order to answer this research question, as the research question relates to patterns of working memory which can be achieved through descriptive statistics.

4.2.5 Research Question 2: What is the magnitude of the socioeconomic and ethnic differences in working memory?

4.2.5.1 Inclusion Criteria

The participants were included if they met the following inclusion criteria:

- Child took part in the Primary School Years wave

- Child completed ≥1 working memory task(s)
- Child age is non-missing
- Child socioeconomic position indicator/ethnic group is non-missing (per analyses)

For Research Question 2, children with age missing were excluded (2.95% of the sample). For the socioeconomic position analyses, children with socioeconomic position missing were not included, and for the ethnic group analyses, children with ethnicity missing were not included.

4.2.5.2 Linear Regression Modelling

Linear regression is a linear approach to modelling the relationship between a continuous response and one or more explanatory variables (Kahane, 2007). I present unstandardized regression coefficients and 95% confidence intervals for age, socioeconomic position, and ethnicity on working memory. As a statistically significant effect is not enough to inform us about the practical significance of an effect (Cumming, 2014), I use and interpret the regression coefficients as measures of effect size. The regression coefficients provide the predicted mean difference in percentage correct on each working memory task, between the baseline group and every other group.

First, I report the unstandardized coefficients and 95% confidence intervals for working memory by age differences in months. The coefficients from the age analysis are used as a benchmark for the regression coefficients in the socioeconomic position and ethnicity analysis – this allows a comparison of the magnitude of the effect between the socioeconomic and ethnic groups to differences in age. The *lincom* command in Stata-16 was used to produce coefficients by age in months for different ages. Next, I produced coefficients for working memory by socioeconomic position and ethnic group. The baseline group for socioeconomic position is the 'least deprived' group, and the baseline group for ethnicity is the ethnic majority group (White British). Regression coefficients were produced using simple linear regression in Stata-16 (StataCorp, 2019).

The following assumptions were checked using postestimation plots (Blance, 2012):

- A linear relationship between the predictor and outcome
- Appropriately distributed standardised residuals. This is checked with post estimation plots of the residuals in a QQ plot, where points should lie along the diagonal line.
- Homogeneity of variance. This will be checked with a scatterplot of fitted versus standardised residuals plot, where points should be evenly spread around the centred line.

4.2.5.3 Model Specification

The regression models are:

1. $FDR_i = \beta 0 + \beta 1 * age_i + \varepsilon_i$
2. $Corsi_i = \beta 0 + \beta 1 * age_i + \varepsilon_i$
3. $BDR_i = \beta 0 + \beta 1 * age_i + \varepsilon_i$
4. $FDR_i = \beta 0 + \beta 1 * socioeconomic\ group_i + \varepsilon_i$
5. $Corsi_i = \beta 0 + \beta 1 * socioeconomic\ group_i + \varepsilon_i$
6. $BDR_i = \beta 0 + \beta 1 * socioeconomic\ group_i + \varepsilon_i$
7. $FDR_i = \beta 0 + \beta 1 * ethnic\ group_i + \varepsilon_i$
8. $Corsi_i = \beta 0 + \beta 1 * ethnic\ group_i + \varepsilon_i$
9. $BDR_i = \beta 0 + \beta 1 * ethnic\ group_i + \varepsilon_i$

Where β_0 is the intercept, each β is a coefficient, and ε_i is the residual error for individual *i*.

4.2.5.4 Understanding Magnitude

In order to understand the magnitude of the differences and compare them to differences in age, I produced graphs that display the regression coefficients by each exposure variable, with coefficients by age overlaid in colours. The coefficients by age in months are displayed for 6, 8, 10, 12, 14, 16, and 18-month differences. The 95% confidence intervals are used to provide the bandwidth for the display of age in months. For example, an age difference of 6 months in FDR gives *B*=2.14 and 95% CI 1.97 to 2.32, so 1.97 to 2.32 is shaded in the graphs with the colour corresponding to a 6-month age difference. As age differences in working memory varied slightly depending on the task (with FDR generally having the smallest differences), 3 different graphs are displayed for each task of working memory.

4.2.6 Research Question 3: How are working memory scores patterned by socioeconomic position within White British and Pakistani ethnic groups?

In this study, I explore the association between socioeconomic position and working memory when stratified by ethnic group.

4.2.6.1 Inclusion Criteria

The participants were included if they met the following inclusion criteria:

- Child took part in the Primary School Years wave
- Child completed ≥1 working memory task(s)
- Child age is non-missing
- Child’s ethnic group is Pakistani or White British
- Child socioeconomic position indicator is non-missing (per analyses)

4.2.6.2 Descriptive statistics

Responses by socioeconomic position are described within the two main ethnic groups (White British and Pakistani), with mean working memory scores and 95% confidence intervals for all 3 working memory tasks for three measures of socioeconomic position: (1) latent class groups of socioeconomic position, (2) latent class ethnic-specific groups of socioeconomic position, and (3) subjective financial status.

4.2.6.3 Linear Regression Modelling

See section 4.2.5.2 for details on linear regression modelling. I conducted linear regression by two indicators of socioeconomic position: (1) groups of socioeconomic position and (2) ethnic-specific socioeconomic groups. I did not conduct regression analyses by subjective financial status because the descriptive results appeared to be very similar, and the subjective financial status indicator was already included within the latent class groupings of socioeconomic position.

4.2.6.4 Model Specification

The regression models are (per ethnic group):

1. $FDR_i = \beta 0 + \beta 1 * socioeconomic\ group_i + \varepsilon_i$
2. $Corsi_i = \beta 0 + \beta 1 * socioeconomic\ group_i + \varepsilon_i$
3. $BDR_i = \beta 0 + \beta 1 * socioeconomic\ group_i + \varepsilon_i$
4. $FDR_i = \beta 0 + \beta 1 * ethnic\text{-}specific\ socioeconomic\ group_i + \varepsilon_i$
5. $Corsi_i = \beta 0 + \beta 1 * ethnic\text{-}specific\ socioeconomic\ group_i + \varepsilon_i$
6. $BDR_i = \beta 0 + \beta 1 * ethnic\text{-}specific\ socioeconomic\ group_i + \varepsilon_i$

Where β_0 is the intercept, each β is a coefficient, and ε_i is the residual error for individual i.

4.3 Results

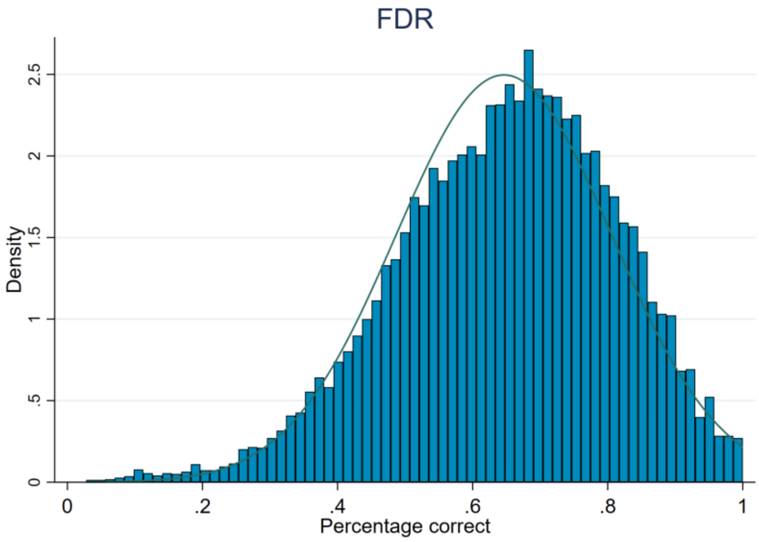
4.3.1 Sample Characteristics

Table 16. Socio-demographic characteristics of Bradford primary school children (n = 15,154) some of whom are also Born in Bradford cohort children (n = 5976)

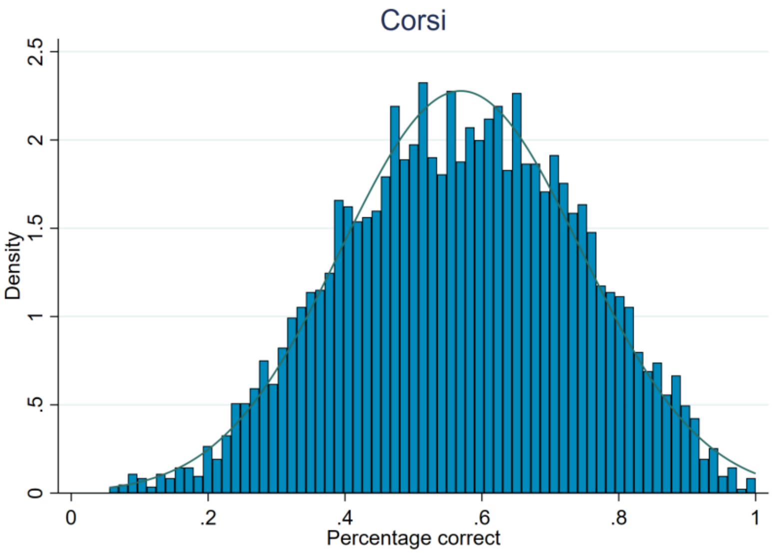
Socio-demographic variable	Count	Percent
Age (years)		
7	5003	32.04
8	6726	43.08
9	3130	20.05
10	295	1.89
Missing	*460*	*2.95*
Gender		
Male	7480	49.36
Female	7674	50.64
Missing	*0*	*0*
Ethnic group		
Pakistani	6,777	44.72
Bangladeshi	447	2.95
Indian	324	2.14
Black or Black British	264	1.74
White British	4,137	27.30
Mixed	866	5.71
Gypsy or Irish traveller	168	1.11
White Other	677	4.47
Other	416	2.75
Missing	*1,078*	*7.11*
Socioeconomic group (BiB only, n = 5976)		
Least deprived and most educated	778	13.02
Employed, not materially deprived	843	14.11
Employed, no access to money	803	13.44
Benefits but coping	1,659	27.76
Most deprived	833	13.94
Missing	*1060*	*17.74*

4.3.2 Research Question 1: How are working memory scores patterned by personal demographic characteristics?

4.3.2.1 Distribution of working memory scores



<u>Figure 20. Histogram of FDR scores (n = 15,476)</u>



<u>Figure 21. Histogram of Corsi scores (n =15,369)</u>

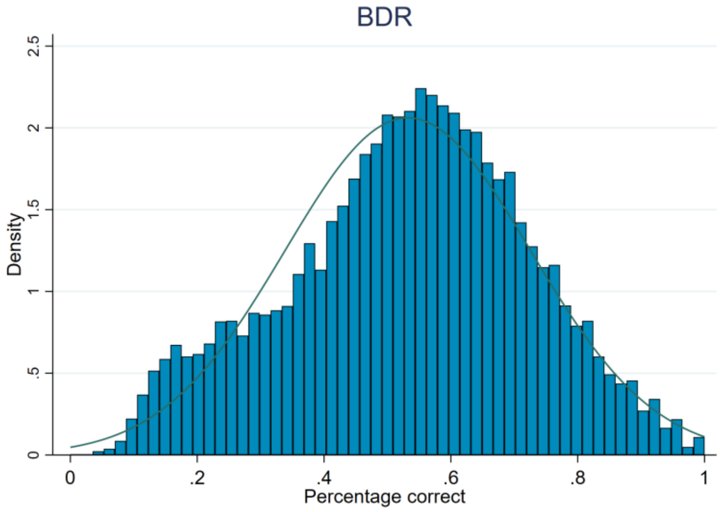


Figure 22. Histogram of BDR scores (n = 15,149)

Figures 20-22 show histograms for each task of working memory. The histograms show a normal distribution for each task. There is a small positive skew in the FDR task, which is likely due to the task being easier than the other two. Next, working memory scores are described by different personal demographic characteristics.

4.3.2.2 Working Memory by Personal Demographic Characteristics

Table 17. Mean working memory scores across whole Primary School Years and BiB only sample by personal demographic characteristics

Variable	**Whole Primary School Years wave (n = 15,149 to 15,476)**				**BiB-only children (n = 5975 to 6065)**			
	*n**	FDR	Corsi	BDR	*n**	FDR	Corsi	BDR
Working Memory								
Total sample size (n)	.	*15,476*	*15,369*	*15,149*	.	*6065*	*6029*	*5975*
Total mean working memory score (sd)	.	.65 (.16)	.56 (.18)	.53 (.19)	.	.66 (.16)	.57 (.18)	.54 (.19)
Interquartile range	.	.54 to .76	.43 to .69	. 41 to .66		.56 to .76	.44 to .69	.43 to .68
Gender								
Female	*7475*	.65 (.16)	.55 (.17)	.55 (.19)	*2962*	.66 (.15)	.56 (.17)	.56 (.18)
Male	*7674*	.64 (.16)	.57 (.18)	.52 (.20)	*3013*	.66 (.15)	.58 (.18)	.52 (.19)
Missing	*0*	.	.	.	*0*	.	.	.
Age								
7	*5000*	.62 (.15)	.52 (.17)	.48 (.19)	*1693*	.63 (.15)	.52 (.17)	.48 (.19)
8	*6725*	.65 (.15)	.57 (.17)	.54 (.19)	*2996*	.66 (.15)	.57 (.17)	.55 (.19)
9	*3126*	.69 (.15)	.63 (.67)	.60 (.19)	*1175*	.69 (.15)	.63 (.17)	.60 (.18)
10	*295*	.71 (.15)	.67 (.16)	.64 (.17)	*109*	.74 (.14)	.67 (.16)	.67 (.17)
Missing**	*0*	.	.	.	*0*	.	.	.
Ethnic group								
Pakistani	*6,778*	.66 (.16)	.56 (.18)	.53 (.20)	*3563*	.66 (.16)	.56 (.18)	.54 (.20)
Bangladeshi	*447*	.67 (.15)	.61 (.18)	.57 (.20)	*205*	.67 (.15)	.63 (.19)	.57 (.21)

Variable	**Whole Primary School Years wave (n = 15,149 to 15,476)**				**BiB-only children (n = 5975 to 6065)**			
	*n**	FDR	Corsi	BDR	*n**	FDR	Corsi	BDR
Indian	*324*	.67 (.16)	.59 (.18)	.56 (.20)	*169*	.66 (.17)	.60 (.17)	.55 (.19)
Black or Black British	*264*	.65 (.17)	.55 (.18)	.53 (.20)	*80*	.65 (.19)	.57 (.18)	.56 (.20)
White British	*4,135*	.63 (.16)	.56 (.17)	.54 (.17)	*1682*	.63 (.16)	.56 (.17)	.54 (.17)
Mixed	*866*	.65 (.16)	.55 (.17)	.52 (.19)	*359*	.66 (.16)	.55 (.17)	.52 (.19)
Gypsy or Irish traveller	*168*	.51 (.17)	.45 (.16)	.38 (.18)	*19*	.51 (.17)	.43 (.17)	.33 (.19)
White Other	*677*	.57 (.16)	.55 (.18)	.47 (.20)	*140*	.59 (.17)	.58 (.18)	.49 (.19)
Other	*416*	.64 (.15)	.58 (.18)	.54 (.19)	*141*	.66 (.14)	.61 (.17)	.55 (.17)
Missing	*1,074*	.68 (.17)	.62 (.18)	.57 (.21)	*166*	.68 (.16)	.63 (.18)	.57 (.21)
Socioeconomic Position	.	.	.	.				
Least deprived and most educated					*777*	.69 (.15)	.61 (.17)	.59 (.18)
Employed not materially deprived					*843*	.67 (.14)	.58 (.17)	.55 (.18)
Employed no access to money					*804*	.67 (.15)	.58 (.17)	.56 (.19)
Benefits but coping					*1658*	.65 (.16)	.55 (.18)	.52 (.20)
Most deprived					*833*	.63 (.17)	.55 (.17)	.51 (.19)
Missing					*1060*	.65 (.15)	.57 (.18)	.54 (.19)
Self-reported financial situation	.	.	.	.				
Living comfortably					*1200*	.67 (.15)	.58 (.17)	.55 (.18)
Doing alright					*2062*	.66 (.15)	.57 (.18)	.54 (.19)
Just about getting by					*1253*	.65 (.15)	.57 (.17)	.54 (.19)
Quite difficult					*303*	.65 (.16)	.55 (.17)	.53 (.19)
Very difficult					*90*	.62 (.16)	.53 (.17)	.48 (.18)
Does not wish to answer					*20*	.59 (.15)	.54 (.15)	.51 (.17)
Missing					*1047*	.65 (.16)	.57 (.18)	.54 (.19)

Variable	**Whole Primary School Years wave (n = 15,149 to 15,476)**				**BiB-only children (n = 5975 to 6065)**			
	*n**	FDR	Corsi	BDR	*n**	FDR	Corsi	BDR
English as an Additional Language (EAL)	.	.	.	.				
No					*2715*	.65 (.16)	.57 (.17)	.55 (.18)
Yes					*3244*	.66 (.15)	.57 (.17)	.53 (.20)
Missing					*16*	.58 (.19)	.57 (.18)	.70 (.13)
Special Educational Needs and Disability (SEND)	.	.	.	.				
Typically developing					*5020*	.68 (.14)	.59 (.48)	.57 (.18)
Has SEND					*943*	.55 (.17)	.48 (.18)	.40 (.18)
Missing					*12*	.43 (.14)	.50 (.14)	.66 (.14)
Parent immigration status	.	.	.	.				
Born within UK					*2859*	.65 (.15)	.57 (.17)	.54 (19)
Born outside UK					*3116*	.66 (.16)	.57 (.18)	.54 (.19)
Missing					*0*	.	.	.

**Displayed n's are for BDR, as this was usually the smallest sample size.*

***For the Primary School Years wave there were 386 children missing age for FDR, 371 missing age for Corsi, and 0 missing age for BDR.*

Table 17 shows working memory scores by each personal demographic characteristic across the whole Primary School Years sample (*n* = 15,149 to 15,476) and the BiB cohort (*n* = 5975 to 6065). When comparing the entire Primary School Years cohort and the BiB cohort subsample, there do not appear to be any concerns regarding selection bias as the scores seem similar across both cohorts.

The summary of differences by personal demographic characteristics are as follows:

- Working memory scores clearly increase by age in years, with 7-year olds consistently having lower working memory scores in all three tasks than 10-year olds.
- There are variances in working memory by gender, but the direction was not consistent. Females scored higher in BDR by 3%, and in FDR by 1%. Males scored higher in Corsi by 2%.
- There are variances in working memory by speaking English as an Additional Language, but the direction was not consistent. There were no differences in Corsi. Small differences were found in FDR (with EAL speakers scoring higher) and BDR (with first language English speakers scoring higher), with differences being ≤2%.
- There were no apparent variances by parent immigration status for Corsi or BDR. Small differences were only found in FDR at 1%, where those born outside the UK score higher.
- There were very large variances by Special Educational Needs or Disability (SEND), where children with SEND had worse working memory by 11-13%.
- There are differences in working memory scores by socioeconomic groups, where the least deprived group appear to have higher working memory scores by 4-5%. These are explored in more detail in the following section.
- There are differences in working memory scores by ethnic group, where scores in FDR ranged between 51% to 68%, in Corsi 45% to 62%, and in BDR 38% to 57%. These are explored in more detail in the following section.

4.3.3 Research Question 2: Magnitude of Socioeconomic and Ethnic Differences

4.3.3.1 Age and Working Memory

Overall, age in years was positively associated with all three tasks of working memory. An age increase in 1 month was associated with the following: FDR (β = 0.36, 0.33 to 0.39), Corsi (β = 0.55, 0.51 to 0.58), and BDR (β = 0.57, 0.54 to 0.61). In general, age gaps in FDR were smaller than for the other two tasks. The following sections explore the magnitude of the socioeconomic and ethnic gaps in working memory by comparing them to differences by age in months. Postestimation plots are provided in Appendices C1, and a summary table providing the unstandardized regression coefficients and 95% confidence intervals for age in months and working memory is provided in Appendices C2.

4.3.3.2 Socioeconomic Position and Working Memory

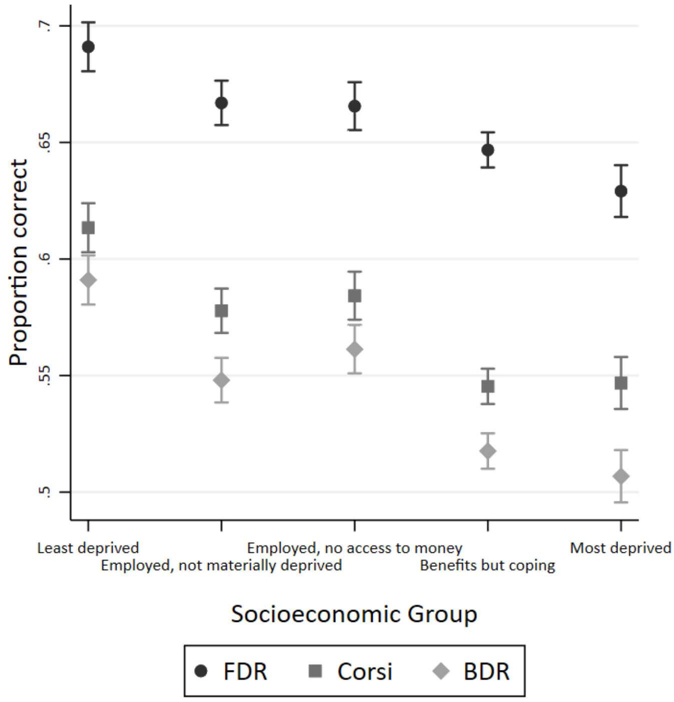


Figure 23. Mean scores and 95% confidence intervals in FDR, Corsi, and BDR by socioeconomic group (n = 4913)

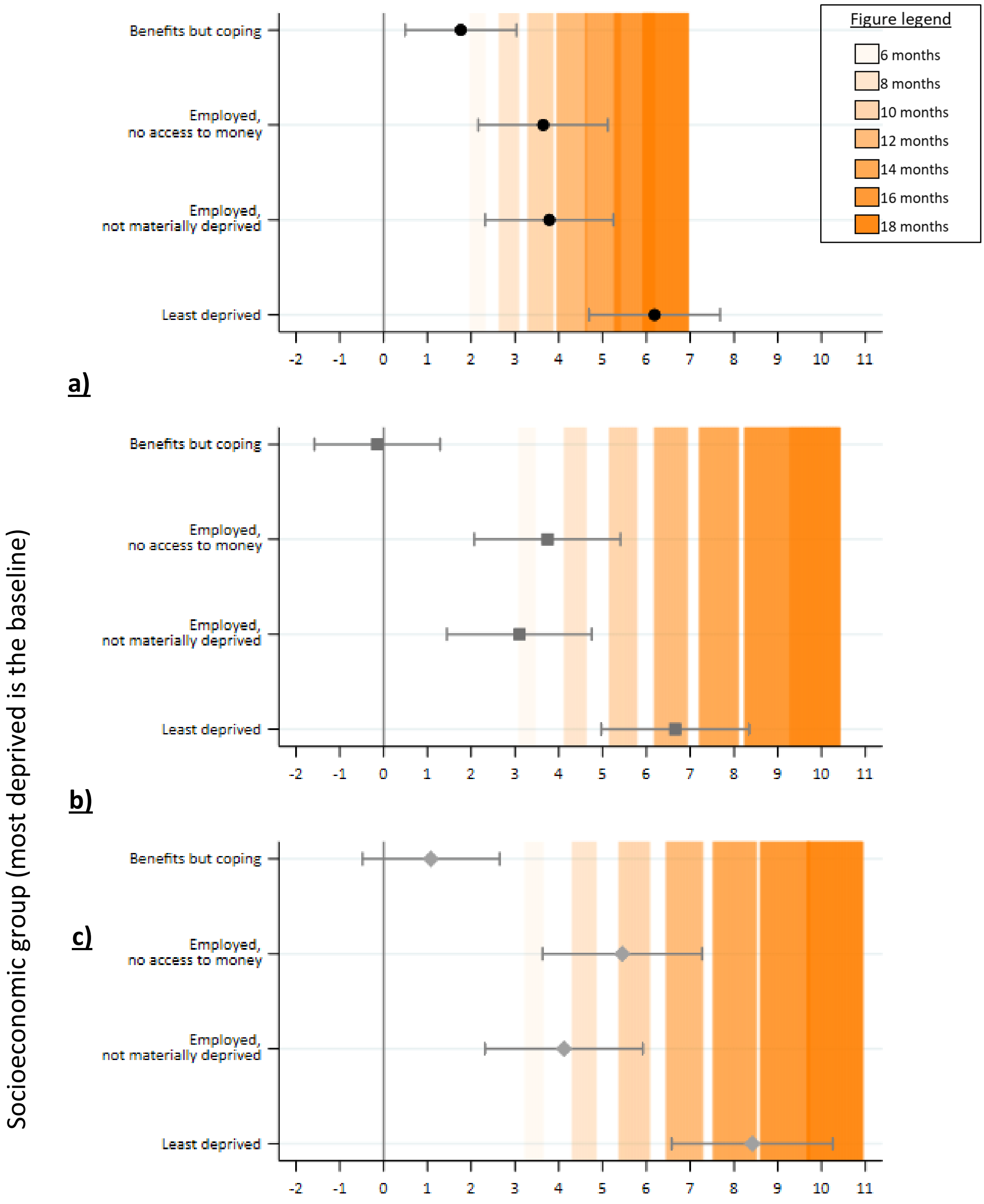
Figure 23 shows that on average, the least deprived socioeconomic group had higher working memory scores than all other socioeconomic groups. On the following page, Table 18 shows the linear regression results for each of the working memory tasks by socioeconomic group (where the reference group is least deprived).

Table 18. Regression results for FDR, Corsi, and BDR by socioeconomic group

	FDR (n = 4895)			Corsi (n = 4872)			BDR (n = 4913)		
Socioeconomic group	***B* (95% CI)**	**t**	**p**	***B* (95% CI)**	**t**	**p**	***B* (95% CI)**	**t**	**p**
Least deprived	.	.	.						
Employed not materially deprived	-2.47 [-3.94 to -0.99]	-3.27	0.001	-3.52 [-5.21 to -1.84]	-4.10	0.000	-4.30 [-6.13 to -2.47]	-4.60	<0.001
Employed no access to money	-2.28 [-3.78 to -0.78]	-2.98	0.003	-2.70 [-4.41 to -0.99]	-3.10	0.002	-2.97 [-4.82 to -1.11]	-3.14	0.002
Benefits but coping	-4.23 [-5.52 to -2.94]	-6.41	<0.001	-6.74 [-8.22 to -5.26]	-8.96	<0.001	-7.34 [-8.94 to -5.73]	-8.98	<0.001
Most deprived	-6.02 [-7.51 to -4.54]	-7.97	<0.001	-6.56 [-8.25 to -4.86]	-7.60	<0.001	-8.42 [-10.26 to -6.58]	-8.98	<0.001
F test	***F(4, 4890) = 19.01***			***F(4, 4867) = 25.85***			***F(4, 4908) = 25.59***		
Unadjusted R^2, p	***.02, <.001***			***.02, <.001***			***.02, <.001***		

Note: Postestimation plots are provided in Appendices C1.

Table 18 shows that all groups scored significantly worse than the 'least deprived' socioeconomic group on all three tasks of working memory. The size of the difference depended on the task, with FDR having smaller differences, and BDR having the largest differences. The following figure compares these differences to age differences in months.



Figures 24a-24c. Regression coefficients by socioeconomic group for (a) FDR, (b) Corsi, and (c) BDR with differences by age in months shaded in orange (6-18months)

Figures 24a-24c show the same data as Table 18, but reverses the regression coefficients so that ‘most deprived’ is the baseline, and presents the regression coefficients graphically. In addition, it has the coefficients for working memory by age in months overlaid in increasingly darker shades of orange. The lightest shade shows the 95% confidence interval for a 6-month age difference, and the darkest shows the 95% confidence interval for an 18-month age difference. Using Figures 24a-24c, it can be interpreted that the ‘benefits but coping’ group had better working memory than the ‘most deprived’ group in only FDR, but this did not reach the 6-month age difference. The ‘employed, not materially deprived’ and ‘employed, no access to money’ groups had better working memory in all three tasks, equivalent to an age difference varying between 6 to 10 months. The ‘least deprived’ group has better working memory in all three tasks, and this difference varied between a 12 to 18-month age difference.

4.3.3.3 Ethnicity and Working Memory

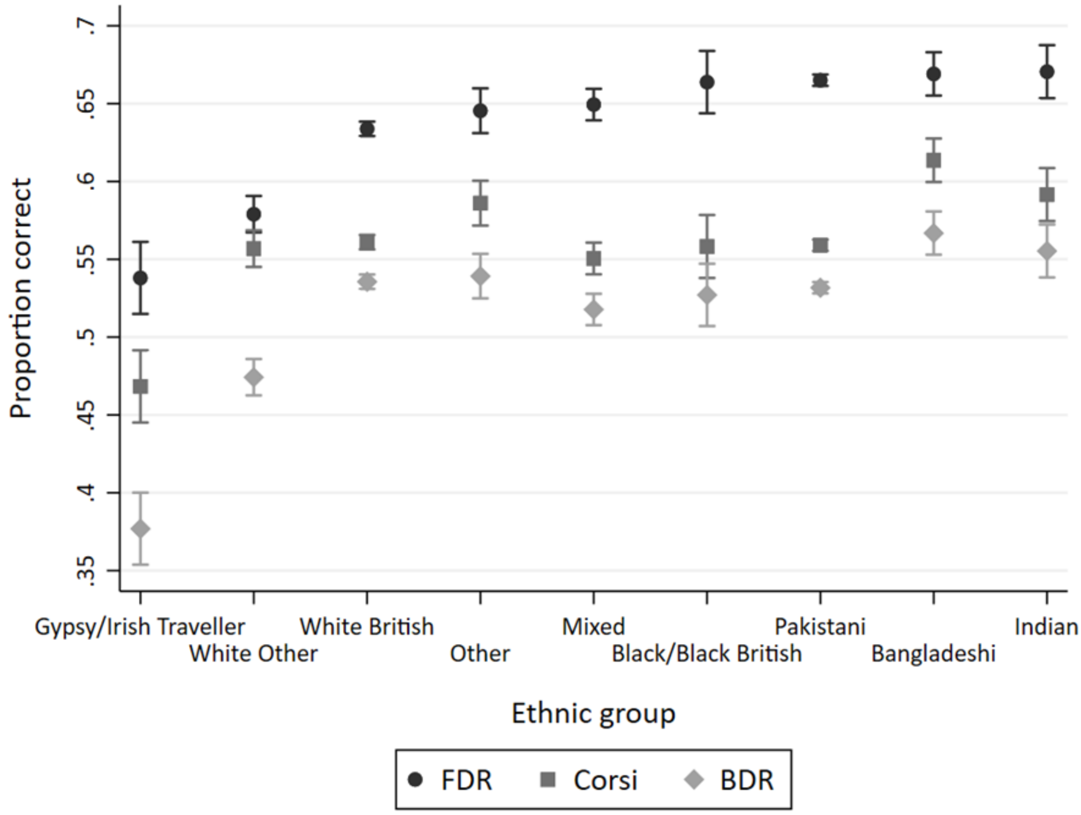


Figure 25. Mean scores and 95% confidence intervals in FDR, Corsi, and BDR by ethnic group, ordered by FDR scores (n = 14,076)

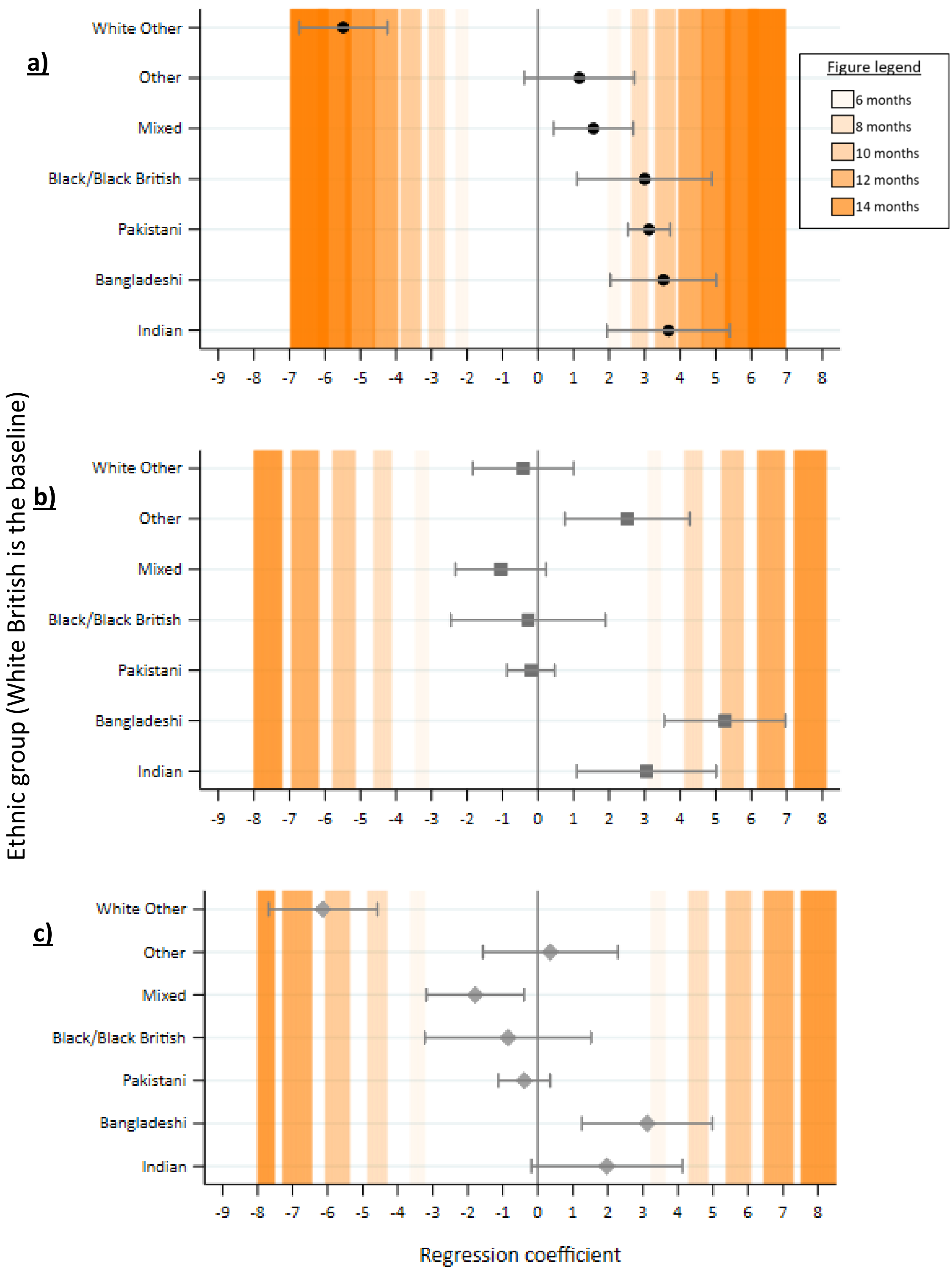
Figure 25 shows the mean working memory scores for all 3 tasks of working memory for all ethnic groups, ordered by the mean score on FDR. On the following page, Table 19 shows the linear regression results for each of the individual working memory tasks by ethnic group (when the reference is White British), with statistically significant results in bold.

Table 19. Regression results for FDR, Corsi, and BDR by ethnic group

	FDR (n = 14,025)			Corsi (n = 13,919)			BDR (n = 14,072)		
Ethnic group	***B* (95% CI)**	**t**	***p***	***B* (95% CI)**	**t**	***p***	***B* (95% CI)**	**t**	***p***
White British	.	.	.	.	.	.			
Gypsy/Irish Traveller	**-9.58 [-11.93 to -7.23]**	**-7.98**	**<0.001**	**-9.27 [-11.95 to -6.59]**	**-6.78**	**<0.001**	**-15.87 [-18.82 to -12.92]**	**-10.56**	**<0.001**
White Other	**-5.48 [-6.72 to -4.24]**	**-8.66**	**<0.001**	-0.42 [-1.83 to 1.00]	-0.58	0.564	**-6.14 [-7.69 to -4.58]**	**-7.75**	**<0.001**
Other	1.16 [-0.38 to 2.71]	1.47	0.141	**2.51 [0.75 to 4.27]**	**2.79**	**0.005**	0.36 [-1.57 to 2.28]	0.36	0.716
Mixed	**1.56 [0.44 to 2.68]**	**2.73**	**0.006**	-1.05 [-2.33 to 0.23]	-1.61	0.108	**-1.79 [-3.19 to -0.39]**	**-2.50**	**0.012**
Black/Black British	**3.00 [-2.45 to 1.90]**	**3.10**	**0.002**	-0.28 [-2.45 to 1.90]	-0.25	0.802	-0.85 [-3.23 to 1.53]	-0.70	0.484
Pakistani	**3.12 [2.53 to 3.71]**	**10.36**	**<0.001**	-0.20 [-0.87 to 0.47]	-0.58	0.382	-0.39 [1.13 to 0.35]	-1.03	0.303
Bangladeshi	**3.53 [2.04 to 5.02]**	**4.64**	**<0.001**	**5.26 [3.56 to 6.96]**	**6.06**	**<0.001**	**3.12 [1.26 to 4.99]**	**3.28**	**0.001**
Indian	**3.67 [1.94 to 5.40]**	**4.17**	**<0.001**	**3.06 [1.09 to 5.02]**	**3.05**	**0.002**	1.97 [-0.19 to 4.13]	1.79	0.073
F test	***F(8, 14016) = 45.48***			***F(8, 13910) = 13.94***			***F(8, 14063) = 24.55***		
Unadjusted R^2	***.03, p < .001***			***.00, p < .001***			***0.01, p < .001***		

Note: Ethnic groups ordered by FDR scores in reference to White British children. Postestimation plots are provided in Appendices C1.

Table 19 shows that in comparison to White British children, Gypsy or Irish Traveller children had lower working memory scores in all three tasks. The 'White Other' group scored lower on two tasks (FDR and BDR). The pattern for the other ethnic groups was mixed. All other children scored higher than the White British children for at least one of the working memory tasks. Pakistani and Black British children both had higher scores on the FDR task, but not on the Corsi or the BDR tasks. In comparison to the White British group, the Bangladeshi and Indian children had higher working memory scores. On the following page, Figures 26a-26c compares these differences to age in months.

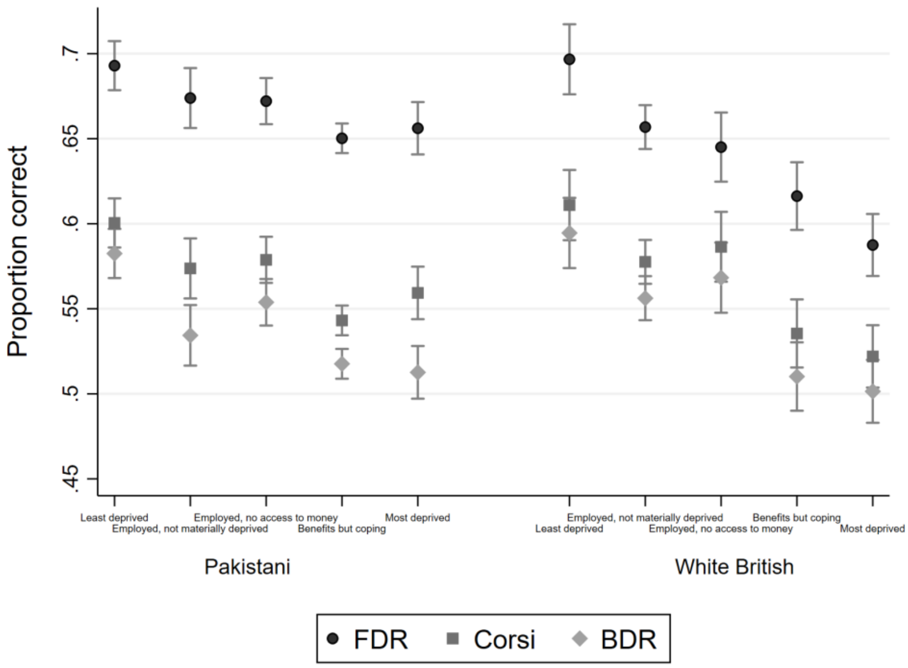


Figures 26a-26c. Regression coefficients by ethnic group for (a) FDR, (b) Corsi, and (c) BDR with differences by age in months shaded in orange (6-14months)

Figures 26a to 26c show the same data as Table 19, but presents the regression coefficients graphically. In addition, the coefficients for working memory by age in months (6 to 14) are overlaid in increasingly darker shades of orange. The lightest shade shows a 6-month age difference, and the darkest shows the 14-month age difference. Figures 26a-26c do not include Gypsy or Irish Traveller children, as their scores were much lower and this reduced the ease in visualising the data. Instead, I note the comparison to age differences for those children here and provide a graph with their scores included in the appendices (C4). The differences for Gypsy and Irish Traveller children were equivalent to at least an 18-month age difference for Corsi, and a 2-year age difference for FDR and BDR. Using Figures 26a-26c, it can be interpreted that the White Other children had much worse working memory, by about 16 months in FDR and 10 months in BDR, however, they did not have significantly worse Corsi scores. Further, the South Asian ethnic groups (Pakistani, Bangladeshi, Indian) all had better FDR scores by about 8 to 10 months. Whilst Pakistani children did not have better Corsi or BDR scores, both Bangladeshi and Indian children had better Corsi and BDR scores (by 6 to 10 months, depending on the task and ethnic group).

4.3.4 Research Question 3: How are working memory scores patterned by socioeconomic position within White British and Pakistani ethnic groups?

4.3.4.1 Patterns by socioeconomic groups



<u>Figure 27. Mean scores and 95% confidence intervals in FDR, Corsi, and BDR by latent class analysis of socioeconomic group for White British and Pakistani ethnic groups</u>

Sample sizes for White British are: 'Least deprived' n = 180, 'Employed not materially deprived' n = 449, 'Employed no access to money' n = 241, 'Benefits but coping' n = 235, and 'Most deprived' n = 290. For Pakistani are: 'Least deprived' n = 439, 'Employed not materially deprived' n = 261, 'Employed no access to money' n = 436, 'Benefits but coping' n = 1282, and 'Most deprived' n = 422.

Figure 27 shows the mean scores in working memory by the latent class analysis of socioeconomic position for White British and Pakistani ethnic groups (the *non-ethnic specific* measure of socioeconomic position). The following page shows regression analyses for this variable stratified by ethnic group.

Table 20. Regression results for FDR, Corsi and BDR by socioeconomic position within White British children

	FDR (n = 1368)			***Corsi (n = 1358)***			***BDR (n = 1370)***		
Socioeconomic group	***B* (95% CI)**	**t**	**p**	***B* (95% CI)**	**t**	**p**	***B* (95% CI)**	**t**	**p**
Least deprived	.	.	.	.	.	.	.	.	.
Employed not materially deprived	**-3.91 (-6.45 to -1.37)**	**-3.02**	**<.001**	**-3.37 (-6.24 to -0.51)**	**-2.31**	**0.02**	**-3.84 (-6.80 to -0.87)**	**-2.54**	**0.01**
Employed no access to money	**-4.78 (-7.63 to -1.93)**	**-3.29**	**<.001**	-2.24 (-5.46 to .99)	-1.36	0.17	-2.63 (-5.95 to 0.69)	-1.55	0.12
Benefits but coping	**-7.51 (-10.37 to -4.64)**	**-5.14**	**<.001**	**-7.59 (-10.82 to -4.36)**	**-4.61**	**<.001**	**-8.44 (-11.77 to -5.11)**	**-4.97**	**<.001**
Most deprived	**-10.37 (-13.11 to -7.62)**	**-7.41**	**<.001**	**-8.75 (-11.85 to -5.65)**	**-5.54**	**<.001**	**-9.31 (-12.51 to -6.11)**	**-5.71**	**<.001**
F test	**F(4, 1365) = 12.35**			**F(4, 1353) = 11.61**			**F(4, 1363) = 16.62**		
Unadjusted R^2, *p*	**.03 <.001**			**.03, <.001**			**.05, <.001**		

Table 21. Regression results for FDR, Corsi and BDR by socioeconomic position within Pakistani children

	FDR (n = 2789)			Corsi (n = 2777)			BDR (n = 2801)		
Socioeconomic group	***B* (95% CI)**	**t**	**p**	***B* (95% CI)**	**t**	**p**	***B* (95% CI)**	**t**	**p**
Least deprived	.	.	.	.	.	.	.	.	.
Employed not materially deprived	-1.93 (-4.29 to 0.43)	-1.60	0.11	-2.67 (-5.40 to 0.05)	-1.92	0.05	**-4.81 (-7.85 to -1.77)**	**-3.10**	**<.001**
Employed no access to money	-1.93 (-3.97 to 0.12)	-1.85	0.06	-2.01 (-4.37 to 0.34)	-1.67	0.09	-2.87 (-5.50 to -0.24)	-2.14	0.03
Benefits but coping	-4.13 (-5.80 to -2.46)	-4.85	**<.001**	**-5.70 (-7.62 to -3.77)**	**-5.80**	**<.001**	**-6.49 (-8.63 to -4.34)**	**-5.93**	**<.001**
Most deprived	-3.79 (-5.85 to -1.74)	-3.62	**<.001**	**-4.24 (6.61 to -1.86)**	**-3.50**	**<.001**	**-6.99 (-9.63 to -4.34)**	**-5.18**	**<.001**
F test	**F(4, 2784) = 6.97**			**F(4, 2772) = 10.09**			**F(4, 2796) = 11.09**		
Unadjusted R^2, *p*	**.00, p <.001**			**.01, p <.001**			**.02, p <.001**		

4.3.4.2 Patterns by ethnic-specific socioeconomic group

Associations between socioeconomic position and working memory within White British and Pakistani groups

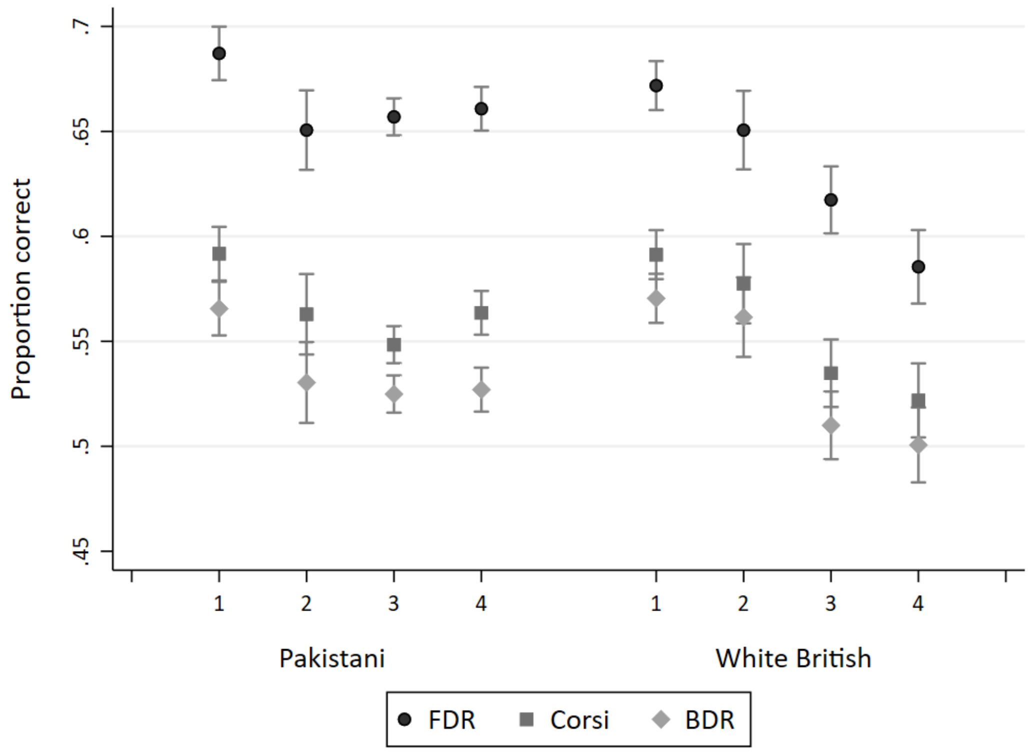


Figure 28. Mean scores and 95% confidence intervals in FDR, Corsi, and BDR by ethnic specific latent class analysis of socioeconomic position for White British (n = 1517) and Pakistani (n = 2895) ethnic groups

[Note: Pakistani classes included the following sample sizes: 1 “Educated, low benefits, not materially deprived” (n = 565), 2 “Woman employed, moderate education, benefits, not materially deprived” (n = 277), 3 “Woman not employed, low education, benefits, not materially deprived” (n = 1212), 4 “Woman not employed, moderate education, benefits, subjectively poor, materially deprived” (n = 841). White British classes included the following sample sizes: 1 “Employed, educated, not materially deprived” (n = 565), 2 “Employed, moderate education, materially deprived” (n = 275), 3 “Low education, benefits, not materially deprived” (n = 354), 4 “Low education, benefits, subjectively poor, materially deprived” (n = 323)]

Figure 28 shows mean working memory scores across the ethnic-specific socioeconomic measure in White British and Pakistani children. Socioeconomic position was a significant factor for White British children's working memory, with those in the most deprived group having lower working memory scores than those in the least deprived group. For Pakistani children, socioeconomic position appears to not have as strong of an association with children's working memory, with those in the least deprived group only having slightly higher working memory scores than the other 3 groups.

Additionally, a pattern of a social gradient is clearer for White British children, where each increasing category of socioeconomic deprivation is associated with incrementally lower working memory scores. This pattern is not as clear for Pakistani children, where those in the three lower socioeconomic groups have similar working memory scores to one another.

The following tables show regression analyses by the ethnic-specific socioeconomic indicator stratified by ethnic group.

Table 22. Regression results for FDR, Corsi and BDR by ethnic-specific socioeconomic group within White British children

	FDR (n = 1479			Corsi (n = 1469)			BDR (n = 1481)		
Socioeconomic group	***B* (95% CI)**	**t**	**p**	***B* (95% CI)**	**t**	**p**	***B* (95% CI)**	**t**	**p**
Employed, educated, not materially deprived (baseline group)	.	.	.						
Employed, moderate education, materially deprived	-1.82 (-3.98 to 0.33)	-1.66	0.10	-1.13 (-3.56 to 1.29)	-0.92	0.36	-0.89 (-3.41 to 1.62)	-0.70	0.49
Low education, benefits, not materially deprived	**-5.09 (-7.07 to -3.11)**	**-5.04**	**<.001**	**-5.56 (-7.78 to -3.33)**	**-4.90**	**<.001**	**-6.05 (-8.37 to -3.73)**	**-5.12**	**<.001**
Low education, benefits, subjectively poor and materially deprived	**-7.99 (-10.04 to -5.94)**	**-7.66**	**<.001**	**-6.51 (-8.81 to -4.20)**	**-5.55**	**<.001**	**-6.98 (-9.38 to -4.59)**	**-5.72**	**<.001**
F test	**F(3, 1475) = 22.36**			**F(3, 1465) = 14.57**			**F(3, 1477) = 16.08**		
Unadjusted R^2	**.04**			**.03**			**.03**		

Table 23. Regression results for FDR, Corsi and BDR by ethnic-specific socioeconomic group within Pakistani children

	FDR (n = 2806)			Corsi (n = 2794)			BDR (n = 2818)		
Socioeconomic group	***B* (95% CI)**	**t**	**p**	***B* (95% CI)**	**t**	**p**	***B* (95% CI)**	**t**	**p**
Educated, low benefits, not materially deprived (baseline group)	.	.	.						
Women employed, moderate education, benefits, not materially deprived	**-3.08 (-5.32 to -0.84)**	**-2.70**	**0.01**	**-2.75 (-5.34 to -0.15)**	**-2.07**	**0.04**	**-3.48 (-6.37 to -0.58)**	**-2.35**	**0.02**
Women not employed, low education, benefits, not materially deprived	**-2.71 (-4.26 to -1.16)**	**-3.42**	**<.001**	**-4.21 (-6.00 to -2.42)**	**-4.62**	**<.001**	**-3.98 (-5.98 to -1.98)**	**-3.91**	**<.001**
Women not employed, moderate education, benefits, subjectively poor and materially deprived	**-2.43 (-4.09 to -0.78)**	**-2.88**	**<.001**	**-2.71 -4.62 to -0.80)**	**-2.79**	**0.01**	**-3.73 (-5.86 to -1.60)**	**-3.43**	**<.001**
F test	**F(3, 2802) = 4.56**			**F(3, 2790) = 7.12**			**F(3, 2814) = 5.62**		
Unadjusted R^2, *p*	**.00**			**.01**			**.01**		

4.3.4.3 Patterns by subjective social status

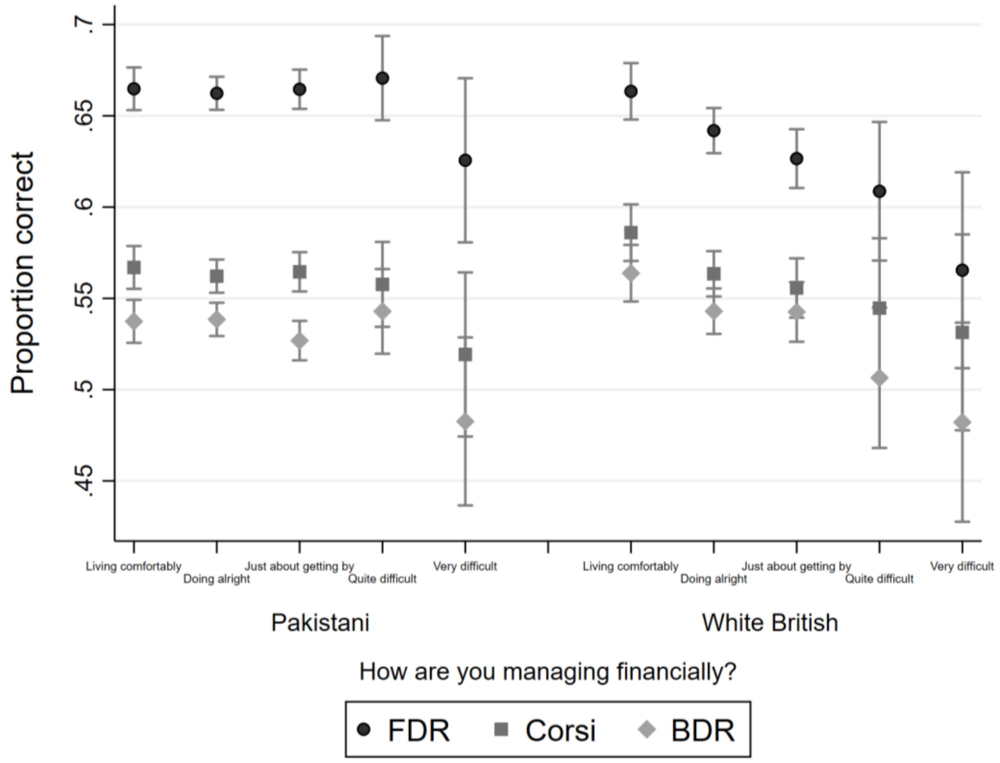


Figure 29. Mean scores and 95% confidence intervals in FDR, Corsi, and BDR by subjective financial status for White British (n = 1517) and Pakistani (n = 2895) ethnic

[Note: Pakistani classes included the following sample sizes for BDR: 'Living comfortably' n = 705, 'Doing alright' n = 1156, 'Just about getting by' n = 710, 'Quite difficult' n = 180, 'Very difficult' n = 42. For White British classes for BDR: 'Living comfortably' n = 338, 'Doing alright' n = 562, 'Just about getting by' n = 376, 'Quite difficult' n = 79, 'Very difficult' n = 31.

Figure 29 shows working memory by self-reported financial status. The pattern of results is very similar to the previous socioeconomic indicators. White British children who were "living comfortably" had substantially higher working memory scores than the other groups, whilst Pakistani children who were "living comfortably" had similar working memory scores to those who reported "quite difficult" financial status. As described in the methods section, I did not include any regression analysis for this socioeconomic indicator.

4.4 Discussion

4.4.1 Key findings

4.4.1.1 Research Question 1: patterns of working memory scores by personal demographic characteristics

This chapter presented results for three research questions. In answer to Research Question 1, I found that working memory scores were patterned by personal demographic characteristics. Variances in working memory were found by gender, English as an Additional Language, and parent immigration status. However, the direction of differences in these characteristics varied depending on the task of working memory. The largest differences in working memory were found by special education needs status, where children with special educational needs were found to have much lower working memory scores. The other personal characteristics that showed the largest differences were found by the constructs of interest to my thesis: socioeconomic position, and ethnicity.

4.4.1.2 Research Question 2: magnitude of socioeconomic and ethnic differences

In answer to Research Question 2, I found that socioeconomic disadvantage was associated with worse working memory scores, where the difference between the 'most deprived' and the 'least deprived' group was equivalent to a 12-18-month age difference. This pattern was consistent across all three working memory tasks, a finding that is consistent with my systematic review. Overall, this lends support to the view that socioeconomic position does influence working memory (e.g. Lawson et al., 2018; Wang & Fitzpatrick, 2019), and contradicts the view that working memory is unrelated to socioeconomic disadvantage (e.g., Vandenbroucke et al., 2016). However, as an aim of this study was to provide a simple overview of the magnitude of group differences, I did not control for any confounding variables or covariates in this study. In the following study, I do this using structural equation modelling.

I also showed that there were substantial differences in working memory by ethnic group. Substantial variation in working memory scores was found across White British children and children from eight other ethnic minority groups. The magnitude of the difference was smaller than the difference between the least and most deprived socioeconomic group. The FDR task had the most significant differences across ethnic groups, and the order from lowest to highest scores was: Gypsy/Irish traveller, White Other, White British, Other, Mixed, Black/Black British, Pakistani, Bangladeshi, and Indian children. Broadly speaking, Gypsy and Irish Traveller children scored the worst, and South Asian children scored the best.

However, the pattern of average mean scores tended to vary across the three working memory tasks by ethnic group (Figure 26a-26c, p.188). The exception to this were Gypsy and Irish traveller children, who scored significantly below all other groups in all three working memory tasks. In comparison to FDR, there were fewer significant differences between ethnic groups on Corsi or BDR, where although there were still some differences between the White British and South Asian ethnic groups – the differences were smaller and less consistent. In Corsi, the Other, Bangladeshi, and Indian ethnic groups had significantly higher scores than White British. In BDR, only the Bangladeshi ethnic group had significantly higher scores than White British. This may be because the Corsi and BDR tasks are not as sensitive to picking up group differences as FDR, or it may be that genuine differences in task performance exist across ethnic groups for a variety of reasons, and some of these reasons are discussed in the following paragraphs.

Generally speaking, most ethnic minority groups scored higher than White British children on at least one measure of working memory (usually FDR). It was surprising that White British children tended to have lower scores than most ethnic minority groups, as they tend to experience higher levels of socioeconomic position in the UK, and fewer forms of other types of disadvantage (e.g. racism) (Chattoo and Atkin, 2019; Coll et al., 1996). Further, this finding was in contrast with most of the studies in my systematic review (Chapter 2). A possible explanation for this is that White British children may instead have lower levels of socioeconomic position than other ethnic minority groups do within Bradford, but this goes undetected due to measurement bias of socioeconomic position within ethnic minority groups. Another possible explanation for this is that socioeconomic disadvantage may impact on working memory *more* for White British children than it does for ethnic minority children – essentially lowering the average scores. I discuss these findings regarding social gradients further in the next section (Section 4.4.1.3).

South Asian children and Black British children scored higher than White British children on at least one measure of working memory. For Bangladeshi and Indian children, this difference was equivalent to an age advantage of 6-10 months, depending on the task. For Black British and Pakistani children, this advantage was equivalent to an age difference of 9 months, but was only present for the FDR task, which measures the ability to store verbal information. This finding highlights a knowledge gap, as it remains unknown why South Asian and Black British children may have better FDR scores than expected given their ethnic minority status. In the final study of my PhD, I address this by exploring the impacts of two potential positive factors on working memory – own ethnic density and Mosque attendance (see Section 7.2.3).

There were two ethnic minority groups which consistently scored worse than White British children on all three tasks of working memory. One was White Other children, who scored significantly below White British children on FDR and BDR, comparable to an age gap of at least 10 months. However, it is difficult to make any inferences about the 'White Other' group, as this is a heterogenous ethnic group. The Office for National Statistics describes this group as including Polish born residents, but no information is provided on any other ethnic groups that may classify as 'White Other' (Office for National Statistics, 2015).

The other exception was Gypsy and Irish traveller children, who scored significantly below White British children, comparable to an age gap of at least 18 months. The integrative model for the study of child development in minority children (Figure 3, Chapter 1 (Coll et al., 1996)) highlights the negative social forces that may be associated with ethnic identity. Considering the model, it can be postulated how Gypsy and Irish traveller children experience a unique form of deprivation, discrimination, and racism that may make them particularly susceptible to poorer development.

National data sources report that nearly a quarter of Roma, Gypsy, and Traveller children experience multiple forms of deprivation (Burchardt et al., 2018). These children also have the lowest educational attainment in the UK, and experience high levels of bullying and racism, poor school attendance, and school exclusion (Foster and Norton, 2012; Parsons, 2019). Further, practitioners describe how Roma, Gypsy and Traveller families often value different skills and knowledge that benefit from a more 'holistic' way of learning, including inclusion in real life projects that involve them as part of the community (e.g. farm work) (Cudworth, 2008). In line with this, the 2011 Census reports that Gypsy or Irish traveller men and women have the lowest employment rates of all ethnic groups (Office for National Statistics, 2015). All these factors are likely to contribute to the differences in working memory between the Roma, Gypsy and Traveller children and children from the settled community, and this will likely have negative consequences for them in formal education. A further study with more focus on the developmental competencies of Roma, Gypsy and Traveller children is required, to fully understand the impact the disadvantage they are likely to face in education.

4.4.1.3 Research Question 3: patterns of working memory by socioeconomic position within two ethnic groups

In Research Question 3, I investigated how socioeconomic position was associated with working memory scores within two ethnic groups. I found that socioeconomic disadvantage was not as strongly associated with Pakistani children's working memory as it was with White British children's working memory. As stated earlier, White British children may have lower levels of overall socioeconomic position than other ethnic minority groups do within Bradford, but this goes undetected due to measurement bias. Although the data indicate that proportions of White British and Pakistani children in the most and least deprived socioeconomic groups are similar to one another, there may be other unmeasured aspects of socioeconomic position that are important in determining socioeconomic position. One unmeasured aspect is social capital, and Pakistani children in Bradford may have higher levels of socioeconomic position through increased social capital in densely populated Pakistani areas (Thapar-Bjorkert and Sanghera, 2010) (see Section 1.2.2).

Related to this, the indicators used to assess social position may not be valid for ethnic minority groups, or may be affected by measurement bias e.g. as education may be received in different countries, and women are not always aware of household earnings (Kelaher et al., 2009; Uphoff, Pickett and Wright, 2016). However, I did try to overcome this by describing working memory by three different indicators of social position; a) subjective assessment, b) a latent class analysis designed to be used across ethnic groups and c) a latent class analysis designed to be used *within* ethnic groups. Since none of these indicators seemed to have as strong an association with working memory for Pakistani children, it is also possible that the finding reflects a true lack of social gradient within this ethnic group.

However, it was not possible to ascertain the certainty of the presence or absence of the social gradients within the ethnic groups without addressing the potential influence of the other variables in this study that have been shown to have associations with working memory (English as an Additional Language, parent immigration status, and Special Educational Needs and Disability). As described in Section 3.4, some of these variables may be confounding the association between socioeconomic position and working memory (e.g. parent immigration status), and therefore need to be adjusted for in order to understand the true direction of associations. In addition, it was important to adjust for covariates to improve the precision of the estimated associations (child gender and age). I therefore investigated this further in Study 2.

The studies in the following two chapters will address some of these remaining research gaps. In Study 2, I a) test the association between socioeconomic position and working memory whilst also controlling for potential confounding variables (parent immigration status, English language status) and covariates (age and gender), b) test whether the home learning environment may explain why we see such large associations between socioeconomic position and working memory, and c) explore moderation by ethnic group for associations between socioeconomic position, the home learning environment, and working memory. In Study 3, I a) test whether high own ethnic density may be why Pakistani children have better working memory scores and b) test whether Mosque attendance may be why Pakistani children have better working memory scores.

4.4.2 Strengths and limitations

A strength of this particular study is the novel approach applied to compare the magnitude of the socioeconomic and ethnic differences in children's working memory to the magnitude of age differences. By creating graphs overlaying the coefficients in working memory by age, an understanding of the magnitude of the differences has been gained.

Another strength is that when exploring social gradients within ethnic minority groups, the breadth of the Born in Bradford data meant that I could explore social gradients by several different indicators of socioeconomic position. In relation to this, the ethnic-specific indicator has the advantage of having been designed for each particular ethnic group, and should represent a more robust indicator of social position within each ethnic group than any previous research.

A final strength is the diverse range of ethnic groups that were included in the study. More often than not, researchers tend to combine several different ethnic minority groups into one heterogenous group, and compare them to the ethnic majority group. However, this approach ignores the many differences between the ethnic minority groups and may bias any associations between ethnicity and different outcomes. In this study, I was able to explore differences across nine distinct ethnic groups. In particular, Gypsy, Roma, and Traveller children have been underrepresented in studies like this, so it is a strength that I was able to include them in this study.

However, a minor limitation related to the above point is that the ethnic groups varied in size. The Pakistani and White British ethnic groups had the largest samples (n = 6777, and n = 4137, respectively) whereas the Black British and Gypsy, Roma, and Traveller groups were much smaller (n = 264, and n = 168, respectively). Unequal sample sizes can reduce power for detecting a significant effect, so it is possible that some differences in the working memory tasks have either gone undetected or are under estimated for the groups with small sample sizes.

Related to this, the socioeconomic position of the smaller ethnic groups was not known due to them not all being BiB participants with linked socioeconomic data. This meant that I could not investigate how much of this ethnic group variance in working memory was explained by socioeconomic position. However, even if socioeconomic position could have been adjusted for, there would have been issues with residual confounding and mediator adjustment – meaning the associations may have been susceptible to bias (see Section 1.1.3) (Kaufman, Cooper and McGee, 1997; Cole et al., 2010; Pearl and Mackenzie, 2018). I therefore decided to explore associations by ethnic group without adjusting for socioeconomic position, and acknowledge that some of this variation may be explained by differences in socioeconomic position.

A final limitation of this study is that as I aimed to represent a simple understanding of the magnitude of differences, I did not control for any covariates or confounding variables. However, this is addressed in the following study.

4.4.3 Summary of future research suggestions

As stated above, future research should investigate the association between socioeconomic position and children's working memory both across and within ethnic groups, whilst controlling for potential covariates and confounders. It should also explore the reasons behind different advantages in working memory for specific ethnic groups by the type of task of working memory. For instance, why do South Asian children have better scores on FDR than White British children? I address these knowledge gaps in the following two studies.

There are other two key future research areas that are beyond the scope of my PhD. First, studies should investigate if these associations generalise beyond Bradford. Second, it should be investigated how unique forms of multiple disadvantage may impact the very low working memory scores for Gypsy, Roma, and Traveller children.

Chapter 5. Study 2: Structural Associations Between Socioeconomic Position, the Home Learning Environment, and Working Memory Ability Across Two Ethnic Groups

This Chapter outlines the introduction, methods, results, and discussion for a study of working memory by socioeconomic position and the home learning environment, and whether these associations are moderated by ethnic group.

Chapter 5. Study 2: Structural Associations Between Socioeconomic Position, the Home Learning Environment, and Working Memory Ability Across Two Ethnic Groups

5.1 Introduction

Through the systematic review and Study 1, I have established that an association exists between socioeconomic position and children's working memory. However, I have not yet controlled for any potential confounding variables in this association. In addition, I have not yet examined any potential factors that may mediate this association. The home learning environment is one potential causal factor in the association between socioeconomic position and working memory. Through the 'resource and investment' perspective, family socioeconomic disadvantage is hypothesised to influence child working memory via a lack of access to learning materials and home environment activities (Duncan, Magnuson and Votruba-Drzal, 2017; Amso and Lynn, 2017). Previous research had found the home learning environment to be a significant mediator between socioeconomic position and working memory, in a sample of 1009 children aged 5 (Hackman et al., 2015) and in a sample of 141 children aged 7-17 years Amso, Salhi and Badre, 2018). Here, I explore this hypothesis in relation to children's working memory.

Ethnicity is a potential moderating factor of the association between socioeconomic position and working memory. One study found in my systematic review revealed that ethnic minority children with higher levels of socioeconomic risks had significantly worse working memory, whilst ethnic majority children at different levels of socioeconomic risks had similar working memory ability to one another (Rhoades et al., 2011). However, the data presented in Study 1 suggests the opposite pattern for Pakistani and White British children, and this highlighted the need to investigate the association between socioeconomic position and children's working memory both across and within ethnic groups, whilst controlling for potential covariates and confounders. I therefore explored the existence of social gradients in the two largest ethnic groups in my sample, whilst controlling for potential confounding variables of these associations.

The remainder of this chapter specifies the methods for the multi-group Structural Equation Model (SEM) that investigated the presence and magnitude of associations between socioeconomic position, the Home Learning Environment (HLE), and working memory across two ethnic groups. Although Study 1 has already shown higher socioeconomic position to be associated with higher working memory, I further confirmed this in Study 2 by controlling for potential confounding variables. I hypothesized that (a) increased socioeconomic disadvantage at birth will predict lower working memory scores and (b) the home learning environment will partially mediate the relationship between socioeconomic position and working memory. Due to the lack of comprehensive research on ethnicity and working memory, I did not produce hypotheses, but investigated (c) does ethnicity moderate the association(s) between socioeconomic position, the home learning environment and working memory?

5.2 Methods

5.2.1 Pre-registration

The data analysis plans specified here were pre-registered on the OSF: https://osf.io/gw79v/

5.2.2 Data Source

I used the BiB-only sample in this study as this is linked to nuanced classes of socioeconomic position, routine education data, and data for the potential mediator variable collected in BiB1000 (the home learning environment).

5.2.3 Structural Equation Modelling

Structural Equation Modelling (SEM) is appropriate for these research questions as it can answer a set of interrelated research questions in a single and comprehensive analysis. It models the relationships amongst multiple independent variables, mediators, and dependent variables simultaneously (Gefen, Straub and Boudreau, 2000). A variable can be both a response in an equation, and appear as an explanatory variable in another equation (Amorim et al., 2010). SEM generally comprises two key components: a structural model and a measurement model. In the structural model, regression analysis statistically estimates model parameters, where a difference in an outcome can be estimated from a one-unit difference in an exposure variable (Kenny, 2011). Path analysis (also known as mediation analysis) can be used to identify the strength and plausibility of potential causal mechanisms.

The measurement model contains latent variables, which explicitly specify and incorporate errors into measurements (whereas traditional methods assume measurement occurs without error) (Suhr, 2006). Latent variables are those that are not directly observed but are inferred from several other observed variables. The observed variables are considered to be indicators of the underlying construct they are trying to present (Byrne, 2013, p.4). In other words, the latent variable exerts influence on the observed behaviours of an individual (Borsboom and Van Heerden, 2003). The relation between the latent variable and the observed score is formally a regression model, where the independent variable is latent rather than manifested in the data. For example, a factor model for working memory would specify that an increase of *n* units in the latent variable leads to an increase of *n* times the factor loading in the expected value of one of the observed indicators (BDR, FDR, Corsi) (Borsboom and Van Heerden, 2003). Additionally, a weighted summary score of working memory can be calculated as a function of the observed variables (Borsboom and Van Heerden, 2003). The outcome working memory will be measured as a latent variable by using the three observed variables (BDR, FDR, and Corsi).

A common method that uses latent variables is factor analysis - which estimates relationships between several latent variables, or "factors" (Byrne, 2013). In factor analysis, continuous latent variables describe differences along one or more continuum using continuous observed indicators (Ruscio and Ruscio, 2008). I used factor analysis to find the best measurement model of the home learning environment.

5.2.4 Exploratory Factor Analysis and Confirmatory Factor Analysis

I used Exploratory Factor Analysis (EFA) on all 9 home learning environment items with the first timepoint of the data (24 months). I chose to use EFA to develop a parsimonious analysis and interpretation of the associations between my constructs of interest (Williams, Onsman and Brown, 2010). EFA is used when links between observed and latent variables are unknown, and Confirmatory Factor Analysis (CFA) is used when the researcher has some knowledge of the underlying latent variable structure (Costello and Osborne, 2005).

5.2.5 Sample Size Considerations

It is widely agreed that SEM requires "large" sample sizes. A small sample size in a SEM could cause failure of estimation convergence, improper solutions, lowered accuracy of parameter estimates, small statistical power, and inappropriate model fit statistics

(Wang and Wang, 2019, p. 391). However, it is not widely agreed what constitutes a large enough sample size for a SEM (Wang and Wang, 2019, p. 392).

There are numerous methods available to calculate a required sample size for estimating a specific SEM (e.g. Monte Carlo simulation, Satorra and Saris' method) (Wang and Wang, 2019, p. 394-422). However, due to the complexity of these methods and time constraints on my PhD, I chose a simpler method. I used an online sample size calculator for SEMs, which estimates the minimum sample size to detect an effect based on the number of latent and observed variables in the model (Soper, 2021). Specifying a small to medium effect size (.2), with statistical power of .8 and a probability level of .05, the minimum sample size to detect an effect in my model was calculated to be n = 296. The sample size in this SEM was expected to be much larger than this (n = 3000 in the larger sample, and n = 500 for BiB1000 data), so sample size was not considered an issue. In addition, this expected sample size is substantially larger than other published SEM's with similar model structures (e.g. n = 115, Arán Filippetti & Richaud, 2016; n = 151, Cassidy et al., 2016; n = 115, Stålnacke et al., 2019).

5.2.6 Inclusion and Exclusion Criteria

- Child and mother are actively participating in BiB cohort
- Child completed all 3 working memory tasks from the Primary School Years wave
- Child's mother completed the BiB baseline questionnaire and has socioeconomic position variable
- Child has ethnicity code and is recorded as being White British or Pakistani ethnicity
- Child is typically developing (absence of SEND)

As socioeconomic position and ethnicity are the key variables in this analysis, participants were only included if they had these data. The child had to be classed as typically developing, as the presence of Special Education Needs or Disability (SEND) may be a confounder between socioeconomic position, the home learning environment, and working memory.

5.2.7 Analysis Software

All data management, exclusions, and descriptive statistics were generated in Stata 16. Data were then be imported to Mplus for all SEM analysis.

5.2.8 Missing Data

As the SEM only included participants with socioeconomic position and ethnicity, missingness is only possible in the four covariates or in the BiB1000 HLE data. Full Information Maximum Likelihood (FIML) methods will be used to deal with missing data. FIML works by estimating a likelihood function for each individual based on the variables that are present so that all the available data are used, meaning it only drops participants when no data are available. FIML has been found to produce efficient and unbiased estimates for missing data (Enders and Bandalos, 2001).

5.2.9 Steps of Model Estimation

The below diagram briefly describes how the SEM was specified. The model estimation steps were based on proposed guidelines to estimate a full SEM (Bollen and Noble, 2011; Kenny, 2011). The full specification methods with technical detail are provided in the appendix (Appendices D2).

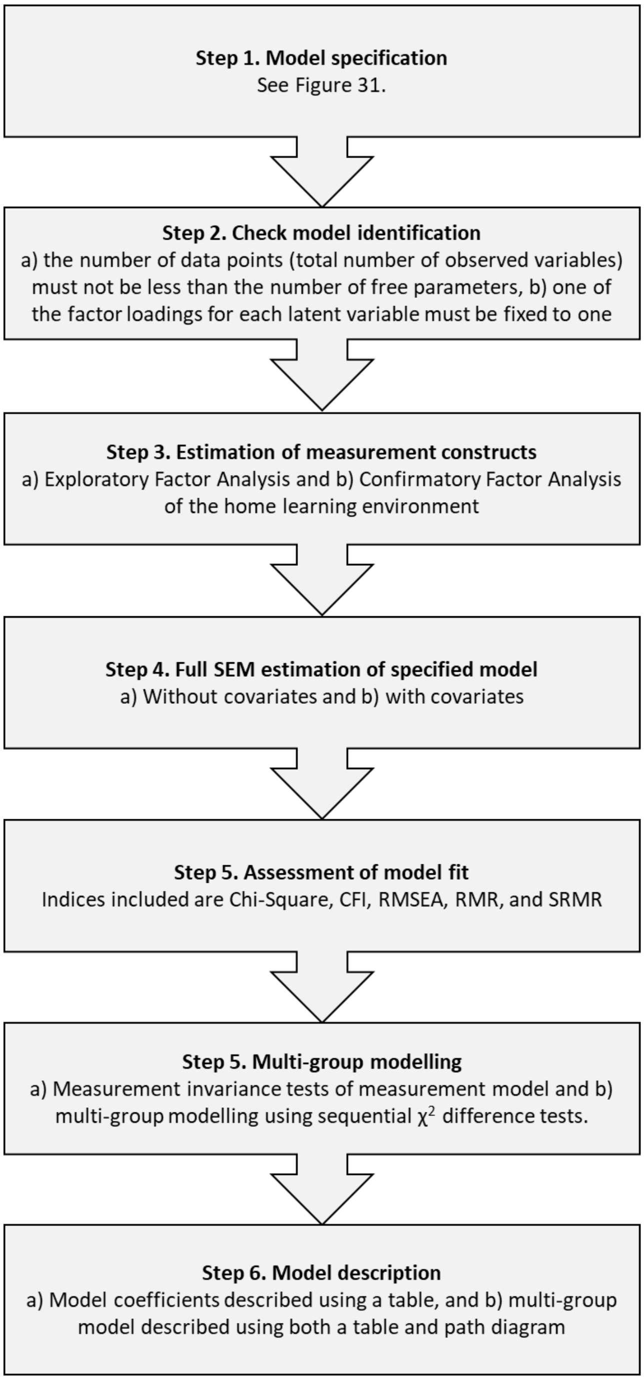
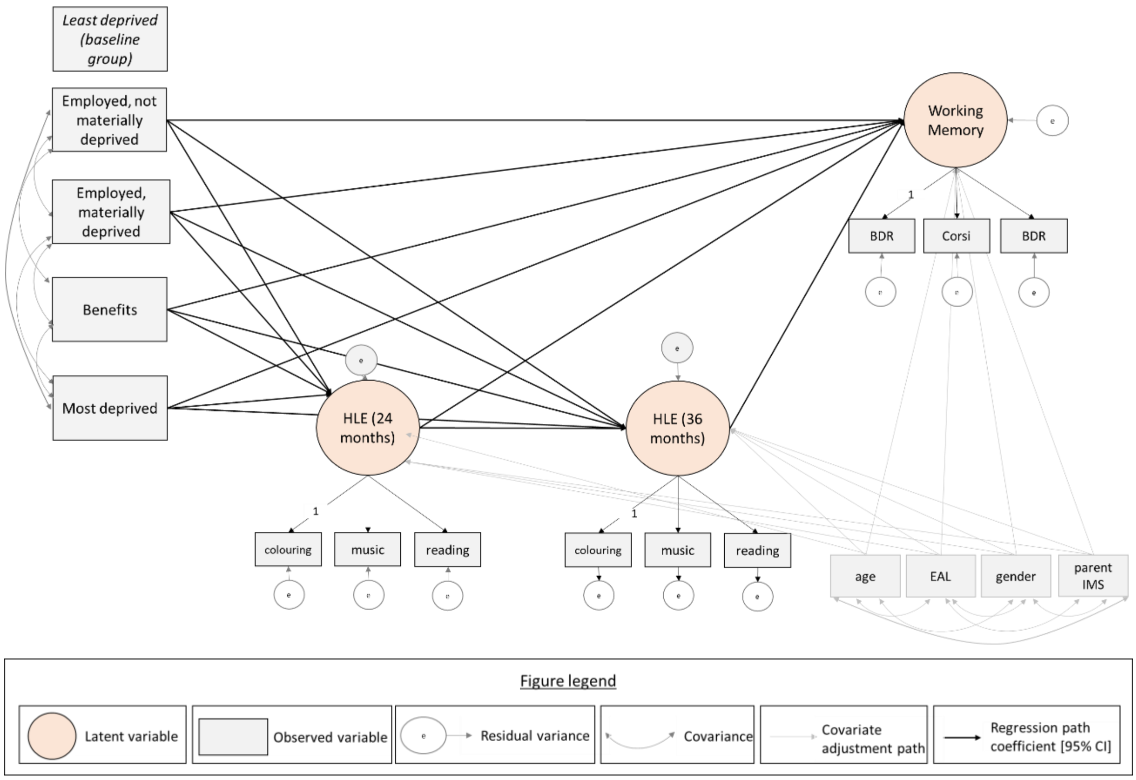


Figure 30. Overview of model estimation steps

Figure 30 provides an overview of the six steps required to estimate the full SEM. Below, Figure 31 provides the model specification for Step 1.



<u>Figure 31. SEM path diagram</u>

[Note: [1]Abbreviations: English as an Additional Language (EAL), parent immigrations status (parent IMS), Backwards Digit Recall (BDR), and Forwards Digit Recall (FDR). [2]SEP is fitted as a categorical variable with 'least deprived' as the baseline group, thus, dummy variables are used to model the associations. [3]Covariance is also modelled between the covariates (age, EAL, gender, parent IMS) and the socioeconomic dummy variables].

5.3 Results

5.3.1 Sample Characteristics

Table 24. Sample characteristics for all participants included in the model(s).

	All (n = 3457)	BiB1000 (n = 500)
Variable	**Count (%)**	**Count (%)**
Ethnicity		
White British	1142 (33)	143 (29)
Pakistani	2315(69)	347 (71)
Socioeconomic Group		
Least deprived and most educated	537 (16)	76 (15)
Employed, not materially deprived	608 (18)	86 (17)
Employed, no access to money	547 (16)	89 (18)
Benefits and not materially deprived	1,203 (35)	166 (33)
Most economically deprived	562 (16)	83 (17)
Gender		
Male (1)	1855 (54)	213 (43)
Female (0)	1602 (46)	287 (57)
Missing	.	.
Age (years)		
6	1 (.03)	.
7	929 (27)	113 (23)
8	1,767 (51)	244 (49)
9	685 (20)	110 (22)
10	75 (2)	33 (7)
Missing	.	.
English as an Additional Language		
Yes (1)	1814 (52)	272 (55)
No (0)	1632 (47)	227 (45)
Missing	11 (0.32)	1 (0.20)
Parent Immigration Status		
Born outside UK (1)	1387 (40)	205 (41)
Born in UK (0)	2070 (60)	295 (59)
Missing	.	.

[Note: Only BiB1000 participants with working memory data were included, hence the sample size being smaller than 1000]

Table 24 summarises the sample size for each category included in the SEMs. The analysis included participants who had completed all 3 working memory tasks, were of White British or Pakistani ethnicity, and had the socioeconomic position variable available. To examine for selection bias into the BiB1000 cohort, Table 24 shows the sample characteristics across all participants (n = 3457), and participants who had HLE data at the second time point (n = 500). The sample characteristics are similar across both samples and so selection bias is not a concern.

To account for missing data, FIML methods only drops participants when they have no available information on all variables (Enders and Bandalos, 2001). The sample size for the full SEM therefore included all participants (n = 3457), and sample sizes were much smaller within the Exploratory Factor Analysis (*n* = 491, 14.2% of total sample) and the Confirmatory Factor Analysis (*n* = 500, 14.46% of total sample), as these analyses only included variables from BiB1000.

5.3.2 Measurement Model of the Home Learning Environment

As specified in Section 5.2.9, I first established the measurement model of the home learning environment (HLE) using Exploratory Factor Analysis with the 24-month data, and then Confirmatory Factor Analysis with the second timepoint at 36 months.

5.3.2.1 Exploratory Factor Analysis

The model was estimated in MPlus specifying a 1, 2 and 3 factor model for analysis. There were 491 participants included. Geomin oblique rotation was used. All items were assessed on the same scale, where 1 = one day a week, and 7 = 7 days per week.

Table 25. Model fit indices for each EFA model

Model	Chi-square	CFI	RMSEA	SRMR
1 factor	27.335, p = .1261	0.91	.027, p = .944	0.034
2 factor	10.257, p = .6728	1	0, p = .993	0.019
3 factor	4.078, p = .7707	1	0, p = .985	0.012

Table 25 shows that the model fit is at least acceptable for all 3 EFA models. However, the models with more factors have better fit, indicated by smaller Chi-square, RMSEA, and SRMR values, and a larger CFI value. To assess the number of factors to be extracted, I produced a screeplot containing the eigenvalues for both the sample correlation matrix and the parallel analysis (Patil, McPherson and Friesner, 2010).

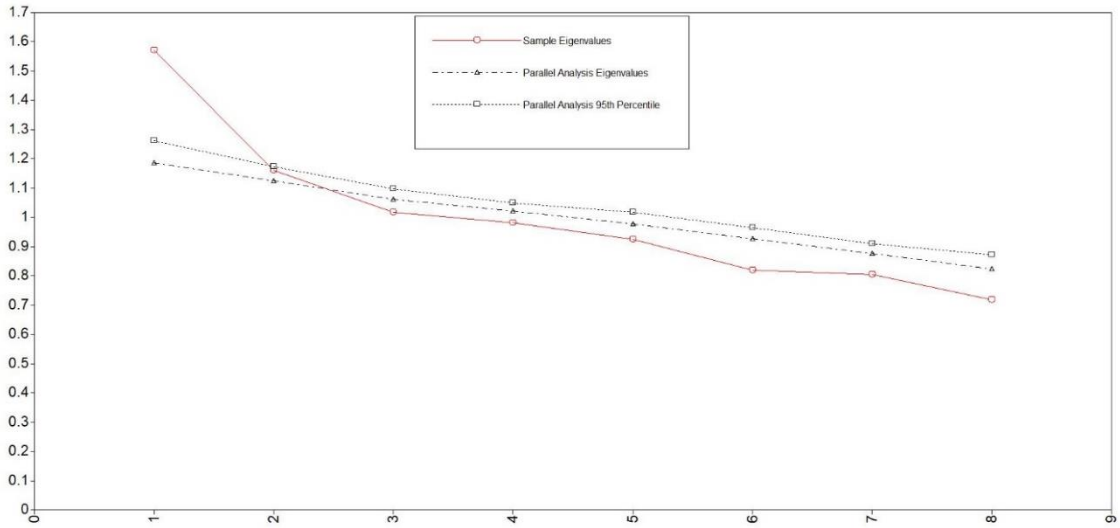


Figure 32. Scree plot presenting eigenvalues from sample correlation matrix and parallel analysis (including 95% confidence interval)

To interpret the scree-plot, a line should be drawn through the smaller eigenvalues where a departure from this line occurs – to identify where a "break" occurs. The points above this "break" indicates the number of factors to be retained (Williams, Onsman and Brown, 2010). Figure 32 shows the red line (labelled sample eigenvalues) indicates a possible break at 1 factor, although it is not as prominent as expected.

To support the decision regarding how many factors to retain, Figure 32 also shows the parallel analysis eigenvalues. The parallel analysis constructed 50 correlation matrices of random variables, based on the same sample size and number of variables in the BiB data set. The average eigenvalues from the random correlation matrices are then compared to the eigenvalues generated from the BiB data set, and only factors with eigenvalues that are greater than the parallel average random eigenvalues should be retained (Hayton, Allen and Scarpello, 2004). Based on the parallel analysis eigenvalues, no more than two factors should be extracted. However, based on the 95th percentile of the parallel analysis eigenvalues, only one factor should be extracted. Next, I examined the factor loadings for the 1 and 2 factor models.

Table 26. Geomin oblique rotated loadings for one and two factor models

Variable	Factor 1	Residual variance unexplained
Colouring	**0.453***	**.795**
Toys	0.133*	.982
TV/DVDs	0.129	.983
Computer	0.117	.986
Music	**0.342***	**.883**
Reading	**0.509***	**.741**
Playing in house	0.256*	.934
Playing in garden	0.198*	.961

Table 27. Geomin oblique rotated loadings for two factor model

Variable	Factor 1	Factor 2	Residual variance unexplained
Colouring	**0.480***	-.016	**.774**
Toys	.110	.042	.983
TV/DVDs	.059	.126	.976
Computer	.255*	-.233	.916
Music	.247*	.195*	.873
Reading	**.528***	.013	.717
Playing in house	.118	.294*	.879
Playing in garden	-.002	**.437***	.810

[Note: [1]The proportion of variance explained in each variable is 1 minus the residual variance. [2] loadings above .30 are bolded and would be extracted if model is chosen]

Tables 26 and 27 show the factor loadings for a one-factor model and two-factor model, with loadings >.30 in bold. Each factor should have ≥3 variables, with loadings of ≥.30 (Costello and Osborne, 2005). The two-factor model does not contain enough variables with loadings above .30, and should therefore not be chosen. The one-factor model contains 3 variables each with loadings of ≥.30, and can be conceptualised a 'general learning activities' model. I therefore validated the structure of the HLE model using Confirmatory Factor Analysis (CFA) of the HLE at 36 months, which allows a testing of the hypotheses of the structure of the HLE data (Costello and Osbourne, 2005).

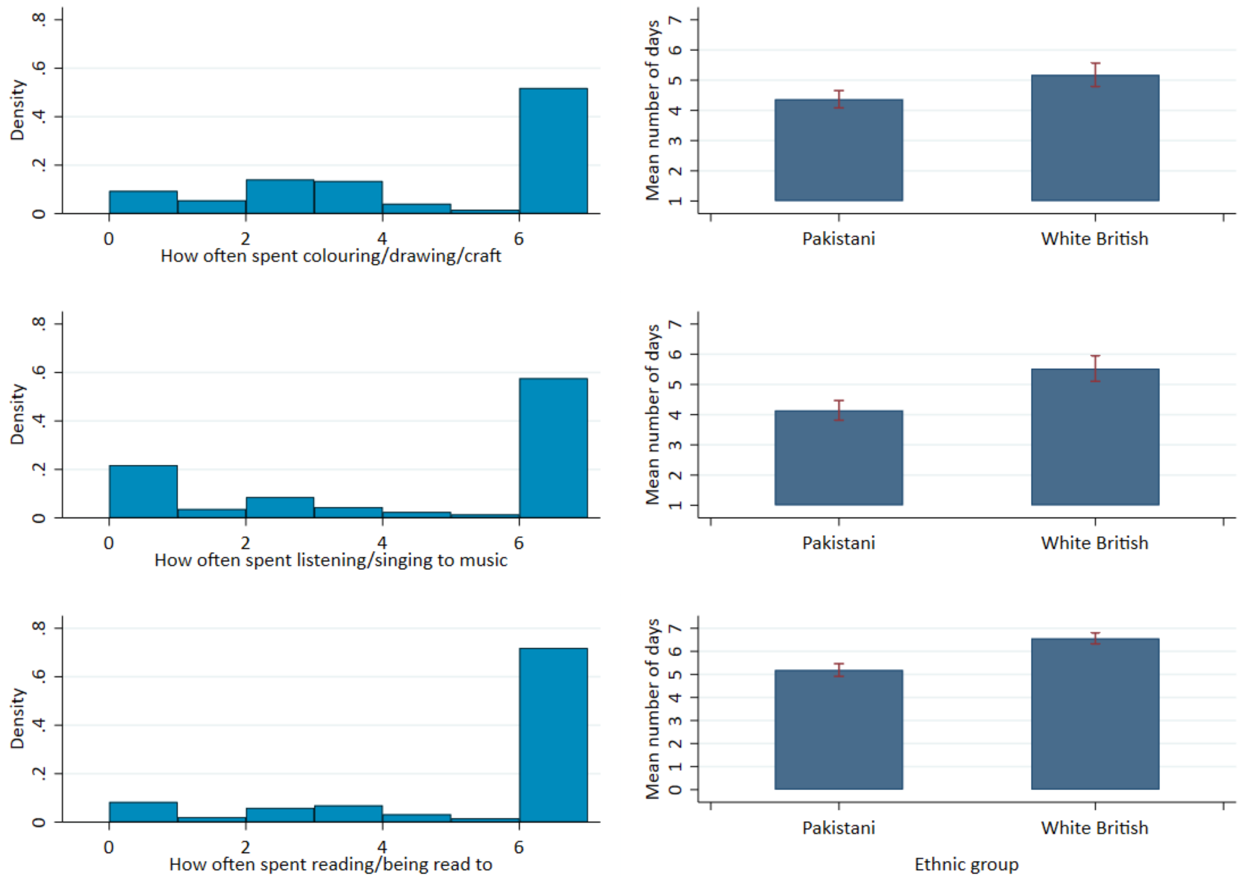
5.3.2.2 Confirmatory Factor Analysis

I ran the CFA with the second timepoint of the HLE data, using the variables identified in the EFA; number of days which the child participated in colouring, listening to music, and reading. There were 500 participants included. As the model is 'just' identified, and has 0 degrees of freedom, model fit cannot be assessed in this model (and appears as 'perfect') ($\chi2$ =70.515(0), p < .001; CFI = 1; RMSEA = 0, SRMR = 0). However, the factor loadings and signs were as expected (see Table 28), and the model fit for the overall SEM will still be assessed, so I continued with the SEM.

Table 28. Factor loadings for CFA of Home Learning Environment at 36 months of age

Variable	**Factor 1**	**Residual variance unexplained[1]**
Colouring	1.00	3.80
Music	.75	7.72
Reading	.77	3.30

The following figure provides histograms for each activity, and number of days which the child participated in each activity per ethnic group.



<u>Figure 33. Histograms and mean number of days spent on activity per ethnic group for three extracted activities</u>

Figure 33 presents the histograms and the mean number of days per ethnic group for each home learning activity. The histograms show there is positive skew in the data, with the vast majority of participants reporting that they engage with these activities 7 days per week. The bar charts show that White British parents tend to report higher number of days these activities take place than Pakistani parents.

5.3.3 Structural Equation Model

5.3.3.1 Structural Equation Model without covariates

As specified in Section 5.2.9, I first estimated the full SEM model between SEP, HLE at 24 months, HLE at 36 months, and working memory, without any of the other covariates in this model. The CFI, RMSEA, and SRMR values indicated very good model fit ($\chi2$ = 92.69(48), p < .01; CFI = .980; RMSEA = .016 [90% CI 0.011 to 0.021], SRMR = .036). Although $\chi2$ would ideally be insignificant, the value is largely affected by the sample size of the model, with larger sample sizes results in significant test statistics (Barrett, 2007). The R^2 value for the latent variable working memory was .063 (p = 0.199), indicating that this model does not significantly explain the variance in working memory. The R^2 values for the 3 observed working memory variables were substantially higher, with Corsi at .340 (p < .001), BDR at .611 (p < .001), and FDR at .400 (p < .001).

The predictor socioeconomic position was fitted as a 5-category variable, with ‘least deprived’ as the baseline group. The coefficients between each level of socioeconomic position and working memory therefore represent the difference between the ‘least deprived’ group and every other socioeconomic group: ‘employed, not materially deprived’, ‘employed, no access to money’, ‘benefits and not materially deprived’, and ‘most economically deprived’. A list of the socioeconomic characteristics within each socioeconomic position category is provided in the Appendices (C3).

Table 29. Unstandardized Beta Coefficients for Structural Equation Model without covariates (n = 3457)

Path coefficient	*B (se)*	*p*
HLE at 24 → working memory	-.033 (.029)	0.257
HLE at 36 → working memory	.034 (.032)	0.286
Employed, not materially deprived→ working memory	-.037 (.014)	.009*
Employed, no access to money→ working memory	-.038 (.017)	.029*
Benefits and not materially deprived→ working memory	-.063 (.014)	<.001*
Most economically deprived→ working memory	-.065 (.018)	<.001*
Employed, not materially deprived → HLE at 24	.000 (.285)	.999
Employed, no access to money → HLE at 24	-.716 (.300)	.017*
Benefits and not materially deprived → HLE at 24	-.780 (.258)	.003*
Most economically deprived → HLE at 24	-.103 (.284)	.715
HLE at 24 → HLE at 36	.692 (.155)	<.001*
Employed, not materially deprived → HLE at 36	-.065 (.253)	.798
Employed, no access to money → HLE at 36	.094 (.263)	.720
Benefits and not materially deprived → HLE at 36	-.191 (.239)	.424
Most economically deprived → HLE at 36	-.383 (.254)	.132

*Note: the baseline socioeconomic group is 'least deprived', * = p <.05.*
Abbreviation(s): Home Learning Environment (HLE)

Table 29 shows that each level of the socioeconomic position variable was associated with significant differences in working memory in the expected direction, where groups with increased socioeconomic disadvantage had lower working memory scores. Two levels of socioeconomic position were associated with the HLE at 24 months; with the 'least deprived' as the baseline compared to 'employed, no access to money' and 'benefits'. The other socioeconomic position levels were not significantly associated with the HLE at either timepoint. The association between HLE at each of the two timepoints was significant. However, neither HLE at 24 months or 36 months had a statistically significant association with working memory. Indirect paths between each socioeconomic position level and working memory via both HLE timepoints were tested, however, none of these paths reached statistical significance.

5.3.3.2 Structural Equation Model including covariates

I next fitted the SEM including the four covariates: gender, age, EAL, and parent immigration status. Although the model fit reduced slightly from that without covariates, it still indicated good fit in all indices (χ^2 = 245.569(72), p < .001), CFI = .937, RMSEA = .026 [.023 to .030], SRMR = .037). The R^2 value for the latent variable working memory was .190 (p < 0.001), indicating the model does explain a significant amount of variance in working memory. The R^2 values for the 3 observed working memory variables are Corsi at .353 (p < .001), BDR at .603 (p < .001), and FDR at .394 (p < .001).

The R^2 value is lower in the latent working memory variable as latent variables explicitly specify and incorporate errors into measurements. The latent variable's variance is therefore a linear combination of all three observed variables variances, which will be larger than the variance of any of the individual terms alone.

Table 30. Unstandardized Beta Coefficients for Structural Equation Model with covariates included (n = 3457)

Path coefficient	*B (se)*	*p*
HLE at 24 → working memory	-.033 (.034)	0.328
HLE at 36 → working memory	.046 (.035)	0.295
Employed, not materially deprived → working memory	-.038 (.016)	.019*
Employed, no access to money → working memory	-.035 (.019)	.064
Benefits and not materially deprived → working memory	-.054 (.016)	.001*
Most economically deprived → working memory	-.064 (.019)	.001*
Age → working memory	.006 (.001)	<.001*
English as an Additional Language → working memory	-.005 (.011)	.652
Parent Immigration Status → working memory	.023 (.024)	.329
Gender → working memory	.010 (.011)	.405
Employed, not materially deprived → HLE at 24	-.227 (.300)	.451
Employed, no access to money → HLE at 24	-.777 (.307)	.011*
Benefits and not materially deprived → HLE at 24	-.669 (.268)	.012*
Most economically deprived → HLE at 24	-.026 (.294)	.931
Age → HLE at 24	-.014 (.010)	.154
English as an Additional Language → HLE at 24	-.409 (.106)	<.001*
Parent Immigration Status → HLE at 24	-.178 (.197)	.366
Gender → HLE at 24	-.653 (.197)	.001*
HLE at 24 → HLE at 36	.729 (.178)	<.001*
Employed, not materially deprived → HLE at 36	-.204 (.297)	.493
Employed, no access to money → HLE at 36	.078 (.310)	.802
Benefits and not materially deprived → HLE at 36	-.283 (.284)	.319
Most economically deprived → HLE at 36	-.362 (.292)	.215
Age → HLE at 36	.005 (.010)	.586
English as an Additional Language → HLE at 36	.156 (.118)	.188
Parent Immigration Status → HLE at 36	-.667 (.210)	.001*
Gender → HLE at 36	-.224 (.209)	.283

*Note: the baseline socioeconomic group is 'least deprived', * = p <.05.*
Abbreviation(s): Home Learning Environment (HLE)

Table 30 summarises the regression paths in the model. A correlation matrix for all variables in the model is provided in the appendices (D1). Socioeconomic position was significantly associated with working memory at a similar magnitude at all levels to the previous model. With the 'least deprived' group as the baseline compared to the following groups: 'employed, not materially deprived' (*B* = -0.038 [-0.69 to -0.006], *p* = .019), 'employed, no access to money' (*B* = 0.035 [-0.072 to 0.002], *p* = .064), 'benefits' (*B* = -0.054 [-0.085 to -0.022] *p* = .001) and 'most deprived' (*B* = -0.064 -0.103 to -0.026], *p* = .001).

Again, two levels of socioeconomic position were associated with HLE at 24 months. With the 'least deprived' as the baseline compared to: 'employed, no access to money' and 'benefits' groups. This indicates that some lower levels of socioeconomic position were associated with lower frequencies of HLE activities. Again, the other socioeconomic position levels were not significantly associated with the HLE, and neither HLE at 24 months or 36 months were associated with working memory. Age was significantly associated with working memory. Two of the covariates were significantly associated with HLE at 24 months; gender and EAL. These covariates may have explained further variance in the HLE at 24 months, which is why socioeconomic position is no longer associated with the HLE at 24 months. Parent immigration status was associated with HLE at 36 months.

Overall, these results confirm the hypothesis that increased socioeconomic disadvantage at birth predicts lower working memory scores. These results reject the hypothesis that the home learning environment partially mediates the association between socioeconomic position and working memory, as none of the indirect effect paths between socioeconomic position and working memory via the HLE at 24 months or 36 months were significant.

5.3.4 Multi-group Structural Equation Model

5.3.4.1 Measurement invariance in the latent variables

As specified in Section 5.2.9, I explored the measurement invariance across the two latent variables in the model: the HLE model and the working memory model.

Table 31. Tests of measurement invariance in the working memory latent variable

	Chi-Square difference test	**RMSEA**	**CFI**	**SRMR**
Configural	0(0), p = .0	0	1	0
Metric	5.871(2), p = .053	.033	.998	.019
Scalar	37.886(2), p = .000	.076	.979	.039

Table 32. Tests of measurement invariance in the home learning environment latent variable

	Chi-Square difference test	**RMSEA**	**CFI**	**SRMR**
Configural	0(0), p = .0	0	1	0
Metric	3.771(2), p = .1517	.06	.965	.028
Scalar	11.203(2), p = .0037	.105	.786	.056

Both the working memory (Table 31) and HLE (Table 32) latent models indicate that metric variance is achieved with non-significant X^2 tests, and acceptable model fit values in RMSEA, CFI, and SRMR. However, scalar invariance is not achieved in either measure indicated by the significant χ^2 test. The χ^2 tests significance may be due to its sensitivity to large sample sizes (at least in the working memory model), and so I also considered the other model fit values. The other model fit values are all considerably worse in the scalar invariance test, however, still considered acceptable or borderline acceptable. The working memory model is acceptable with the values being judged as the following; RMSEA is ‘fair’, CFI is ‘acceptable’, and SRMR is ‘good’. The HLE model is borderline acceptable with the values being judged as the following; RMSEA is ‘mediocre’, CFI is below acceptable, and SRMR is ‘acceptable’.

Since the importance of scalar invariance is debated (Parker and Nagengast, 2016), and the measurement invariance tests may be influenced by the smaller sample size in the White British group (n = 157 in the HLE model), I continued with the multi-group model. Additionally, this potential scalar measurement invariance may be viewed as a useful source of information on cross-group differences, and multi-group models can be used to explore item differences. Furthermore, the inclusion of covariates in the full multi-group model (such as parent immigration status and EAL) may improve the measurement equivalence properties of the scales (Davidov et al., 2014).

5.3.4.2 Multi-group model

Upon testing the unconstrained multi-group model across the ethnic groups, a linear dependency arose in the two timepoints for the HLE within the White British group. Linear dependency means that some observed variables are perfectly predictable by others, and the SEM cannot be estimated when this occurs (Suhr, 2006). This indicates that parents answered questions about the HLE very similarly across the two timepoints, which is unsurprising. It is not known why this would occur in only the White British group, however, it may be due to less participants and therefore less variability being available in the White British group. Since the HLE mediation can still be tested with the second timepoint, I removed the first timepoint so that the model could be fitted.

I tested the unconstrained and constrained multi-group models in MPlus and obtained the following chi-square values for the unconstrained (χ^2 = 243.285(88)) and constrained (X^2 =275.849(105)) models. A chi-square difference test using these values indicated a significant difference (χ^2 = 32.564(17), p = .013), suggesting that there are significant differences between the Pakistani and White British groups in these associations and the next stage of the analysis was to deduce where the differences lay using multi-group modelling. To do so, I first examined the Beta coefficients from the unconstrained multi-group model. The model fit for the unconstrained model indicated good fit in all indices (χ^2 = 243.285(88), $p < .001$), CFI = .939, RMSEA = .032 [.027 to .037], SRMR = .051).

Table 33. Unstandardized Beta Coefficients for Structural Equation Model in unconstrained multi-group model for White British and Pakistani children, and paths tested for moderation identified by A to I.

Path coefficient	Pakistani (n = 2315)		White British (n = 1142)		Paths
	B (SE)	*p*	B (SE)	*p*	
Employed, not mat dep → working memory	-0.041 (.014)	.004**	-0.021 (.033)	.523	A
Employed, no access money → working memory	-0.013 (.013)	.320	-0.002 (.036)	.954	B
Benefits → working memory	-0.041 (.013)	.002**	-0.054 (.038)	.148	C
Most deprived → working memory	-0.042 (.013)	.001**	-0.076 (.041)	.062*	D
Age → working memory	0.007 (.000)	<.001**	0.005 (.001)	<.001**	
Gender → working memory	0.018 (.010)	.076*	0.039 (.044)	.373	
EAL → working memory	-0.009 (.004)	.035**	-0.081 (.058)	.164	
Parent IMS → working memory	-0.004 (.011)	.741	0.006 (.079)	.941	
HLE → working memory	0.010 (.011)	.360	0.059 (.058)	.311	E
Employed, not mat dep → HLE	-0.286 (.403)	.478	-0.425 (.300)	.156	F
Employed, no access money → HLE	-0.537 (.358)	.133	-0.458 (.326)	.161	G
Benefits → HLE	-0.785 (.315)	.013**	-0.454 (.359)	.207	H
Most deprived → HLE	-0.382 (.365)	.296	-0.574 (.332)	.084*	I
Age → HLE	-0.007 (.012)	.533	-0.006 (.011)	.590	
Gender → HLE	-0.667 (.225)	.003**	-0.738 (.236)	.002**	
EAL → HLE	-0.042 (.125)	.736	0.214 (.864)	.804	
Parent IMS → HLE	-0.725 (.229)	.002**	-0.241 (1.249)	.847	

Note: sample sizes in each ethnic group for HLE data are smaller at Pakistani n = 343 and White British n = 157, * p <.10, ** p <.05, *the baseline socioeconomic group is 'least deprived'. Abbreviation(s): Home Learning Environment (HLE), Parent Immigration Status (IMS), English as an Additional Language (EAL).*

Table 33 shows the unstandardized beta coefficients across the two groups for all paths in the model, and the paths identified by A-I are the paths of interest to my research questions regarding the moderation of these association by ethnic group. I therefore tested the paths A to I to assess the difference between the constrained model and models where all paths apart from those specified above were constrained.

Although some other paths between covariates and working memory show some potential differences across the ethnic groups, I did not test these as they had only been fitted as covariates to improve the precision of the estimates and were not of interest to my research questions.

Table 34. Chi-square difference tests between constrained model and models with paths unconstrained.

Models	χ^2	df	χ^2 change	*p* value
Constrained	275.849	105	.	.
A) Employed, not mat dep → working memory	272.951	104	2.898	0.089*
B) Employed, no access money → working memory	274.7	104	1.149	0.284
C) Benefits → working memory	275.291	104	0.558	0.455
D) Most deprived → working memory	264.534	104	11.315	0.001**
E) HLE → working memory	264.634	104	11.215	0.001**
F) Employed, not dep → HLE	275.841	104	0.008	0.929
G) Employed, mat deprived → HLE	275.632	104	0.217	0.641
H) Benefits → HLE	275.015	104	0.834	0.361
I) Most deprived → HLE	271.293	104	4.556	0.033**

* $p < .10$, ** $p < .05$

Table 34 shows the χ^2 change between the constrained multi-group model and models where paths A to I were unconstrained. The results reveal that the paths between SEP→working memory and SEP→HLE significantly differed between the two ethnic groups at particular levels, and the path between HLE→working memory significantly differed between the two ethnic groups.

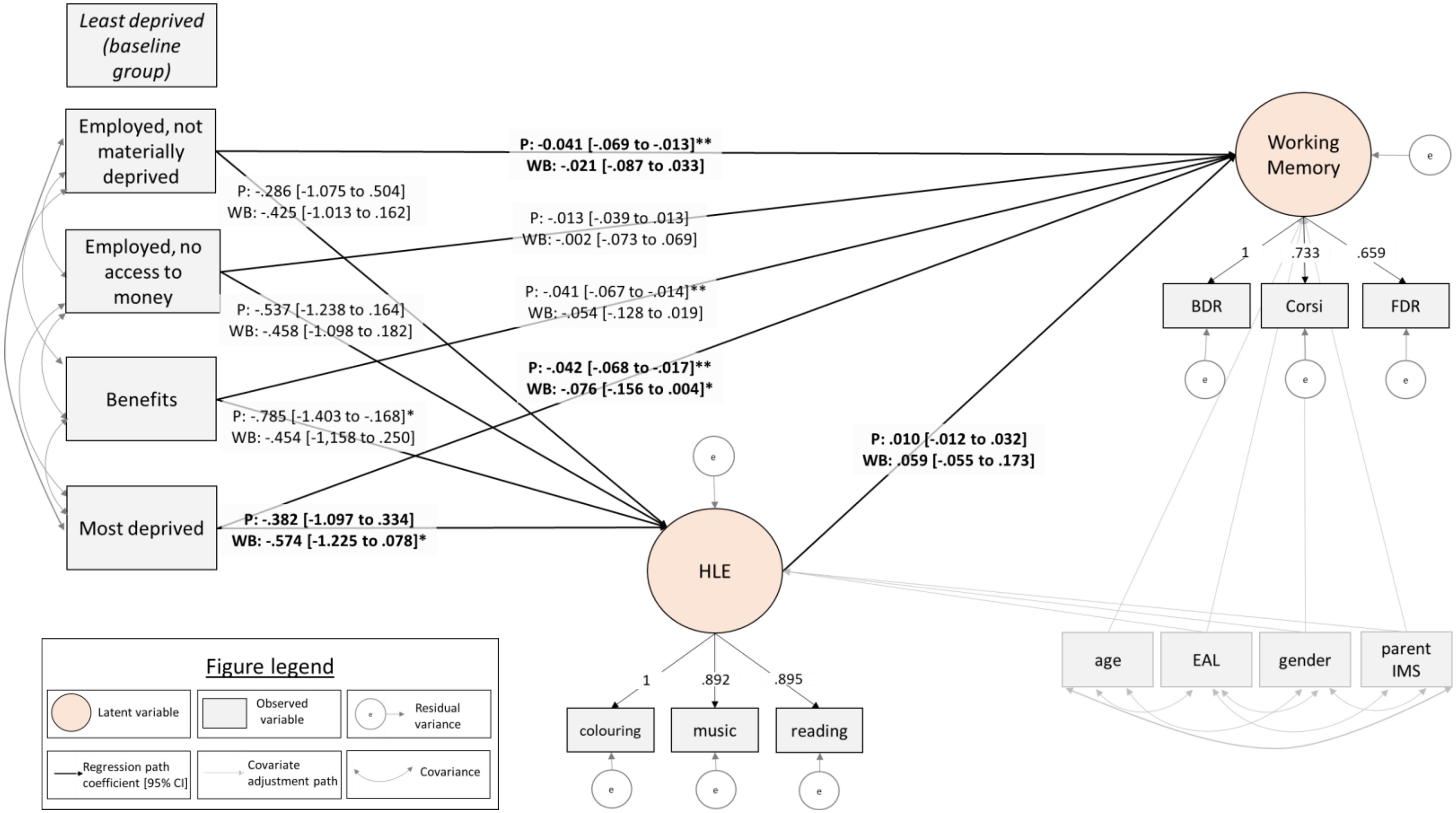


Figure 34. Figure of the associations between socioeconomic position, the home learning environment, and working memory for Pakistani and White British groups.

*[Note: [1]Beta coefficients are indicated on each regression path with 95% confidence interval in square brackets, and statistical significance for a single path is indicated with * = p<.10 and ** = p <.05. Paths that indicated moderation through χ^2 difference testing are bolded (p<.10). [2]Covariance is also modelled between all socioeconomic position variables and all covariates, but it not depicted in the figure to reduce its complexity]*

This multi-group model investigated whether ethnic group moderated the associations between socioeconomic position, the home learning environment, and working memory. Figure 34 summarises the multi-group model findings, which indicates that ethnic group does moderate some of these associations. The difference between the 'least deprived' and the 'employed, not materially deprived' group was significantly larger for Pakistani children. In contrast, the difference between the 'least deprived' and 'most deprived' group was significantly larger in White British children. The association between socioeconomic position and working memory therefore appears to be moderated by ethnic group, however, the direction of this moderation was not consistent.

The association between socioeconomic position and the home learning environment was moderated by ethnic group, where the difference between the least and most deprived socioeconomic group was significantly larger in White British children. The association between the home learning environment and working memory also appeared to be moderated by ethnic group, where White British children had a stronger association.

5.4 Discussion

5.4.1 Key findings

5.4.1.1 Hypotheses 1: increased socioeconomic disadvantage predicts lower working memory scores

This study confirmed a significant association between socioeconomic disadvantage and lower working memory scores, when working memory was modelled as a latent variable and by using a more comprehensive analysis that controlled for potentially confounding variables (parent immigration status and learning English as an Additional Language), and potentially important covariates (gender and age). Again, the largest difference was between the least and most deprived socioeconomic groups, and this was similar to an age difference of approximately 16 months.

5.4.1.2 Hypotheses 2: the home learning environment will partially mediate the association between socioeconomic position and working memory scores

This study tested the prediction that the home learning environment would mediate the relationship between socioeconomic position and working memory, however, the indirect effects between socioeconomic position and working memory via the home learning environment were not statistically significant. A possible explanation for these results is that the home learning environment is not as important for children's working memory as other factors might be. Research should attempt to replicate this null finding of the mediating pathway of the home environment, and compare this pathway to other potential mediators. A more important mediator between socioeconomic position and working memory may be children's experience of stress, which is hypothesised to interfere with working memory (Evans and Schamberg, 2009; Goodman, Freeman and Chalmers, 2018). In an empirical study, Evans and Schamberg (2009) found that a biological marker of chronic stress mediated the association between poverty and adult working memory. In a systematic review, Goodman, Freeman, and Chalmers (2018) found a small association between early life stress and working memory in a meta-analysis of 23 studies.

However, since this finding is contrary both to my expectations, and to previous research which found the home learning environment to be a significant mediator between socioeconomic position and working memory (Hackman et al., 2015; Amso, Salhi and Badre, 2018), I explore other possible explanations for this non-significant finding here.

The contrary findings could be due to differences in the way the home learning environment was measured. A general definition and common operationalisation of the home learning environment does not yet exist (Niklas et al., 2016). I therefore constructed a measure using factor analysis that assessed engagement with the activities found to have the highest factor loadings onto the home learning environment: colouring, music, and reading. However, the previous research with significant mediating results used the Home Observation for Measurement of the Environment (HOME) inventory (Hackman et al., 2015; Amso, Salhi and Badre, 2018), which contains 60 questions and has undergone psychometric validation (Linver, Brooks-Gunn and Cabrera, 2011). It is possible that the measure I constructed of the home environment may not have been as sensitive and valid as the HOME inventory.

Furthermore, there were minor issues with the BiB1000 home environment data which may have reduced its statistical power. First, there was substantial positive skew in the responses to the home environment questions – where the vast majority of participants responded that they engaged with most activities 7 days per week (Figure 33, Chapter 5). The lack of variation in the data may have reduced the size of any effects. Second, the sample sizes were smaller between the linked BiB1000 and Primary School Years data (n=500), which may have reduced the likelihood of detecting a significant effect. Further research is needed into how to measure the home learning environment with a less intense survey than the HOME inventory (Linver, Brooks-Gunn and Cabrera, 2011).

It is important to note that some results indicated that socioeconomic disadvantage was associated with lower frequency of activities in the home environment for both Pakistani and White British children. The multi-group model showed substantial evidence of moderation by ethnic group, where the magnitude of the associations between the variables tended to be larger for White British children than for Pakistani children. However, the groups were unbalanced as there were far fewer White British children in the sample, which may explain why there was no significant mediation effect for this group. It is therefore possible that associations between socioeconomic position, the home learning environment, and working memory do exist – but only for White British children. This moderation by ethnic group is further explored next.

5.4.1.3 Research question 3: does ethnicity moderate the associations between socioeconomic position, the home learning environment, and working memory scores?

I also investigated whether ethnicity moderated the associations but did not have a specific hypothesis about the direction of the moderation. This investigation built on Study 1 by using a more comprehensive analysis that controlled for potentially confounding variables and covariates. The multi-group investigation of the associations over White British and Pakistani ethnic groups revealed that these associations may differ between the two groups. The unconstrained model presented coefficients across the two groups, showing that within the White British group, increasing levels of socioeconomic deprivation resulted in worsened working memory scores. In contrast, within the Pakistani group, increasing levels of socioeconomic deprivation resulted in worse working memory at a similar magnitude. The exception to this was the difference between the 'least deprived' and the 'employed, not materially deprived' group, where the differences in both ethnic groups were very small in magnitude.

The finding of the absence of social gradients in ethnic minority groups may either be due to inaccurate measurement, as indicators of social position may not be valid or reliable for ethnic minorities (Kelaher et al., 2009). Or, it may reflect that social gradients in working memory are truly flatter for ethnic minority groups. I did try to overcome measurement problems by using numerous indicators of social position in Study 1, all of which suggested there was a weaker social gradient for ethnic minority groups. Next, I discuss some reasons why social gradients in working memory may truly be attenuated for ethnic minority groups.

A lack of social gradient in scores may result from working memory scores being better than expected for ethnic minority children with lower socioeconomic position, or conversely, working memory scores being worse than expected for ethnic minority children with *higher* socioeconomic position. The data presented in Study 1 supports the former conclusion; as Pakistani children have better working memory scores than White British children overall, and children from the two ethnic groups with higher socioeconomic position tend to score similarly to one another. Thus, it appears that Pakistani children with low socioeconomic position tend to have better working memory scores than expected.

In relation to previous literature, one previous study has revealed that ethnic minority children with lower socioeconomic position had significantly worse working memory, whilst ethnic majority children at different levels of socioeconomic position had similar working memory ability to one another. This study was based in the USA and compared African American to White children (Rhoades et al., 2011). My study appears to conflict with these findings, since it presented the opposite pattern – where social gradients were stronger for White British children, and not for the Pakistani ethnic minority children. However, my study was generally in line with previous research with the Born in Bradford cohort, where social gradients are stronger for the White British population in health outcomes (Mallicoat, Uphoff and Pickett, 2020; Uphoff, Pickett and Wright, 2016).

These contradicting findings could be explained by the different settings and cultural contexts within the different locations of these studies. The Born in Bradford cohort represents the city of Bradford, which has a very large ethnic minority community that live in particular areas with high own minority ethnic density (Bradford Council, 2017; Small, 2012). These findings may therefore reflect that the Pakistani community in Bradford may be protected or buffered against the negative effects of socioeconomic disadvantage. Social networks within densely populated Pakistani neighbourhoods may make poor families less vulnerable to the negative effects of social disadvantage through providing financial, social, and emotional support (Thapar-Bjorkert and Sanghera, 2010; Din, 2006).

The mechanisms that underpin weak associations between socioeconomic position and outcomes in Pakistani communities remain unclear, and this highlights two key knowledge gaps. First, understanding regarding the existence of social gradients within ethnic minority groups for child working memory remains limited, and future research should address whether my findings are generalisable to Pakistani children living in the UK, but outside of Bradford. It would also be interesting to examine the presence of social gradients for working memory within different ethnic minority and majority groups in other countries, to examine if the associations found here are replicated. Second, these findings also highlighted the need to understand potential positive factors for Pakistani children's working memory, and to address this knowledge gap, I explored two potential positive factors for ethnic minority children's working memory in Study 3.

There were also some differences in the associations between socioeconomic position and the home learning environment, and between the home learning environment and working memory across the two ethnic groups. First, the difference between the 'least deprived' and 'most deprived' socioeconomic groups had larger discrepancies in the home learning environment for White British children than Pakistani children. In other words, White British children with high levels of socioeconomic disadvantage appeared to have lower home learning environment scores. Second, the home learning environment had a larger influence on working memory for White British children than Pakistani children. This pattern of results, again, indicates weaker associations between these variables for Pakistani children. Again, this finding could be due to measurement challenges in the ethnic minority population, in that the typical 'home environment' activities are based on assumptions about White, Educated Industrialised Rich Democratic (WEIRD) populations (Nielsen et al., 2017). It may be that Pakistani children engage in different activities at home, and so the measure I constructed of the home learning environment here is not valid for them. I conducted measurement invariance tests in order to assess this (see Section 5.3.4), and this did indicate that scalar invariance may not be achieved in the home learning environment measurement model across the two ethnic groups.

On the other hand, the findings may truly reflect that the home learning environment is a more important factor for White British children's working memory than it is for Pakistani children's working memory. However, we cannot be as confident in these results as the individual path coefficients were not statistically significant, and the sample sizes were much smaller for home learning environment data. Future research is needed into the home learning environment in ethnic majority and minority children, with the priority of investigating if the measurements we use are valid and reliable in both populations.

5.4.2 Strengths and limitations

A strength of this study is that I was able to explore associations between socioeconomic position, the home learning environment, and working memory within two ethnic groups. This would not be possible with many other cohort study data; however, the sampling of Bradford's very large Pakistani population made this possible. This is a unique contribution to the literature, as these associations had not previously been studied within an ethnic minority group.

Another strength is that the data included follow a longitudinal trajectory between socioeconomic position at birth, the home learning environment in the early years, and working memory ability in middle childhood. The results from this study are less likely to be biased than those of a cross-sectional study, and we can be more confident in the significant associations found here. Related to this, a strength of the analysis is that the structural equation model allowed an understanding of the mediation path via the home learning environment, whilst controlling for variables on each of these paths.

Another strength is the measurement of working memory used a latent variable approach based on three individual tasks of working memory. Latent variables explicitly specify and incorporates errors into measurements, producing more accurate parameter estimates (Seo et al., 2015; Suhr, 2006). This means we can be more confident in the measure of latent working memory than we could be when using any individual task alone.

The main limitation of this study relates to the issues already discussed regarding the home learning environment variable. Due to these limitations, I have been unable to make conclusive inferences about the home learning environment's role in shaping children's working memory in this study.

5.4.3 Summary of suggestions for future research

An outstanding area of knowledge remains regarding the potential positive factors that may buffer the negative effects of socioeconomic disadvantage for ethnic minority children's working memory. In the following study, I address this by looking at two potential positive factors for ethnic minority children's working memory.

There are also several outstanding areas of knowledge that are beyond the scope of my PhD. First, there is a need to investigate how to measure the home learning environment with high validity and low participant burden, particularly with ethnic minority populations. Following this, potential mediating factors between socioeconomic position and working memory should be investigated. For example, future studies should replicate the null finding of the home learning environment, and investigate chronic stress as a mediator.

Finally, it should be explored the whether social gradients in child working memory in different ethnic minority groups discovered here are generalizable across the UK and beyond. This could be done in other cohort studies in the UK, although these studies are unlikely to have a large ethnic minority group that will allow for an adequately powered investigation.

Chapter 6. Study 3: Exploring Potential Positive Factors for Ethnic Minority Children's Working Memory

This chapter outlines the introduction, methods, results, and discussion for a study of two potential positive factors for ethnic minority children's working memory; first, own ethnic density and second, Mosque/Madrassa attendance.

6.1 Is own ethnic density associated with working memory ability?

6.1.1 Introduction

Study 1 showed that particular ethnic minority groups tend to have higher working memory scores than White British children on the simple verbal task of working memory, and Study 2 showed that Pakistani children tended to have weaker associations between socioeconomic position and working memory. This highlighted the need to investigate the reasons behind potential advantages in working memory for specific ethnic groups by the type of task of working memory. In this exploratory study, I therefore investigate what factors may be positively associated with ethnic minority children's working memory.

As outlined in Section 1.2.2, the integrative model for the study of ethnic minority children emphasises potential promoting factors for child development (Coll et al., 1996). There may be a number of 'protective' or 'buffering' factors that mean children are less effected by negative effects of socioeconomic disadvantage. A positive factor that I investigate in this study is own ethnic density – the proportion of one's own ethnic group living within the same area, or attending the same school. As outlined in Section 1.2.2, own ethnic density is hypothesised to have an association with outcomes through the positive effects of social integration, and reduced exposure to the negative effects of stigma and racism (Pickett and Wilkinson, 2008).

As previously described (Section 1.2.2), reviews have generally indicated that higher ethnic minority density is more likely to be protective of physical and mental health than have negative effects (Bécares et al., 2012; Shaw et al., 2012). An empirical study with the Born in Bradford sample found it to be associated with lower odds of only smoking during pregnancy, but not with other health behaviours (Uphoff et al., 2016). There is only one previous study on own ethnic density and children's cognitive development. In England, own ethnic density was associated with reduced expressive vocabulary scores after controlling for area deprivation, but only for Bangladeshi children (Zhang et al., 2017). At present, there are no studies examining the association between own ethnic density and children's working memory. Own ethnic density may explain why Pakistani children of low socioeconomic position have higher working memory scores than expected.

As own ethnic density is thought to have effects through mechanisms of increased social integration and capital, and decreased exposure to racism, this paragraph describes studies that have looked at these variables and children's cognitive development. To the best of my knowledge, there is only one previous study about social capital and children's working memory. In a sample of 428 immigrant children living in the US, results indicated that social capital was not associated with children's working memory (Jeong and You, 2013). With regards to racism, there is some previous research with 2136 mothers in the UK Millennium Cohort Study suggesting that experiences of perceived racism are associated with increased risk of poor child outcomes, including socioemotional difficulties and spatial abilities (Kelly, Becares and Nazroo, 2013). However, there does not yet appear to be any studies of the association between racism and working memory specifically.

In this study, I therefore explore whether own ethnic density resulted in an improvement in ethnic minority children's working memory. In the remainder of this chapter, I describe the methods and provide the results to answer the following research question:

1. Is own ethnic density associated with working memory ability?

6.1.2 Methods

6.1.2.1 Data Source

The Primary School Years sample is used in this Study, including both the BiB and non-BiB children. The Primary School Years sample is much larger than if the sample was restricted to only BiB children, allowing adequate power to explore effects of own ethnic density and Mosque attendance.

6.1.2.2 Multilevel Modelling

Multilevel modelling is used in the analysis of data that have a hierarchical or clustered structure. Multilevel linear regression analysis is a type of multilevel modelling (Hox and Moerbeek, 2017). Multilevel modelling is appropriate when data are clustered, as ignoring hierarchical structure ignores the lack of independence in the data. Ignoring the lack of structure in the data would not use the data to its full potential (Blance, 2012, p.73). Multilevel analysis is appropriate for the research questions here as individual level data on the outcome of working memory ability is clustered by individual children within different schools.

The assumptions of multi-level modelling are the same as a single level linear model. The following assumptions are checked using postestimation plots (Blance, 2012):

- A linear relationship between the predictor and outcome
- Appropriately distributed standardised residuals.
- Homogeneity of variance

6.1.2.3 Analysis Software

All data cleaning, management, and analysis were run in Stata-16.

6.1.2.4 Missing Data

Multiple imputation will be used to impute missing data if necessary. Multiple imputation uses the distribution of the observed data to estimate multiple values that reflect the uncertainty around the true value (Rubin, 1996). If missingness is higher than 5% in the covariates (Jakobsen et al., 2017; Rubin, 1996) (area deprivation and child age) then multiple imputation will be used for missing covariate values. If missingness is lower than 5% then data can be assumed to be Missing Completely at Random (MCAR), and complete case analysis will be used (Jakobsen et al., 2017).

6.1.2.5 Inclusion Criteria

Participants were included if:

- Child took part in the Primary School Years wave and completed all three working memory tasks
- Child's ethnicity is White British or Pakistani
- Child age was non missing

Within Bradford, White British and Pakistani ethnic groups are the two most populous, and there is meaningful variation in own ethnic density within these groups. Other ethnic groups are not included as they do not have the same area level variations in own ethnic density. Although studies of ethnic density do not always include the ethnic majority population because they aim to examine experiences unique to ethnic minority populations (e.g. Zhang et al., 2017), I included White British children in a separate model in order to compare the presence (or absence of) own ethnic density effects between the two groups.

6.1.2.6 Included Variables and Justification

Table 35. Variables included in model(s)

	1. Is own ethnic density associated with working memory ability?
Level	School
Exposure	Own ethnic density within the school
Outcome(s)	Working Memory
Covariates	Child age
	Area deprivation

Table 35 presents the variables included. Child age is obtained from the Primary School Years data. Area deprivation was obtained by matching the school's postcode with publicly available Index of Multiple Deprivation (IMD) 2019 data; the official measure of relative deprivation in England. Each school is located within a Lower Layer Super Output Area (LSOAs), which are boundaries created by the Office for National Statistics to report area based statistics in the UK (Ministries of Housing Communities and Local Government, 2019a; Office for National Statistics, 2016).. School postcodes were used to identify the LSOA with the IMD 2019 to assign the decile of school area deprivation for each child in the analysis.

The exposure in this research question is own ethnic density within school. Own ethnic density was obtained via publicly available data for schools, where proportions of ethnic groups within schools in England are reported (GOV.UK, 2019b). Proportions of own ethnic group within own school were matched to White British and Pakistani children in the Primary School Years data. A strong correlation between own ethnic density and area deprivation exists in the Pakistani mothers in BiB, indicating that ethnic density may also be an indicator of social disadvantage in the BiB cohort (Uphoff et al., 2016). Whilst problems with multicollinearity may affect the reliability of the results, area deprivation was nevertheless included as a covariate. Ethnic density effects may appear to be negative and detrimental, and the direction of the effect in relation to social cohesion has been found to change after adjustment for area deprivation (Bécares et al., 2011). Area deprivation is therefore included in the model as without it, it would be impossible to disentangle the effects of deprivation from ethnic density.

I expected any effect of own ethnic density to be consistent across the three working memory tasks, and therefore created a factor score of working memory from the three tasks for parsimonious estimation. Factor scores are linear combinations of the observed variables which consider both shared variance and what is not measured (the error term variance). I used the regression method to create the factor scores, which produces standardized scores similar to a Z-score metric. Regression factor scores predict the location of each individual on the factor or component, where the computed factor scores are standardized to a mean of zero (Distefano, Zhu and Mîndrilã, 2009).

6.1.2.7 Descriptive Statistics

The mean and standard deviations obtained from the factor scores for working memory are described. The sample characteristics for each covariate (age, index of multiple deprivation, and own ethnic density) are described across White British and Pakistani children. Own ethnic density was presented by categories as the association between ethnic density and outcomes may not be linear, and categories can help us to identify at which levels ethnic density may have protective or adverse effects. Areas were categorised as having 0–4.9, 5–29.9, 30–49.9, and ≥50% own ethnic density. These cut-offs were chosen as they were consistent with previous studies (Pickett et al., 2009; Zhang et al., 2017).

I then described continuous ethnic density distributions across schools, and continuous ethnic density distributions compared to the IMD of the school. I also described working memory scores by own ethnic density using a scatter plot stratified by White British and Pakistani participants.

6.1.2.8 Model Specification

The regression models are (per ethnic group):

10. Working $memory_{ij}$ = β0 + β1*area $deprivation_{ij}$ + β2*ethnic $density_{ij}$ + β3*child age_{ij} + u_j + ε_{ij}

11. Working $memory_{ij}$ = β0 + β1*area $deprivation_{ij}$ + β2*ethnic $density_{ij}$ + β3*child age_{ij} + u_j + ε_{ij}

As any effect of ethnic density on working memory could be nonlinear, I also fitted two multilevel models with a quadratic term included. I compared the model fit between the two types by conducting a likelihood ratio test, and comparing the AIC and BIC values between them. I compared Model's 1 and 2 to these (per ethnic group):

12. Working $memory_{ij}$ = β0 + β1*area $deprivation_{ij}$ + β2*ethnic $density_{ij}$ + β3*ethnic $density_{ij}^2$ + β4*child age_{ij} + u_j + ε_{ij}

13. Working $memory_{ij}$ = β0 + β1*area $deprivation_{ij}$ + β2*ethnic $density_{ij}$ + β3*ethnic $density_{ij}^2$ + β4*child age_{ij} + u_j + ε_{ij}

where β_0 is the intercept, each β is a coefficient, u_j is the random intercept for school *j,* and ε_{ij} is the residual error for individual *i* within school *j*. The letters identify the levels within the model, where *i* is the individual and *j* is the school. Without the random intercepts, this would be a normal regression model without multilevel variation. The random intercepts allow for responses within the same school to be correlated with one another.

6.1.3 Results

6.1.3.1 Working Memory outcome

The working memory factor score had a mean of 0.00 and a standard deviation of 0.81. The minimum value was -2.785 and maximum value was 2.211.

6.1.3.2 Sample Characteristics

The sample was restricted to only include children who had completed all three working memory tasks, and only Pakistani and White British children (n = 10,823). There were a total of 78 schools included, with between 1 and 276 observations in each school.

Table 36. Sample characteristics across Pakistani and White British children

	Pakistani (n = 6,859)	**White British (n = 3,964)**
Mean age in months (SD)	99.24 (7.88)	101.40 (8.86)
IMD decile of school (%)		
1	4,529 (69%)	1,187 (30%)
2	1,354 (21%)	349 (9%)
3	549 (8%)	954 (34%)
4	27 (0.4%)	321 8%)
5	35 (0.5%)	261 7%)
6	1 (0.02%)	155 (4%)
7	82 (1.24%)	328 (8%)
8	0 (0%)	229 (6%)
9	0 (0%)	0 (0%)
10	12 (0.18%)	180 (5%)
Missing	90 (1.35%)	113 (2.78%)
Own ethnic density within school (%)		
0-4.9%	98 (1%)	82 (2%)
5-29.9%	252 (4%)	302 (8%)
30-49.9%	487 (7%)	437 11%)
≥50%	5752 (87.30%)	3,143 (80%)
Missing	90 (1.35%)	113 (2.78%)

Table 36 describes the sample characteristics for the covariates included in the models across Pakistani and White British children. The majority of Pakistani children attend schools located in the most deprived decile (69%), whereas the majority of White British children attend schools located in deciles 1-3 (73%). The majority of children in both ethnic groups attend schools with high levels of own ethnic density, with 87% of

Pakistani children and 80% of White British children attending schools with ≥50% of own ethnic density.

As two schools were missing from the local authority database (one of which was a new school, and one of which was a grammar school), there were some missing data in the IMD and ethnic density columns. However, the missingness in data was less than 5%, so this was assumed to be missing at random and multiple imputation was not necessary.

6.1.3.3 Descriptive Statistics: School level

This section provides descriptive statistics at the school level for all schools included in the Primary School Years wave.

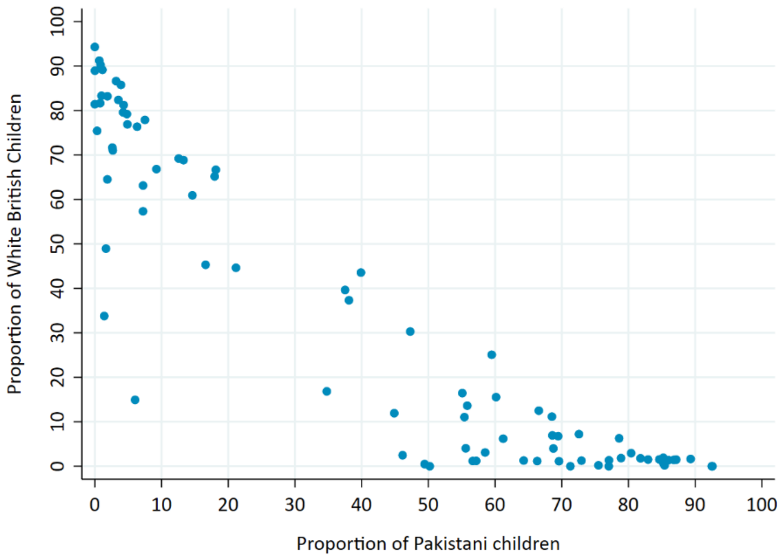


Figure 35. Proportion of White British children versus proportion of Pakistani children in schools included in Primary School Years sample

Figure 35 shows the proportion of children of Pakistani or White British ethnic origin within each school. It reveals that many schools either have high proportions of Pakistani children or high proportions of White British children, with very few schools having equal proportions from each ethnic group.

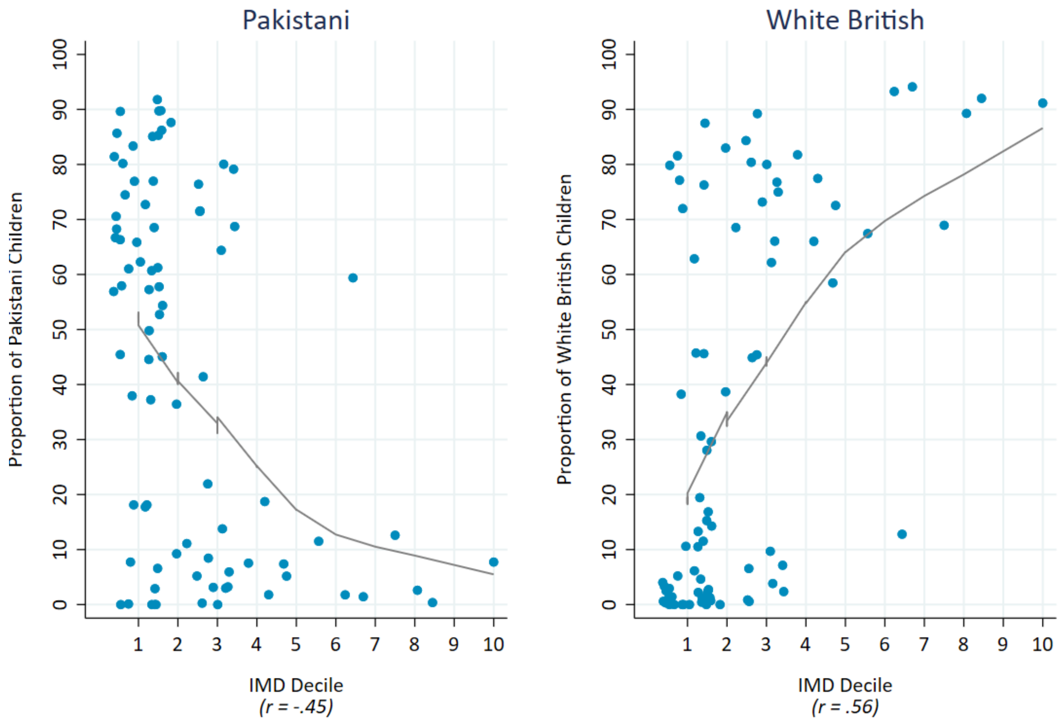


Figure 36. Proportion of Pakistani and White British ethnic density versus IMD decile per school

Figure 36 shows the proportion of each ethnic group versus the IMD decile of the school, with a locally weighted scatterplot smoothing line overlaid. Overall, schools in this sample are concentrated in the more deprived deciles (1-3). The locally weighted scatterplot smoothing line reveals that schools with higher proportions of Pakistani children are more likely to be in more deprived areas, whereas schools with higher proportions of White British children are more evenly spread throughout the deprivation deciles. Further, it shows a positive association between White British ethnic density and IMD decile, in contrast to a negative association between Pakistani ethnic density and IMD decile.

6.1.3.4 Descriptive Statistics: Individual level

Figure 37. Scatterplot of the association between own ethnic density and working memory scores with quadratic fit line & 95% confidence interval in grey

[Note: the quadratic fit line calculates the prediction of working memory from a linear regression of working memory on ethnic density & ethnic density^2 and plots the resulting curve]

Figure 37 shows scatterplots between own ethnic density and working memory scores for Pakistani and White British participants. The scatterplots show a large amount of 'noise' in the data, as there does not appear to be a clear association between own ethnic density and working memory scores for either ethnic group. A quadratic fit line has been overlaid to show there is not strong evidence of nonlinearity, as the line does not appear to have a strong curve.

6.1.3.5 Multilevel Model Results

I first compared the models with and without a quadratic term for ethnic density, to examine whether including a quadratic term would improve the fit of the model.

Table 37. Comparison of model fit for models with and without quadratic term

	AIC	BIC	Likelihood ratio tests
White British			
Ethnic density	8758.353	8796.063	LR chi2(1) = 3.72
Ethnic density^2	8756.63	8800.625	p = 0.054
Pakistani			
Ethnic density	15551.65	15592.41	LR chi2(1) = 0.96
Ethnic density^2	15552.69	15600.24	p = 0.326

As seen in Table 37, the likelihood ratio tests indicated non-significance, and the AIC and BIC scores were very similar in both models. Although the likelihood ratio test for White British children is borderline statistically significant, the previously presented scatterplot (Figure 36) does not show evidence of nonlinearity. I therefore did not include a quadratic term in the model, as these tests do not indicate strong evidence of nonlinearity and the linear model is easier to interpret. In the following section I describe the results for the linear multilevel model for own ethnic density on working memory scores.

Table 38. Multilevel model results for Pakistani participants (*n* = 6589)

	B (95% CI)	*p*
Constant	-3.010 (-3.302 to -2.717)	<.001
Age in months	.031 (.028 to .033)	<.001
IMD Decile	.017 (-.013 to .046)	0.271
Ethnic density	-.001 (-.002 to .001)	0.413
Variance at school level (SE)	***.014 (.004)***	
ICC (95% CI)	***.022 (.013 to .039)***	

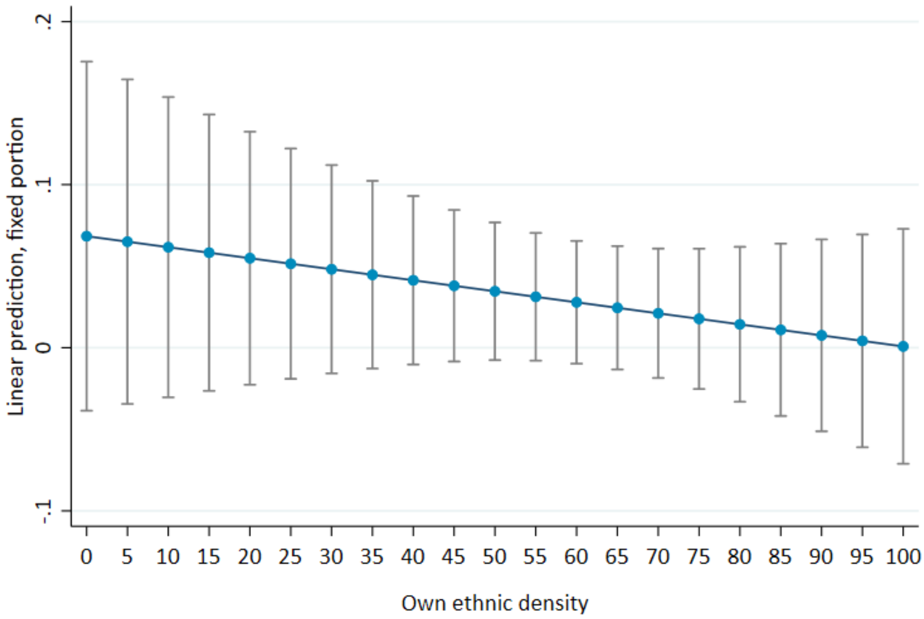


Figure 38. Margins plot to show estimated marginal mean for working memory for levels of own ethnic density (Pakistani participants)

[Note: Margins are statistics calculated from predictions of a fit model at fixed values of some covariates and averaging or otherwise integrating over the remaining covariates]

Table 39. Multilevel model results for White British participants (*n* = 3964)

	B (95% CI)	*p*
Constant	-2.678 (-2.972 to -2.384)	<.001
Age in months	0.024 (.021 to .026)	<.001
IMD Decile	0.051 (.029 to .072)	<.001
Ethnic density	0.001 (-.001 to .003)	0.199
Variance at school level (se)	***.018 (.005)***	
ICC (95% CI)	***.032 (.018 to .057)***	

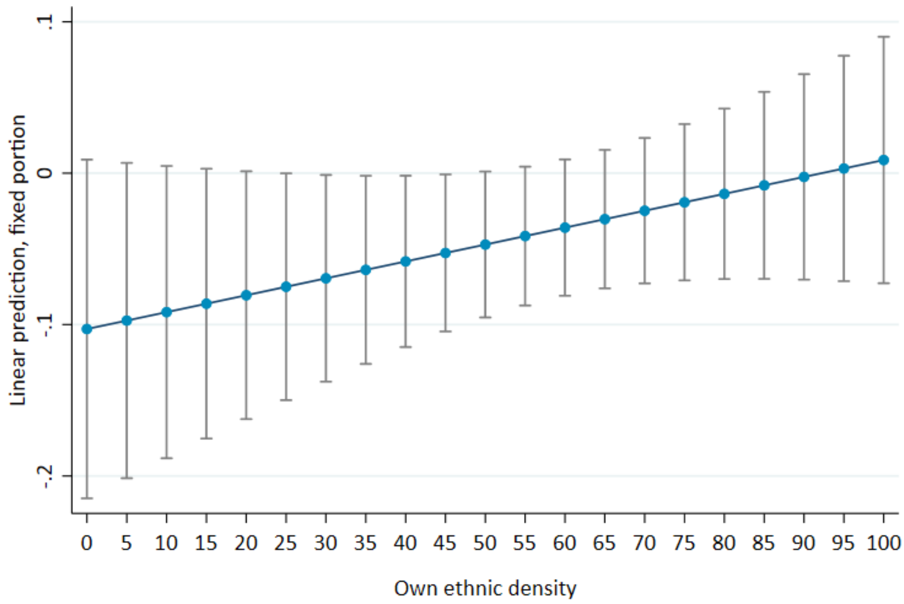


Figure 39. Margins plot to show estimated marginal mean for working memory for levels of own ethnic density (White British participants)

Tables 38 and 39 present the model results for each ethnic group. The tables show that for both Pakistani and White British children, own ethnic density does not have a statistically significant association with working memory. Figures 38 and 39 show the margins plots to show the estimated marginal means for the effect of ethnic density on working memory. The margins plots suggest although non-significant, the association between own ethnic density and working memory is negative for Pakistani children, and positive for Pakistani children.

6.1.4 Discussion

6.1.4.1 Key findings

Own ethnic density was not significantly associated with working memory in either ethnic group, suggesting this is unlikely to be an influential factor in ethnic minority children's working memory. I hypothesised that children from Pakistani families of low socioeconomic position may be 'buffered' from any detrimental effects of social disadvantage on their working memory through increased access to social networks, and reduced exposure to stigma and racism (Thapar-Bjorkert and Sanghera, 2010; Din, 2006). However, this hypothesis was not confirmed in this study through investigating own ethnic density and working memory.

Previous research has generally indicated that higher ethnic minority density is more likely to be protective of physical and mental health than have any negative effects (Bécares et al., 2012; Shaw et al., 2012; Uphoff et al., 2016). In contrast, the only other study to investigate own ethnic density and children's cognitive development found that own ethnic density had some negative associations with expressive vocabulary for Bangladeshi children in England (Zhang et al., 2017). Comparison of my findings with those of other studies indicates that whilst own ethnic density *may* have specific positive associations with physical and mental health characteristics for minority groups, it does not appear to have a positive association with children's cognitive development (including working memory). The null finding in my study may either be because children's cognitive development is not shaped by families having access to increased social networks and reduced exposure to racism, or because the measure of own ethnic density in my study was not sensitive to detecting change in these factors.

It is possible that the null finding in my study indicates that children's working memory was not influenced by the mechanisms which own ethnic density is thought to work through - families having access to increased social networks and reduced exposure to racism. To the best of my knowledge there is only one previous study related to social integration and working memory, though it looked at social capital and children's working memory (ie. not social integration). In a sample of 428 immigrant children living in the US, results indicated that parental social capital was not associated with children's working memory (Jeong and You, 2013). My study adds to this emerging literature, and suggests that in addition to social capital, social integration is unlikely to have positive associations with children's working memory. With regards to racism, there is some previous research suggesting that mothers' experiences of perceived racism are associated with worse outcomes for children, including socioemotional difficulties and spatial abilities (Kelly, Becares and Nazroo, 2013). However, this study did not look at working memory. This may suggest that children's experiences of racism may have specific associations with children's outcomes. Future research could specifically examine associations between different types of social capital and working memory, social integration and working memory, and experiences of racism and working memory.

However, it is also possible that the measure of own ethnic density in my study was not sensitive to detecting change in social integration and/or racism. I constructed a measure of own ethnic density through accessing local authority records regarding the number of children from different ethnic groups attending a school. I therefore measured own ethnic density within a school, rather than within the neighbourhood that the child lives in. It may be that measuring own ethnic density at the school level is not sensitive enough to detecting differences in social integration for ethnic minority families, since social integration may be more likely to operate within a neighbourhood that a family lives in. This difference in the measure might explain why a previous BiB study using a measure of neighbourhood ethnic density found it to have some positive associations with health (Uphoff et al., 2016), whilst I did not find any positive associations in my study. To develop a full understanding of the effects of ethnic minority density, an area of interest for future studies is to test whether neighbourhood ethnic density and school ethnic density have different associations with children's outcomes (including both health and cognitive development). Then, hypotheses may be made about the mechanisms by which own ethnic density either does or does not have an influence on children's outcomes. In addition, it would be interesting to investigate these associations beyond Bradford – since the city of Bradford has a unique demography in the UK in that it has very high numbers of Pakistani people living there.

Finally, it is important to note that the trend in the figures showed a negative association with working memory for Pakistani children and a positive association with working memory for White British children. As there was more area deprivation in areas with more Pakistani children, and less deprivation in areas with more White British children (Figure 35), the trend in the figures may indicate that despite including school area deprivation as a covariate, area deprivation was not adequately accounted for in these models. Area deprivation may therefore be negatively biasing any association between ethnic minority density and working memory, meaning it has not been fully revealed in my study. Future research is required in how to adequately control for area deprivation in studies of own ethnic density, since the two variables are highly correlated.

6.1.4.2 Strengths and limitations

A strength of this study is that the Born in Bradford data could be linked to school data obtained from local authority databases, allowing own ethnic density for each child within their school to be linked at an individual level for all children who had completed working memory tasks. This allowed for a very large sample to explore ethnic density in White British and Pakistani children.

A limitation is that the majority of White British (80%) and Pakistani (87%) children attended schools with higher than 50% of their own ethnic density. This may mean there was reduced power to detect differences between those who had very low levels of own ethnic density and those who had higher levels of own ethnic density. However, this simply reflects the clustering of the two ethnic groups residing in different areas within Bradford (Small, 2012). To overcome this, data would be required across the UK including multiple areas with varying levels of ethnic minority density.

A limitation is that I did not explore own ethnic density at the neighbourhood level, so the effects of this on working memory remain unknown. However, it would not have been possible to link own ethnic density at the neighbourhood level for the children were not included in the Born in Bradford study – which would have resulted in a smaller sample size and reduced power.

6.1.4.3 Summary of future research suggestions

This study did not reveal own ethnic density to be a positive factor for children's working memory. However, future research should still investigate the associations between the mechanisms underlying own ethnic density; social integration, and exposure to racism. Future studies should also investigate other potential positive factors for ethnic minority children's working memory – one of which I address in the following study.

The limitations of this study have highlighted some areas for future research. It should be investigated how to adequately control for area deprivation in studies of own ethnic density, in order to fully be able to disentangle the effects of ethnic density from area deprivation. My use of school ethnic density as an exposure variable was novel, but also reveals that it remains to be understood whether neighbourhood ethnic density and school ethnic density have different associations with children's working memory, and other outcomes more broadly. Finally, it should be investigated if these associations generalise for minority groups outside of Bradford.

6.2 Mosque and Madrassa attendance

6.2.1 Introduction

Memorisation techniques based on repetition are thought to be associated with the ability to store and repeat verbal information, and these techniques have previously been suggested as an explanation for higher scores on FDR across cultures (Mattys et al., 2018). When South Asian children attend Mosque, it is common practice to learn the Quran off by heart (Dogra, Barber and Sheard, 2020). It is therefore possible that learning the Quran may improve FDR scores, through only one previous study has investigated the association between learning the Quran and memory, where no differences were found in measures of long term memory capacity (Black et al., 2020). However, the study sample sizes were relatively small, and they did not address working memory ability. I therefore investigated whether Mosque attendance was associated with specifically the FDR task (as this reflects the ability to store and repeat verbal information), by comparing the strength of the association between Mosque and attendance and FDR to the association with Corsi and BDR.

In the remainder of this chapter, I describe the methods and provide the results to answer the following research questions:

2. Is Mosque and/or Madrassah attendance associated with FDR, Corsi, and BDR scores?

6.2.2 Methods

As the methods for this research question were similar to the previous one, see section 6.2.1 to 6.2.4 for information on data source, multilevel modelling, analysis software, and missing data.

6.2.2.1 Inclusion and Exclusion Criteria

Participants were included if:

- Child took part in the Primary School Years wave and completed all three working memory tasks
- Child's ethnicity is Pakistani, Bangladeshi, or Indian
- Child responded to question about whether they attended Mosque (response is nonmissing)
- Child age was nonmissing

Previous research shows that the majority of the South Asian childhood population in the UK attend Islamic Religious settings (including Mosque) after school (Dogra, Barber and Sheard, 2020; Din, 2006), and the data reported here supports this (see Section 1.2.2). Whilst I did not want to homogenise people from different ethnic backgrounds as this may mask experiences by particular ethnic groups, I did want to utilise all the data available and maximise the power of the analysis for detecting an effect of Mosque attendance. I therefore included children of any South Asian ethnicity for this research question (Pakistani, Bangladeshi, and Indian), but also presented an analysis for Pakistani participants only. In the multilevel model, I restricted the sample to include firstly only Pakistani participants (as this is the largest ethnic minority group in the cohort), and then included all South Asian ethnicities (Pakistani, Bangladeshi, and Indian) in a second analysis.

6.2.2.2 Included Variables and Justification

Table 40. Variables included in model(s) for Research Question 2

Variable type	2. Is Mosque and/or Madrassah attendance associated with FDR, Corsi, and BDR scores?
Level	School
Exposure	Mosque and/or Madrassah attendance
Outcome(s)	(1) FDR, (2) Corsi, (3) BDR
Covariates	Child age
	Area deprivation

Table 40 presents the included variables in the model. In contrast to Research Question 1, I expected any effect of Mosque and/or Madrassah attendance to be most strongly associated with the FDR task, and to either have very weak or no association with the other tasks. This is because memorisation techniques based on repetition would be most strongly associated with the ability to store and repeat verbal information, and these techniques have previously been suggested as an explanation for higher scores on FDR (Mattys et al., 2018). I therefore conducted three separate regression models to analyse the association between Mosque attendance on FDR, Corsi, and BDR.

Mosque and/or Madrassah attendance is the exposure variable in this analysis. I report descriptive statistics in response to both Mosque attendance and frequency of Mosque attendance, but only included the Mosque attendance question (where the response is yes or no) in the regression model.

6.2.2.3 Descriptive Statistics

I present Mosque and/or Madrassah attendance by all ethnic groups in the Primary School Years wave. Although the data were not available to explore Mosque attendance in a multilevel model across all ethnic groups, it was useful to understand patterns of Mosque attendance across all of the ethnic groups in the Primary School Years wave. I described mean scores and 95% confidence intervals for all three working memory tasks by Mosque attendance, and frequency of Mosque attendance for the South Asian children.

6.2.2.4 Model Specification

The regression models for Pakistani participants are[1]:

14. $FDR_{ij} = β0 + β1$*area deprivation$_{ij}$ + β2*Mosque and/or Madrassah attendance$_{ij}$ + β3*child age$_{ij}$ + $u_j + ε_{ij}$
15. $Corsi_{ij} = β0 + β1$*area deprivation$_{ij}$ + β2*Mosque and/or Madrassah attendance$_{ij}$ + β3*child age$_{ij}$ + $u_j + ε_{ij}$
16. $BDR_{ij} = β0 + β1$*area deprivation$_{ij}$ + β2*Mosque and/or Madrassah attendance$_{ij}$ + β3*child age$_{ij}$ + $u_j + ε_{ij}$

I then estimated the models including the Pakistani, Bangladeshi, and Indian ethnicities. The regression models for all ethnicities are[1]:

17. $FDR_{ij} = β0 + β1$*area deprivation$_{ij}$ + β2*Mosque and/or Madrassah attendance$_{ij}$ + β3*child age$_{ij}$ + $u_j + ε_{ij}$
18. $Corsi_{ij} = β0 + β1$*area deprivation$_{ij}$ + β2*Mosque and/or Madrassah attendance$_{ij}$ + β3*child age$_{ij}$ + $u_j + ε_{ij}$
19. $BDR_{ij} = β0 + β1$*area deprivation$_{ij}$ + β2*Mosque and/or Madrassah attendance$_{ij}$ + β3*child age$_{ij}$ + $u_j + ε_{ij}$

[1] where $β_0$ is the intercept, each β is a coefficient, u_j is the random intercept for school *j,* and $ε_{ij}$ is the residual error for individual *i* within school *j*. The letters identify the levels within the model, where *i* is the individual and *j* is the school.

6.2.3 Results

6.2.3.1 Descriptive Statistics

This section describes working memory scores at the child level. First, I describe working memory scores by all of the extracurricular activities asked about in the Primary School Years survey, including attendance to Mosque or Madrassa.

Table 41. Mosque attendance by ethnic group for all available ethnic groups (n = 14,928)

Ethnicity of child	No (%)	Yes (%)	Missing (%)
Pakistani (n = 6679)	302 (5)	5,797 (87)	580 (9)
Bangladeshi (n = 439)	16 (4)	379 (86)	44 (10)
Indian (n = 322)	7 (2)	154 (48)	161 (50)
Black or Black British (n = 259)	7 (3)	50 (19)	202 (78)
White British (n = 4077)	25 (1)	17 (1)	4,035 (98)
Mixed (n = 854)	69 (8)	293 (34)	492 (58)
White Other (n = 667)	6 (1)	12 (2)	649 (97)
Other (n = 405)	38 (9)	234 (58)	133 (33)
Unknown (n = 1059)	202 (19)	567 (54)	290 (27)
Total (n = 14,928)	675 (5)	7,509 (50)	6,744 (45)

[Note: Gypsy or Irish Traveller children are not presented in this table due to risk of identification]

Table 41 presents Mosque attendance by ethnic group for all available ethnic groups in the Primary School Years wave. The majority of Pakistani children (87%) report attending Mosque. Very high proportions of other ethnic groups also attend Mosque, including Bangladeshi (86%), Indian (48%), Mixed (34%), Other (58%), and Unknown (54%). There are also very high levels of missingness, as nearly half (45%) of all children did not respond to this question.

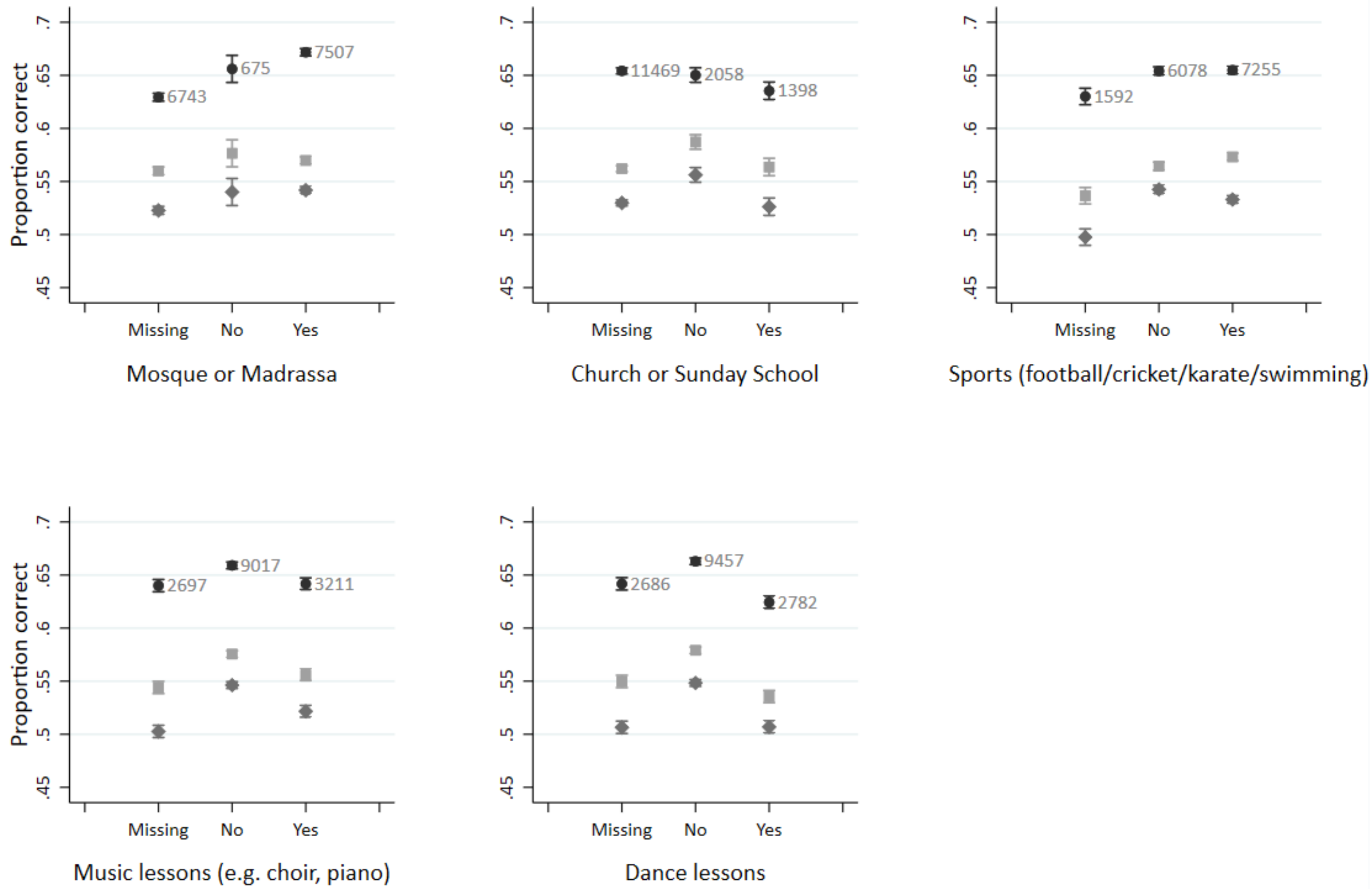


Figure 40a-40d. Mean working memory scores across extracurricular activities for all children in Primary School Years (n = 15,176)

Figures 40a-40d shows mean working memory scores across all extracurricular activities asked in the Primary School Years questionnaire. I included missing responses in this questionnaire mainly due to the high missingness in the question of interest – Mosque or Madrassa attendance. The response to this question for White British children had very high missingness (98%), where it is extremely likely that the correct response would usually be 'no' (see Table 41).

The pattern of results indicate that Mosque or Madrassa attendance is the only activity out of all five that is associated with higher FDR scores. All other activities are either associated with lower FDR scores, or very similar FDR scores.

Next, I restricted the sample to South Asian children only, since these are the children included in the multilevel model. The following section provides descriptive statistics for all three working memory tasks by Mosque attendance for South Asian children.

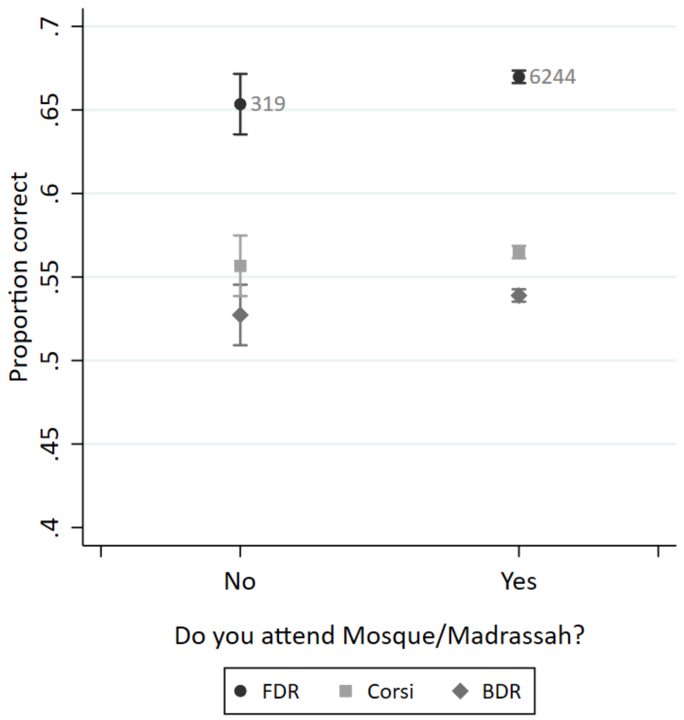
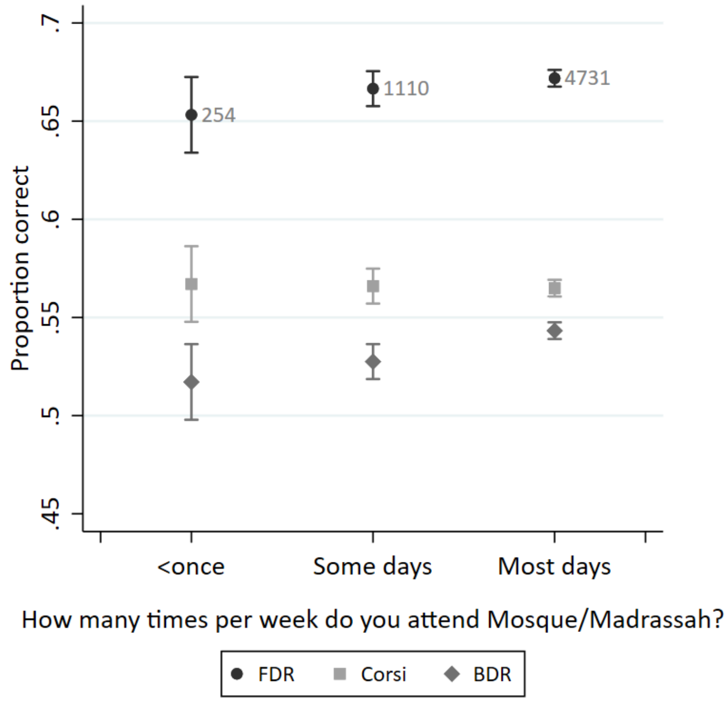


Figure 41. Working memory scores by Mosque attendance for South Asian children (n = 6563)



<u>Figure 42. Working memory scores by how many times per week children attend Mosque (n = 6095)</u>

Figure 41 shows that South Asian children who report attending Mosque/Madrassah have slightly higher working memory scores than those who report not attending it, however, the 95% confidence intervals clearly overlap. Figure 42 shows that children who report attending Mosque 'some' or 'most' days have higher FDR and BDR scores than children who report attending Mosque less than once per week, but not higher Corsi scores. Again, the 95% confidence intervals overlap.

6.2.3.2 Multilevel model results

Table 42. Characteristics for South Asian children included in multilevel model (n = 6563)

	Pakistani (n = 6012)	Bangladeshi (n = 393)	Indian (n = 158)
Mean age in months (SD)	99.21 (7.92)	98.77 (7.12)	99.25 (7.40)
Mean IMD decile of school (SD)	1.50 (1.01)	1.32 (.99)	1.47 (.90)

Table 42 shows the characteristics for all of the children included in the multilevel models, separated by ethnic group.

Table 43. Regression analyses for mean scores in FDR, BDR, and Corsi from whether child reports Mosque attendance for Pakistani ethnic group (n = 6012)

	FDR (n = 6012)				Corsi (n = 6012)				BDR (n = 6012)			
	B	Lower 95%	Upper 95%	*p*	*B*	Lower 95%	Upper 95%	*p*	*B*	Lower 95%	Upper 95%	p
Constant	0.254	0.193	0.314	.001	-0.006	-0.075	0.064	0.866	-0.109	-0.187	-0.030	<.001
Age in months	0.004	0.003	0.004	<.001	0.005	0.005	0.006	<.001	0.006	0.006	0.007	<.001
IMD Decile	0.003	-0.002	0.008	0.276	0.002	-0.004	0.007	0.545	0.004	-0.003	0.010	0.257
Mosque Attendance	0.013	-0.004	0.030	0.130	0.011	-0.009	0.031	0.292	0.006	-0.016	0.028	0.598
Variance at school level (se)	*.000 (.000)*				*.000 (.000)*				*.000 (.000)*			
ICC (95% CI)	*.017*				*.010*				*.017*			

$FDR_{ij} = \beta0 + \beta1*\text{area deprivation}_{ij} + \beta2*\text{Mosque and/or Madrassah attendance}_{ij} + \beta3*\text{child age}_{ij} + u_j + \varepsilon_{ij}$

$Corsi_{ij} = \beta0 + \beta1*\text{area deprivation}_{ij} + \beta2*\text{Mosque and/or Madrassah attendance}_{ij} + \beta3*\text{child age}_{ij} + u_j + \varepsilon_{ij}$

$BDR_{ij} = \beta0 + \beta1*\text{area deprivation}_{ij} + \beta2*\text{Mosque and/or Madrassah attendance}_{ij} + \beta3*\text{child age}_{ij} + u_j + \varepsilon_{ij}$

Table 44. Regression analyses for mean scores in FDR, BDR, and Corsi from whether child reports Mosque attendance for South Asian ethnic groups (n = 6563)

	FDR (n = 6563)				Corsi (n = 6563)				BDR (n = 6563)			
	B	Lower 95%	Upper 95%	*p*	*B*	Lower 95%	Upper 95%	*p*	*B*	Lower 95%	Upper 95%	*p*
Constant	0.247	0.189	0.306	<.001	-0.003	-0.070	0.065	0.941	-0.122	-0.198	-0.047	0.002
Age in months	0.004	0.003	0.004	<.001	0.006	0.005	0.006	<.001	0.000	0.007	0.006	0.006
IMD Decile	0.003	-0.002	0.008	0.220	0.001	-0.004	0.007	0.623	0.003	-0.003	0.010	0.336
Mosque Attendance	0.015	-0.001	0.032	0.068	0.006	-0.014	0.025	0.568	0.009	-0.012	0.031	0.403
Variance at school level (se)	.000 (.000)				.000 (.000)				.000 (.000)			
ICC (95% CI)	.014				.012				.017			

$FDR_{ij} = \beta 0 + \beta 1$*area deprivation$_{ij}$ + $\beta 2$*Mosque and/or Madrassah attendance$_{ij}$ + $\beta 3$*child age$_{ij}$ + $u_j + \varepsilon_{ij}$

$Corsi_{ij} = \beta 0 + \beta 1$*area deprivation$_{ij}$ + $\beta 2$*Mosque and/or Madrassah attendance$_{ij}$ + $\beta 3$*child age$_{ij}$ + $u_j + \varepsilon_{ij}$

$BDR_{ij} = \beta 0 + \beta 1$*area deprivation$_{ij}$ + $\beta 2$*Mosque and/or Madrassah attendance$_{ij}$ + $\beta 3$*child age$_{ij}$ + $u_j + \varepsilon_{ij}$

Table 43 shows the multilevel regression results for the association between Mosque attendance and FDR, Corsi, and BDR for Pakistani children (n = 6012), and Table 44 shows the same results when the South Asian groups are included (n = 6563). In the Pakistani only analyses, Mosque attendance was not significantly associated with any of the three working memory tasks. However, the strength of the association between Mosque attendance and FDR (.013) was stronger than for Corsi (.011) or BDR (.006). This pattern was consistent in the analyses including the other ethnic groups, where Mosque attendance was more strongly associated with FDR (.015) than Corsi (.006) or BDR (.009). Additionally, the association between Mosque attendance and FDR was borderline statistically significant (*B* = .015 [-0.001 to 0.032] *p* = .068).

Postestimation plots for the multilevel models including only Pakistani participants are provided in the Appendices (D2). These showed some evidence of skew, although not serious concerns. Postestimation plots are not provided for the second set of models, as they showed very similar patterns.

6.2.4 Discussion

6.2.4.1 Key findings

This study found that Mosque and/or Madrassah attendance was not significantly associated with working memory in any of the models. The direction and the pattern of the strength of the associations between Mosque attendance and the three tasks did fit with the hypothesis that rote learning the Qu'ran would influence FDR task performance, but it was not strong enough to be statistically significant. The strength of association between Mosque attendance and working memory was stronger for FDR, than Corsi or BDR. This hypothesis was also supported by descriptive statistics, where children who reported a higher frequency of Mosque attendance had higher FDR scores. Additionally, descriptive statistics showed that none of the other activities (e.g. Church, Sport, Music, or Dance) were associated with positive increases in children's working memory. To summarise, it is possible that Mosque attendance may indeed be a positive factor for children's working memory, however, its effects are very small (if any), and specific to the FDR task.

In the only other previous study to examine the association between learning the Quran and memory, there were no differences found in measures of long term memory (Black et al., 2020). It is important to note that Black et al. (2020) only looked at long term memory capacity (ie. not working memory), where the task required learning a list of words with delays of thirty minutes. Since I found some evidence to suggest positive associations with working memory, it is possible that learning the Quran may have specific impacts on working memory, and not on long term memory. However, it is also possible that the previous study (Black et al., 2020) did not have a large enough sample to detect small differences in long term memory, since they only had 32 participants.

In this study, I used an indicator of Mosque attendance as a proxy for measuring whether children learn the Quran. Whilst previous authors of relevant studies have said that many children learn the Quran at the same time as attending Mosque (Dogra, Barber and Sheard, 2020; Din, 2006), we do not have the actual figures to describe how many children do and do not do this in Bradford. It is therefore possible that within the children who indicate that they attend Mosque, there are children who are not learning the Quran – and this would reduce any effect on FDR scores. Future research should aim to ask children about whether they are learning the Quran and see if this has stronger associations with their simple verbal working memory scores.

I highlighted in Chapter 1 that Mosque attendance creates a sense of community and is generally a positive aspect of Pakistani children's identities in Bradford (Din, 2006; Thapar-Bjorkert and Sanghera, 2010). Indeed, other work in Bradford has found Islamic religious settings have the potential for having positive influences on children's health (Dogra, Barber and Sheard, 2020). As I tentatively suggest that Mosque attendance *may* be associated with slightly better scores on one task of working memory, Islamic religious settings can and should be viewed as potentially constructive and beneficial environments to enhance ethnic minority children's development. Perhaps these settings could be investigated as sites that might support research and interventions to support ethnic minority children's development.

To summarise, this study has not explained why South Asian children have better scores on the simple verbal task of working memory. Even if Mosque attendance does have an association with working memory, it is very small in magnitude. This is still therefore an important issue for future research, as understanding this advantage in working memory may reveal important mechanisms about how children's working memory develops.

6.2.4.2 Strengths and limitations

This is the first study to investigate the association between Mosque attendance and children's working memory, and I was able to do this using a very large sample of ethnic minority children. Again, this is the advantage of the Born in Bradford study having recruited a large number of participants belonging to the Pakistani and broader ethnic minority community.

Another strength of this study is that the investigated hypotheses here could be supported by the various questions asked in the Primary School Years study. The Primary School Years study included questions about the frequency of Mosque attendance, and about involvement with other extracurricular activities outside of school. The descriptive statistics reported on this able to support the interpretation of the results.

Similar to the previous study, a limitation is that the group sizes were unbalanced, as many more children responded yes to Mosque attendance (n = 6244), than no (n = 319). This reflects that the vast majority of South Asian children in Bradford attend Mosque. However, since the number of children not attending Mosque is much smaller, this may have reduced the power of this study for detecting a significant effect.

6.2.4.3 Summary of future research suggestions

This study has not ruled out that Mosque attendance may be associated with improved simple verbal working memory through children learning the Quran. Future research should therefore investigate the direct association between learning the Quran and simple verbal working memory scores, instead of using Mosque attendance as a proxy. However, this may be unlikely to fully explain the advantage that many ethnic minority groups had for working memory scores. An outstanding area of knowledge therefore still remains regarding why we see such variation in ethnic groups across working memory. Future studies should examine other potential positive factors for South Asian children's simple verbal working memory – this is expanded upon in the general discussion (Section 7.3).

Section C: Discussion

This section contains the discussion of all results.

- Section 7.1 summarises the key findings and implications
- Section 7.2 describes the strengths and limitations of the cohort study data
- Section 7.3 makes recommendations for future research, and Section 7.4 makes recommendations for policy and practice
- Section 7.5 provides the chapter summary

Chapter 7. Discussion

7.1 Summary of findings

The key objective of this thesis was to investigate the associations between socioeconomic position and children's working memory, and between ethnicity and children's working memory. The secondary objective was to investigate potential causal factors in associations between socioeconomic position, ethnicity, and working memory. This discussion revisits these objectives, by summarising the findings of the studies within my thesis.

7.1.1 Associations between socioeconomic position and children's working memory.

My thesis has consistently showed that higher socioeconomic position is associated with better working memory, through a systematic review and meta-analyses (Chapter 2), and analyses of cohort study data (Chapters 4-5). A key finding is that the difference between the least and most deprived socioeconomic groups was equivalent to a 12 to 18-month age gap, revealing the magnitude of the socioeconomic gap between these groups. This difference was between socioeconomic position at birth and working memory at age 7-10 years, highlighting the longstanding detrimental associations that early socioeconomic disadvantage has with children's working memory.

This finding lends support to the view that socioeconomic position does influence working memory (e.g. Lawson et al., 2018; Wang & Fitzpatrick, 2019), and contradicts the view that working memory is unrelated to socioeconomic disadvantage (e.g., Vandenbroucke et al., 2016). Previously, some researchers have viewed working memory ability as impervious to the negative effects of socioeconomic disadvantage, and conceptualised it as a cognitive ability that is independent of acquired knowledge and skills (e.g. Alloway & Copello, 2013; Engel, Santos, & Gathercole, 2008). However, my thesis strongly suggests that this view is unsubstantiated, and that working memory is more likely to be a malleable ability that can be shaped by socioeconomic position.

These associations between socioeconomic position and working memory are generally in accordance with the broader literature that finds lower socioeconomic position to have negative associations with childhood outcomes (e.g. Feinstein, 2003; Vignoles, Jerrim and Vignoles, 2011; Kelly et al., 2011; Linberg et al., 2019). In particular, this finding is consistent with previous literature that finds socioeconomic disparities in children's executive functions, which encompass working memory ability (Lawson, Hook and Farah, 2018). However, this previous work had not looked at associations between socioeconomic position and the distinct components of working memory guided by the multicomponent working memory model (Baddeley, Hitch and Allen, 2021). I have addressed this knowledge gap by presenting socioeconomic disparities by each component of working memory, and confirmed that socioeconomic disparities are broadly consistent across each component.

Child poverty is a substantial and rising issue in the UK (United Nations, 2019), and many teachers (60%) view child poverty as worsening since 2015 (National Education Union and Child Poverty Action Group, 2018). There are strong links between working memory and other aspects of learning (e.g. Peng et al., 2017; Allen, Higgins and Adams, 2019), health (Stautz et al., 2016) and broader cognitive abilities (Gruszka and Nęcka, 2017). Given that my research has highlighted that children with low socioeconomic position are at risk for poor working memory, and as a cumulative consequence of this, may also be at risk of reduced educational attainment, learning abilities in school, cognitive development, and health, it is very concerning that the number of children living in socioeconomic disadvantage in the UK is continuing to grow.

My thesis has addressed the shaping of working memory by one of the most important sociodemographic factors in UK society – socioeconomic position. As I have stated, the associations I have found between socioeconomic position and working memory are generally in accordance with the broader literature that finds lower socioeconomic position to have negative associations with childhood outcomes. The following sections describe how my thesis has addressed the shaping of working memory by another sociodemographic factor – ethnicity. The associations between ethnicity and working memory were revealed to be more complex. Given the multiple complex mechanisms that may underpin ethnic differences in childhood outcomes, it is perhaps unsurprising that these associations were not always simple (García et al., 1996).

7.1.1 Associations between ethnicity and children's working memory.

My thesis is the first study to investigate children's working memory between ethnic majority and numerous ethnic minority groups. First, I systematically reviewed the literature, and found that ethnic minority children tended to have lower working memory, however, it was not possible to make conclusive inferences due to methodological constraints. The studies included in the forest plot only measured verbal working memory, so it was not possible to ascertain the magnitude of the associations across different types of working memory. Further, several of the studies combined different ethnic minority groups into one heterogeneous ethnic group (e.g. Finch and Obradović, 2017; Flouri, Papachristou and Midouhas, 2019; Stevenson, Heiser and Resing, 2016).

I built on this limited knowledge by exploring variation in three working memory tasks across nine different ethnic groups, using the cohort study data. Substantial variation was found in working memory across the nine ethnic groups. Many ethnic minority groups tended to have higher working memory scores on at least one task (usually FDR) - equivalent to an age difference that varied between 6 and 10 months. However, the association between ethnicity and working memory varied across the type of task of working memory. This was an unexpected finding, since I hypothesised that the heightened disadvantage faced by ethnic minority groups relative to the White British group would result in them having lower working memory scores. To summarise, the combination of findings in my systematic review and findings from Study 1 provide support for the suggestion that ethnic differences do exist in children's working memory. However, the association between ethnicity and working memory appears to vary by the particular ethnic minority group and across countries, perhaps depending on the disadvantage and the cultural differences experienced by different ethnic minority groups.

A complexity of investigating ethnicity as a social determinant of working memory was the paucity of evidence purposefully addressing this association. Evidenced by my systematic review, there had been relatively few studies looking at ethnic minority status as a sociodemographic factor in the context of childhood working memory. To the best of my knowledge, my research using the cohort study data was the first to systematically compare variation in numerous working memory tasks across numerous ethnic groups within the same country. Whilst this makes my study novel, it also meant that it was difficult to compare these findings to previous literature. In comparison to the growing literature about socioeconomic position and children's working memory, ethnicity appears to have been a relatively neglected sociodemographic factor in the context of working memory.

7.1.2 Associations between socioeconomic position and working memory ***within*** ethnic groups.

Another unique contribution my research has made is by exploring social gradients in working memory across ethnic majority and minority groups. I found that social gradients in working memory were less pronounced for Pakistani children, and that Pakistani children of low socioeconomic position tend to have better working memory than expected considering their socioeconomic disadvantage.

In relation to previous literature, this finding was in contrast to the only other previous study exploring social gradients in working memory, where social gradients were stronger for African American children than for White children living in the US (Rhoades et al., 2011). However, my findings were generally in line with previous studies with the Born in Bradford cohort, where social gradients in health appear to be stronger within the White British ethnic group (Mallicoat, Uphoff and Pickett, 2020; Uphoff, Pickett and

Wright, 2016). My study therefore contributes to a growing number of studies that appear to suggest the Pakistani community in Bradford may be buffered against the negative effects of socioeconomic disadvantage through other potential positive factors. Taking these contrasting findings of Rhoades et al. (2011) with my study, these conflicting findings highlight that much remains to be revealed about social gradients and child development outcomes within ethnic minority groups.

These findings demonstrated the complex intersection between socioeconomic position and ethnicity when investigating children's working memory, and more broadly, children's developmental outcomes. As I have described, it has contributed to an emerging body of literature that suggests that across ethnic groups, socioeconomic position may not have the same associations with children's outcomes through the same mechanisms. More broadly, this study has highlighted the shortcomings of studies that only look at associations between socioeconomic position and children's outcomes within White Educated Industrialised Rich Democratic (WEIRD) populations, and emphasises the importance of including ethnic minority groups into these kind of studies in the future (Nielsen et al., 2017).

7.1.3 Potential causal factors between socioeconomic position, ethnicity, and working memory.

In an investigation of potential causal factors between socioeconomic position and working memory, I found that the home learning environment was not a statistically significant mediator. This finding was contrary to both my expectations and to previous research which found the home learning environment to be a significant mediator between socioeconomic position and working memory (Hackman et al., 2015; Amso, Salhi and Badre, 2018). A possible explanation for these results was that the home learning environment was not as important for children's working memory as other factors (e.g. chronic stress), or because of several limitations with the data.

My final study explored a novel area of research – the potential positive factors for ethnic minority children's working memory. In this investigation, I was not able to explain *why* ethnic minority children in Bradford have better working memory scores than expected, as neither own ethnic density nor Mosque attendance were significant factors for working memory. Alike to the paucity of research addressing ethnicity as a social determinant in the context of working memory, these were relatively underexplored factors, since only one previous study had looked at minority ethnic density and children's cognitive development (Zhang et al., 2017), and only one previous study had looked at learning the Quran and working memory (Black et al., 2020).

The previous study found that own ethnic density was associated with reduced expressive vocabulary scores after controlling for area deprivation, but only for Bangladeshi children (Zhang et al., 2017). Since my study did not find any significant associations between own ethnic density and working memory, it seems unlikely that this will be a strong positive factor for children's cognitive development. Nonetheless, since minority ethnic density is hypothesised to have positive effects through increased social integration and reduced exposure to racism (Pickett and Wilkinson, 2008), future research should investigate direct associations between social integration, racism, and working memory. This has the potential to reveal some of the underlying mechanisms by which ethnic minority children in Bradford may be protected against the negative effects of socioeconomic disadvantages.

With regards to the potential effects of attending Mosque, it remains possible that learning the Quran may be associated with higher scores on simple verbal working memory, since the pattern of results indicated stronger associations between Mosque attendance and FDR than Corsi or BDR. It was previously found that learning the Quran was not associated with long term memory (ie. *not* working memory) (Black et al., 2020). To generate further understanding of this, future studies should assess the direct association between learning the Quran and children's working memory. Still, any effect of Mosque attendance on working memory appeared to be very small in magnitude, and unlikely to fully explain why Pakistani children have higher FDR scores. Together, these studies highlight that an investigation of other potential positive causal factors for Pakistani children's working memory is still needed.

7.2 Strengths and limitations of the cohort study data

The data collected by Born in Bradford were well suited to my research questions due to the large ethnic minority population and high levels of deprivation. This allowed an exploration of the associations with adequate power to find socioeconomic and ethnic differences in working memory, which would not be possible in many other UK cohort studies due to having low numbers of ethnic minority groups. In particular, an exploration of Mosque attendance and own ethnic density would not have been possible without the very large ethnic minority population. Whilst it should be acknowledged that Bradford is not necessarily demographically representative of the UK, the results are likely to be generalisable to other cities in the UK with large ethnic minority populations and high levels of deprivation.

Another strength is that despite the difficulties in measuring socioeconomic position in ethnic minority groups that I have already described (see Chapter 1, p.36), I was able to use an ethnic-specific indicator of socioeconomic position that had already been developed (Fairley et al., 2014). This ethnic-specific indicator achieved a more valid measure of socioeconomic position *within* the White British and Pakistani ethnic groups, meaning the construct of socioeconomic position was more accurately measured without bias, and should correspond more accurately to these participants real world experiences of socioeconomic position. I was able to compare this ethnic-specific indicator to the general socioeconomic indicator in order to make inferences about the presence or absence of social gradients. There is very little previous research investigating or applying the use of ethnic-specific indicators of socioeconomic position, and these may be useful in the future to investigate social gradients.

A minor limitation in relation to the measures of socioeconomic position is that the association between individual indicators of socioeconomic position and working memory could not be explored due to missing data in some of the indicators (e.g. educational attainment for ethnic minority groups). Previous studies have employed several measures of socioeconomic position to test if they have different associations with outcomes, which may reveal some information about the mechanisms by which they are associated.

Finally, I was not able to explore other possible mediation pathways between socioeconomic position and working memory as they had not been measured. I found that the home learning environment did not mediate the association between socioeconomic position and working memory, and it would have been beneficial to compare this to other mediators. However, this gap highlights an interesting area for future research - to investigate child experiences of stress as a mediator between socioeconomic position and working memory. I expand upon the implications of these limitations for future research below.

7.3 Recommendations for Future Research

Besides the specific recommendations for future research provided within each study, my thesis has generated several general recommendations for future studies.

7.3.1 Causality and mediating factors

The previous section highlighted both the utility and the difficulties with using observational cohort study data. These data represent the lives of children, without any experimental manipulation. The cohort study presented the ideal opportunity to investigate these complex longitudinal associations between socioeconomic position, ethnicity, and working memory. However, observational studies such as these cannot establish that the association between socioeconomic position and children's working memory is causal. Without an experimental design, causality can only be inferred, and not proven (Vandenbroucke, Broadbent and Pearce, 2016). Thus, a natural progression of my work would be to investigate the causality of these associations. The best way of investigating causal associations is through randomised control trials, although these are obviously logistically difficult to achieve in the context of socioeconomic variation.

Despite these logistical challenges, an ongoing randomised control trial is currently investigating whether poverty reduction is associated with better child development. One thousand new mothers with low incomes across four sites in the USA have been recruited and randomised to either receive $333/month or $20/month for the first 40 months of their child's life. Data are being collected on a variety of cognitive child development measures (including executive functions) just after birth and then at 12, 24, and 36 months of age (ClinicalTrials.gov, 2021; Baby's First Years, 2018). The results from this trial will be of great interest and may support my inference that the associations I have found between socioeconomic position and working memory are indeed causal.

Of relevance to this is that the potential causal mediating factors require further investigation. A knowledge gap remains regarding the mediating links between socioeconomic position, ethnicity and working memory. I found that the home learning environment did not explain the strong association between socioeconomic position and working memory. Future research should attempt to replicate the null findings between socioeconomic position, the home learning environment and working memory, and compare this to other potential mediating factors (e.g. chronic stress). Ideally, this would be done within a similar longitudinal study to Born in Bradford that has collected data on these factors across several timepoints.

Further, future research should investigate positive factors for ethnic minority children's working memory. First, the factors I investigated should be investigated again with the same ethnic groups in different settings. It should be established if learning the Quran and minority ethnic density is a positive factor for South Asian children's working memories – since my study had a few limitations that may have resulted in an insignificant finding. Second, other potential positive factors for South Asian children's working memory should be investigated – and the hidden talents approach may provide some guidance for this. The approach proposes that adversity may shape abilities in different directions; for example, enhance one ability whilst impairing another (Frankenhuis, Young and Ellis, 2020; Nweze et al., 2021). It may be that some ethnic minority children in Bradford have better developed working memory skills due to the heightened experiences of adversity that they face, in order to cope with stressful situations that they encounter more often. For instance, a future study could investigate whether ethnic group differences exist across several different cognitive skills, to understand if there are different patterns between ethnicity and different cognitive abilities.

7.3.2 Educational attainment

A question of interest for future research is whether working memory may mediate the association between socioeconomic position and educational attainment, and this will be possible with the Born in Bradford study when children take part in educational assessments and these data become available. There is a plethora of research showing that children from socioeconomically disadvantaged families tend to achieve less at all stages (Education Endowment Foundation, 2018; Parsons, 2019), and there is also a body of evidence showing working memory as extremely important predictor for children's educational attainment (Mulder, Pitchford and Marlow, 2010; Jarvis and Gathercole, 2003; Friso-Van Den Bos et al., 2013). Indeed, some studies have explored executive functions as mediators between socioeconomic position and attainment (Lawson and Farah, 2017), however, these studies have tended to combine the executive function measures (including working memory) into one composite. Since I found such a strong association between socioeconomic disadvantage and working memory, it would be interesting to see if working memory is a more important mediator than other executive functions are for children's educational attainment. This could be achieved through mediation analysis exploring children's early socioeconomic position, middle childhood working memory, and their educational outcomes at either GCSE or A Levels. This would be a practically useful finding, as it would reveal the mechanisms by which socioeconomic inequality results in large differences in children's educational attainment.

With regards to ethnicity, it is interesting to consider how the ethnic group differences in working memory map onto the ethnic group differences in national educational attainment that were described in Chapter 1. In Study 1, White British children tended to score worse than ethnic minorities on at least one measure of working memory. As described in Chapter 1, White British children of low socioeconomic position score much lower than other ethnic groups with similar socioeconomic position in the national pupil database in the UK (Strand, 2021). A question for future research may be whether low working memory scores for low socioeconomic position White British children can explain their lower than expected average attainment in the national pupil database. The Education Committee cite several potential factors that may combine to put low socioeconomic position White British pupils at a disadvantage, such as multigenerational disadvantage, regional economics, family experiences of education, lack of social capital, disengagement from the curriculum, and a failure to address low participation in higher education. However, there is not yet much data exploring these factors, and the causal factors behind the low attainment remain under investigated and unknown (Curnock Cook, 2020; Education Committee, 2021). A further study with more focus on potential causal factors for low attainment for socioeconomically disadvantaged White British pupils is therefore required, and my research suggests that low working memory could be investigated as a potential factor.

On average, Pakistani and Black children of any socioeconomic position tend to have worse attainment in the national pupil database than White British children when averaged across socioeconomic position (Strand, 2011a). It is therefore interesting to consider the Pakistani and Black ethnic groups higher simple verbal working memory scores in relation to their worse than average attainment at school. This may be seen as evidence of the Pygmalion effect, where teacher expectations affect both the teacher behaviour and student performance (White and Locke, 2000). In a previous study that compared teacher assessments to blindly assessed key stage assessments, the Pygmalion effect was found to be evident for assessments of several ethnic minority group pupils relative to White British pupils, including Black and Pakistani ethnic groups (Burgess and Greaves, 2015). To summarise, whilst previous research indicates that Black and Pakistani children are systematically marked as having worse attainment in school, my research indicates that Black and Pakistani children have at least equal working memory capabilities to White British pupils. My research therefore gives support to the suggestion that this discrepancy in children's educational attainment across teacher and blind assessments is evidence of the Pygmalion effect. However, the data in my study and data from Burgess and Greaves (2015) are from different samples at different time points, and the Pygmalion effect would not explain why White British children with low socioeconomic position have disproportionately worse attainment. Clearly, there are complex mechanisms underpinning socioeconomic and ethnic group differences in attainment.

To explore this further, it will be interesting to look at the associations between ethnicity, children's working memory, and their later educational attainment in the Born in Bradford study when the data become available. Though I have discussed how the different data from my study, Strand's (2011; 2021) studies, and Burgess and Greaves (2015) can be interpreted together, it would be advantageous to conduct a longitudinal analysis of these factors within the same group of children. This will be possible in the coming years with the Born in Bradford study, as children move through school and complete educational assessments. This may reveal if low working memory scores can explain why socioeconomically disadvantaged White British children have disproportionately worse educational attainment. It may also give support to the theory of the Pygmalion effect, if Black and Pakistani children score worse on teacher assessments despite their higher working memory scores.

7.3.3 Intervention research

Since my research has highlighted previously unknown groups of children who are, on average, more likely to struggle with working memory, my research underlines the need to investigate ways to support children with poor working memory. A body of research has already investigated working memory training, with commercially available training programmes typically involving computerized span tasks that trainees practice several times per week for several weeks, with the aim of improving individual working memory capacity (Redick et al., 2015). Several randomized control trials have investigated this working memory training as a means of improving children's learning abilities (e.g. Roberts et al., 2016; Dunning, Holmes and Gathercole, 2013). However, a review of the evidence found that whilst working memory training can improve working memory scores, the training does not appear to transfer to other assessments in school (e.g. maths assessments). Given the cost and time invested in working memory training, it is therefore not currently considered to be worthwhile (Redick et al., 2015).

More recently, interventions *without* the use of repetitive computerized span tasks have been investigated. These interventions instead aim to target working memory within everyday contexts, for instance, by adapting the classroom environment, or embedding training within typical activities in children's every day contexts (Rowe et al., 2019). For example, performing an instruction at the time of hearing it appears to be associated with improvements in children's ability to recall instructions (Waterman et al., 2017; Jaroslawska et al., 2016a). Further, children with low working memory have been found to perform better on working memory tasks when the task environment is structured in an organised manner (rather than in a randomly organised manner) (Berry, 2017). Work is ongoing to investigate whether these strategies can be used to improve working memory for children with poor working memory from any socioeconomic or ethnic group. Since I have found such strong associations between socioeconomic position and working memory, my research emphasises the need to understand if children's working memory can be improved using these everyday strategies on a long-term basis – as these strategies may also be effective for reducing socioeconomic inequalities in children's working memory.

7.4 Recommendations for Policy and Practice

This section discusses the implications for policy and practice from my thesis. Policy approaches could either focus on: (1) reducing social inequality or (2) reducing the link between disadvantage and children's working memory.

7.4.1 Reduce social inequality

If we infer the association between socioeconomic disadvantage and children's working memory to be causal, reducing social inequality at its core would improve socioeconomically disadvantaged children's working memory, and perhaps translate into improvements in educational attainment and other outcomes. Thus, a policy recommendation from my thesis is to reduce social inequality at its core, in order to improve children's working memory and other outcomes.

The Marmot Review (2010) summarised the immediate policy requirements required to reduce social inequalities in health in the UK. Policy suggestions included redistribution of incomes through taxes and benefits, legislation for a minimum income for a healthy life, and provision of both universal and targeted services to people with low incomes (Marmot et al., 2010). These policies would likely generalise beyond implications for health, and also reduce socioeconomic gaps in children's working memory, and perhaps some ethnic differences in working memory. Disappointingly, the more recent Marmot (2020) report highlights that in the absence of any of these progressive policies, social inequalities in health have continued to grow over the past 10 years (Marmot, 2020).

7.4.2 Reduce the link between disadvantage and children's working memory

As described above, the most effective strategy to reduce socioeconomic inequalities in children's working memory would be to address the root cause and reduce the levels of socioeconomic inequality in society. In lieu of the implementation of the policies outlined above, there are a few implications that my research has for practice.

First, these findings may provide useful insights for teachers. A survey of 1425 teachers found that teachers overestimate working memory duration, and report a variety of signs associated with working memory impairments (Atkinson, Allen and Waterman, 2021). Since this survey indicates that teachers have some gaps in their understanding of working memory generally, this indicates that teachers are unlikely to be aware of the specific links between socioeconomic position, ethnicity and working memory. A survey of 908 teachers found that a large majority of UK teachers (87%) consider poverty to negatively affect the learning of their students (National Education Union and Child Poverty Action Group, 2018), so teachers may not be surprised that socioeconomic disadvantage has strong detrimental associations with working memory. Nonetheless, the very strong associations that I have revealed in my PhD suggest that it would be useful for practitioners to receive some training regarding working memory, and the potential socioeconomic and ethnic differences in working memory. If practitioners are aware of these differences, they may be able to assist these children in classroom settings more often – reducing the link between disadvantage and working memory.

Second, although there will be individual children with poor working memory within all socioeconomic and ethnic groups, my research has revealed the particular socioeconomic and ethnic groups that on average have much lower working memory scores. This knowledge may therefore be utilised to more efficiently screen and test for children with working memory difficulties by targeting children attending schools located in the most socioeconomically deprived areas – and perhaps schools with high proportions of particular ethnic groups (e.g. Gypsy and Irish Traveller children). Once this information regarding working memory has been obtained, these children can then be assisted in the classroom – perhaps using some of the strategies I have described above (Section 6.5.3).

7.5 Chapter Summary

In this chapter I have discussed how my thesis has contributed to and added new understanding of inequalities in children's working memory - a core capability that is vital for children to succeed in education. The key finding is that children from socioeconomically disadvantaged families have worse working memory, and that substantial variation across ethnic groups exists in working memory. In particular, some ethnic minority groups have better working memory scores than ethnic majority groups.

My research contributes to a growing body of literature demonstrating social inequalities in children's cognitive development. Given the links between working memory and educational attainment, and between educational attainment and later health, these differences found in working memory may have adverse consequences for children's future health and wellbeing.

I have also discussed recommendations for future research and for policy and practice. The key research prioritisations are to investigate causality with regards to these associations, investigate the implications of these associations for social inequalities in children's educational attainment, and to develop effective interventions to support children with working memory difficulties. The key policy implications are to reduce social inequality, or, in the absence of this, to reduce the link between socioeconomic disadvantage and working memory.

Appendices

A. <u>Further information for Chapter 2</u>

A1. PRISMA checklist

Section/topic	#	Checklist item	Reported on page #
TITLE			
Title	1	Identify the report as a systematic review, meta-analysis, or both.	1
ABSTRACT			
Structured summary	2	Provide a structured summary including, as applicable: background; objectives; data sources; study eligibility criteria, participants, and interventions; study appraisal and synthesis methods; results; limitations; conclusions and implications of key findings; systematic review registration number.	2
INTRODUCTION			
Rationale	3	Describe the rationale for the review in the context of what is already known.	3-6
Objectives	4	Provide an explicit statement of questions being addressed with reference to participants, interventions, comparisons, outcomes, and study design (PICOS).	6
METHODS			
Protocol and registration	5	Indicate if a review protocol exists, if and where it can be accessed (e.g., Web address), and, if available, provide registration information including registration number.	7
Eligibility criteria	6	Specify study characteristics (e.g., PICOS, length of follow-up) and report characteristics (e.g., years considered, language, publication status) used as criteria for eligibility, giving rationale.	7-8
Information sources	7	Describe all information sources (e.g., databases with dates of coverage, contact with study authors to identify additional studies) in the search and date last searched.	8

Search	8	Present full electronic search strategy for at least one database, including any limits used, such that it could be repeated.	Supplementary online materials (SOM)
Study selection	9	State the process for selecting studies (i.e., screening, eligibility, included in systematic review, and, if applicable, included in the meta-analysis).	9-11
Data collection process	10	Describe method of data extraction from reports (e.g., piloted forms, independently, in duplicate) and any processes for obtaining and confirming data from investigators.	8
Data items	11	List and define all variables for which data were sought (e.g., PICOS, funding sources) and any assumptions and simplifications made.	9
Risk of bias in individual studies	12	Describe methods used for assessing risk of bias of individual studies (including specification of whether this was done at the study or outcome level), and how this information is to be used in any data synthesis.	9
Summary measures	13	State the principal summary measures (e.g., risk ratio, difference in means).	10
Synthesis of results	14	Describe the methods of handling data and combining results of studies, if done, including measures of consistency (e.g., I^2) for each meta-analysis.	11

A2. Search strategy

Search strategy for Psycinfo:

Database: PsycINFO <1806 to April Week 5 2019>
Search Strategy:

-
1 neighborhoods/ (7490)
2 exp Marital status/ (3731)
3 neighbo?rhood*.mp. (21686)
4 residential environment*.mp. (497)
5 rural*.mp. (42697)
6 inner?city.mp. (69)
7 housing instability.mp. (220)
8 housing insecurity.mp. (63)
9 housing strain.mp. (2)
10 housing security.mp. (25)
11 mortgage problems.mp. (0)
12 foreclosure.mp. (682)
13 eviction*.mp. (251)
14 housing loss.mp. (14)
15 home repossession*.mp. (2)
16 home ownership.mp. (407)
17 (repossess* adj3 hous*).mp. (4)
18 (repossess* adj3 propert*).mp. (2)
19 mortgage delinquency.mp. (5)
20 mortgage arrears.mp. (2)
21 mortgage debt*.mp. (24)
22 overcrowding.mp. (603)
23 (living adj1 (outside or inside or near* or adjacent)).mp. (750)
24 (household adj2 size).mp. (406)
25 (marital status or marraige status).mp. (13965)
26 (widow* or cohabit* or divorce* or single parent* or live* alone).mp. (29775)
27 or/1-26 (107175)
28 minorit*.mp. (52945)
29 exp Sociocultural Factors/ (113360)
30 Cross Cultural Differences/ (50372)
31 Immigration/ (20908)
32 Minority groups/ (14312)
33 exp Social Discrimination/ (10907)
34 "Racial and Ethnic Relations"/ (3475)
35 exp "Racial and Ethnic Groups"/ (120850)
36 "Racial and Ethnic Differences"/ (32024)
37 "Race and Ethnic Discrimination"/ (4479)
38 Racism/ (7254)
39 exp Prejudice/ (7539)
40 Refugees/ (5389)
41 migration background.mp. (255)
42 racial.mp. (76071)
43 racism.mp. (12953)
44 ethnology.mp. (2312)
45 race.mp. (66347)
46 ethnic*.mp. (121362)
47 non?English.mp. (13)
48 language other than.mp. (341)
49 latino*.mp. (28850)
50 latina*.mp. (23526)
51 hispanic*.mp. (25591)
52 whites.mp. (27838)
53 caucasian*.mp. (14856)
54 non?white.mp. (736)
55 Torres Strait Islander.mp. (392)
56 aboriginal.mp. (3534)
57 native american.mp. (3817)
58 inuit.mp. (717)
59 eskimo.mp. (274)
60 first nation*.mp. (1548)
61 indigenous.mp. (12979)
62 english as a second language.mp. (1998)
63 foreign language.mp. (25379)
64 or/28-63 (394142)
65 Occupations/ (8188)
66 Unemployment/ (4044)
67 occupations.mp. (17198)
68 unemployment.mp. (10409)
69 or/65-68 (27362)
70 exp Gender Identity/ (13758)
71 Sex Discrimination/ (2174)
72 gender differences.mp. (41376)
73 (sex disparit* or sex difference?).mp. (125333)
74 gender identity.mp. (11315)
75 sex role.mp. (16943)
76 wom#n* role?.mp. (1203)
77 m#n* role?.mp. (3231)
78 gender* role?.mp. (10524)
79 servicewomen.mp. (62)
80 or/70-79 (169413)
81 exp Educational Background/ (10881)
82 Schooling.mp. (13024)
83 educational status.mp. (1151)
84 (education* adj2 level?).mp. (30089)
85 ((higher or better or worse or less) adj educated).mp. (3016)
86 ((higher or better or worse or less) adj level? of education).mp. (1127)
87 or/81-86 (49728)
88 Religion/ (18036)
89 religi*.mp. (83086)
90 or/88-89 (83086)
91 "Equity (Social)"/ (2085)
92 Distributive Justice/ (725)
93 Poverty/ (8605)
94 exp Deprivation/ (19990)
95 exp Psychosocial Factors/ (33152)
96 exp Income Level/ (13316)
97 exp Socioeconomic Status/ (48279)
98 Family Socioeconomic Level/ (1618)
99 exp Disadvantaged/ (7286)
100 disparit*.mp. (28366)
101 inequalit*.mp. (21424)
102 inequit*.mp. (6128)
103 equity.mp. (13705)
104 deprivation.mp. (28072)
105 gini.mp. (424)
106 concentration index.mp. (139)
107 Social class*.mp. (14634)
108 social determinants.mp. (2872)
109 social status.mp. (8213)
110 social position.mp. (1630)
111 social background.mp. (1441)
112 social circumstance*.mp. (990)
113 socio-economic.mp. (12894)
114 socioeconomic.mp. (57221)
115 sociodemographic.mp. (23176)
116 socio-demographic.mp. (9508)
117 SES.mp. (17901)
118 disadvantaged.mp. (16387)

119 impoverished.mp. (3379)
120 poverty.mp. (23042)
121 economic level.mp. (453)
122 assets index.mp. (7)
123 income*.mp. (60504)
124 or/91-123 (304943)
125 Stigma/ (11192)
126 social capital/ (5706)
127 exp Social Networks/ (18106)
128 Social control/ (2581)
129 Social Support/ (34182)
130 exp Social Environments/ (147846)
131 Trust/ (9721)
132 Social isolation/ (6852)
133 Anomie/ (366)
134 social exclusion.mp. (3024)
135 (social adj (capital or cohes* or organis* or organiz*)).mp. (15311)
136 (community adj3 (cohes* or participa*)).mp. (11159)
137 ((neighbourhood or neighborhood) adj cohes*).mp. (194)
138 social relationships.mp. (10388)
139 social network*.mp. (31215)
140 collective efficacy.mp. (1331)
141 civil society.mp. (1957)
142 informal social control.mp. (313)
143 neighbo*rhood disorder.mp. (270)
144 social disorgani?ation.mp. (772)
145 anomie.mp. (990)
146 social support.mp. (60156)
147 social participation.mp. (2542)
148 trust.mp. (33793)
149 emotional support.mp. (6476)
150 psychosocial support.mp. (1806)
151 community capital.mp. (14)
152 neighbo*rhood cohesion.mp. (189)
153 social influence.mp. (5485)
154 (soci*context* or soci*-context*).mp. (22873)
155 or/125-154 (333960)
156 Health Disparities/ (7094)
157 health*care disparit*.mp. (249)
158 health care disparit*.mp. (610)
159 health status disparit*.mp. (54)
160 health disparit*.mp. (10126)
161 health inequalit*.mp. (1935)
162 health inequit*.mp. (615)
163 medically underserved.mp. (459)
164 or/156-163 (12429)
165 27 or 64 or 69 or 80 or 87 or 90 or 124 or 155 or 164 (1087026)
166 Short Term Memory/ (24704)
167 exp Executive Function/ (14672)
168 ("working memory" or "executive function*" or "short?term memory").mp. (54666)
169 166 or 167 or 168 (66288)
170 (Child* or infant or school child* or adolescen* or preschool* or pre-school* or boy* or girl* or young people or teenager* or teen* or youth*).mp. [mp=title, abstract, heading word, table of contents, key concepts, original title, tests & measures] (950781)
171 165 and 169 and 170 (2570)

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A3. Converting between effect sizes

CONVERTING FROM *r* TO *d*

We convert from a correlation (*r*) to a standardized mean difference (*d*) using

$$d = \frac{2r}{\sqrt{1 - r^2}}. \tag{7.5}$$

The variance of *d* computed in this way (converted from *r*) is

$$V_d = \frac{4V_r}{(1 - r^2)^3}. \tag{7.6}$$

For example, if $r = 0.50$ and $V_r = 0.0058$, then

$$d = \frac{2 \times 0.50}{\sqrt{1 - 0.50^2}} = 1.1547$$

and the variance of *d* is

$$V_d = \frac{4 \times 0.0058}{\left(1 - 0.50^2\right)^3} = 0.0550.$$

In applying this conversion we assume that the continuous data used to compute *r* has a bivariate normal distribution and that the two groups are created by dichotomizing one of the two variables.

Source: Borenstein et al. (2009)

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B. Further information for Chapter 3

B1. Required variables

Variable (source)	Variable name in data dictionary
Maternal baseline questionnaire	
Socioeconomic position (5 group LCA)	mbqlcasep5gp
Woman's employment status	job0mumemp
Baby's father's employment status	job0fthemp
Mother's education	Edu0mumede
Baby's father's education	edu0fthede
Subjective poverty	fin0manfin
Being in receipt of means tested benefits	ben0mentst
Up to date with bills	fin0upbill
Housing tenure	res0hseten
Woman's employment status	job0mumemp
Able to afford a holiday from home	fin0frshol
Able to afford family and friends for a drink or meal at least once a month	fin0frsffm
Able to afford two pairs of all weather shoes	fin0frssho
Able to afford enough money to keep home in decent state of decoration	fin0frsdec
Able to afford household contents insurance	fin0frshci
Able to afford money to make regular savings of £10 a month	fin0frssav
Able to afford money to replace any worn out furniture	fin0frsfur
Able to afford money to replace or repair major electrical goods	fin0frselg
Able to afford a small amount of money to spend on yourself each week	fin0frsysf
Able to afford a hobby or leisure activity	fin0frshob
In winter are you able to keep home warm enough	fin0frshwm
Country born	fbqcountrybirth
Country of birth if other	fbqcountrybirthother

HLE (BiB1000 24m)	
How often spent colouring/drawing/craft	bib24l01ahowoften,
How often spent sitting playing with toys	bib24l01bhowoften
How often spent watching TV/DVDs	bib24l01chowoften
How often spent playing on the computer	bib24l01dhowoften
How often spent listening/singing to music	bib24l01ehowoften
How often spent reading/being read to	bib24l01fhowoften
How often spent playing actively inside the house	bib24l01ghowoften
How often spent playing actively in the garden	bib24l01hhowoften
How often spent engaging in physical activity	bib24l01ihowoften
HLE (BiB1000 36m)	
How often spent colouring/drawing/craft	bib36i01ahowoften
How often spent sitting playing with toys	bib36i01bhowoften
How often spent watching TV/DVDs	bib36i01chowoften
How often spent playing on the computer	bib36i01dhowoften
How often spent listening/singing to music	bib36i01ehowoften
How often spent reading/being read to	bib36i01fhowoften
How often spent playing actively inside the house	bib36i01ghowoften
How often spent playing actively in the garden	bib36i01hhowoften
How often spent engaging in physical activity	bib36i01ihowoften
Other covariates (educational records)	
Academic term of child birthday	edcont_actermbirth
Whether English is an additional language	edcont_eal
Child Ethnic Origin Code	edcont_ethnic_origin
Whether child in receipt of free school meals	edcont_fsm
Special educational needs category	edcont_gender
	edcont_sen
Working Memory (Primary School Years)	
All data available	All data available

B2. Data application and sharing agreement

Bradford Teaching Hospitals NHS Foundation Trust

Collaboration and Information Sharing Agreement between Bradford Teaching Hospitals NHS Foundation Trust and University of York (“The Investigator’s Institution”) in relation to Born in Bradford approved study SP358 (“The Study”).

i. Background to the Agreement:

Born in Bradford is a family of research studies including three longitudinal multi-ethnic birth cohorts (Born in Bradford; Born in Bradford’s Better Start and BiB4All). These cohort studies aim to examine the impact of environmental, psychological and genetic factors as well as specific interventions on maternal and child health and wellbeing. Ethical approval for the data collection was granted by Bradford Research Ethics Committee, as follows:

07/H1302/112	Born in Bradford: A longitudinal cohort study of babies born in Bradford and their mothers and fathers
15/YH/0455	Born in Bradford's Better Start Cohort Study. A cohort study of babies born in Bowling and Barkerend, Bradford Moor and Little Horton areas of Bradford, and their mothers and partners
17/YH/0202	BiB4All: A data linkage cohort study of babies born in Bradford and their mothers

The studies are referred to collectively as “Born in Bradford” or “BiB”.

It is critical to the success of the Born in Bradford approved study SP358 What is the influence of socioeconomic position and ethnicity on working memory abilities in children? ("The Study") that the information to which this agreement relates is handled in accordance with relevant UK data protection regulations.

This agreement sets out the roles of each party to the agreement in relation to the information shared and their responsibilities therein.

1. Parties to the Agreement:

Details be included for all agencies which are party to the Agreement:

a) **Professor John Wright, Director of Research**

Bradford Teaching Hospitals NHS Foundation Trust

Bradford Royal Infirmary

Duckworth Lane

Bradford

BD9 6RJ

b) **"The Investigator"**

Kate Mooney

"The Investigator's Institution"

University of York

2. Purposes of the Agreement:

This agreement is in place to ensure the protection and security of data shared between Bradford Teaching Hospitals NHS Foundation Trust (BTHFT) and The Investigator's Institution for the purposes of The Study.

3. Information to be shared

Research data from Born in Bradford cohort participants will be shared between the parties. Only data necessary for the Investigator to carry out the Study will be shared ("The Data"), and this will be determined by the Born in Bradford Executive Group. Person identifiable data will not be shared. The Data will be pseudonymised.

4. Methods used for sharing:

The Data will be transferred from BTHFT to The Investigator at The Investigator's Institution using the IronPort encrypted email service or the Kiteworks secure filesharing service. If the file size is too big for Ironport or Kiteworks, or there are other barriers to accessing these at The Investigator's Institution, one of two transfer methods will be used:

1. A secure sftp or secure https connection will be provided by The Investigator's Institution to allow BTHFT to upload The Data. The folder to which The Data is uploaded will only be accessible by The Investigator.
2. The Data will be downloaded to a SafeXs encrypted memory stick and transferred physically to The Investigator at The Investigator's Institution by a member of BTHFT staff.

5. Need to know

For BTHFT:

Prof John Wright, Director of Research, BTHFT

BTHFT staff members in the Born in Bradford Data Team involved in processing The Data. For The Investigator's Institution: The Investigator.

6. Supporting processes:

The Investigator has read and will abide by the "Guidance for BiB Collaborators" set out in Appendix 1. The Investigator has read and will abide by the "Terms and Conditions for Data Transfers" set out in Appendix 2.

7. Information retention issues:

The Investigator will retain all information for as long as necessary to complete The Study. The Investigator will delete The Data and any data items derived from The Data from the Investigator's Institution's information systems at the request of BTHFT or upon completion of The Study, whichever is earlier. Participant data will be held in accordance with the relevant legislation (in particular the Data Protection Act 1998); Records Management: NHS Code of Practice and each agency's relevant policies and procedures.

8. Staff development issues:

Both parties to this agreement will ensure that their staff carry out information governance training appropriate to their role.

All staff at BTHFT complete annual mandatory training in Information Governance procedures. Staff are made aware of their responsibilities under the Data Protection and Freedom of Information Acts, which are laid out in the Trust's DPA and FOI policies and procedures.

9. Consent from service users:

All participants in Born in Bradford give explicit consent for their data to be used for research purposes. The consent forms make clear that they can withdraw their consent at any time by contacting the Born in Bradford office, at which point a member of the Born in Bradford team follows a standard operating procedure to action the withdrawal..

10. Incident Reporting

Incidents are to be reported immediately and in writing to the Director of Research, BTHFT

11. Any other relevant issues

Further information in relation to the Born in Bradford Cohort Study can be obtained by contacting the project office on +441274 364474

This agreement to be reviewed annually.

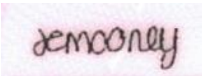
Approved by (PRINT NAME): Professor John Wright

Signature:

Institution: Bradford Teaching Hospitals NHS Foundation Trust

Date:

Approved by (PRINT NAME): KATE MOONEY

Signature: 

Institution: University of York

Date: 16/09/2019

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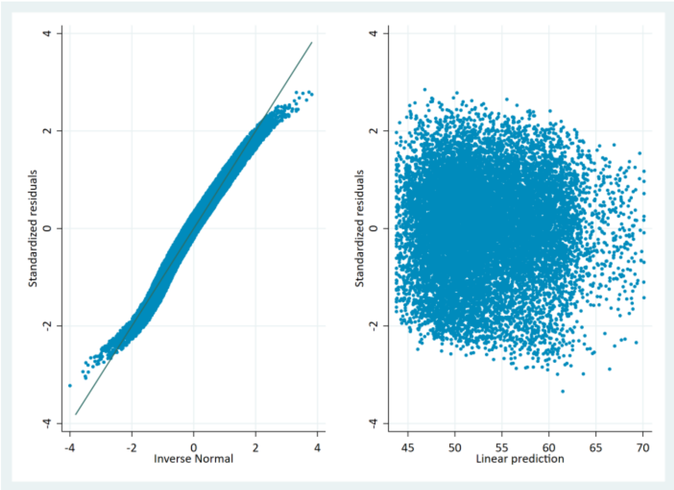
C. Further information for Chapter 4

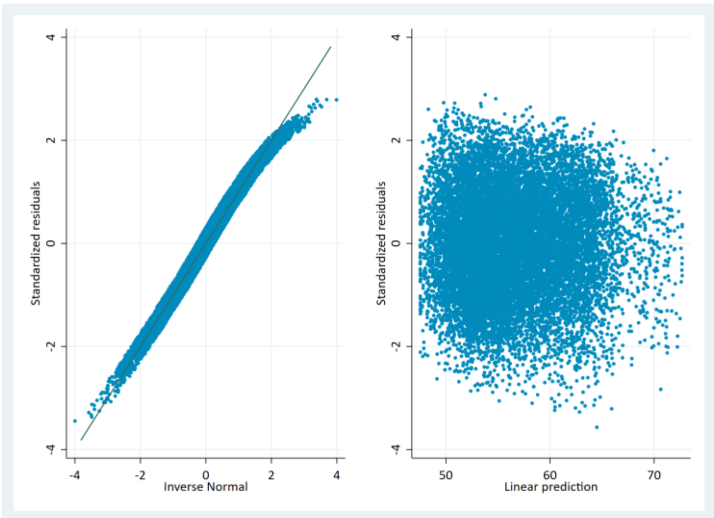
C1. Study 1: postestimation plots

i. Age

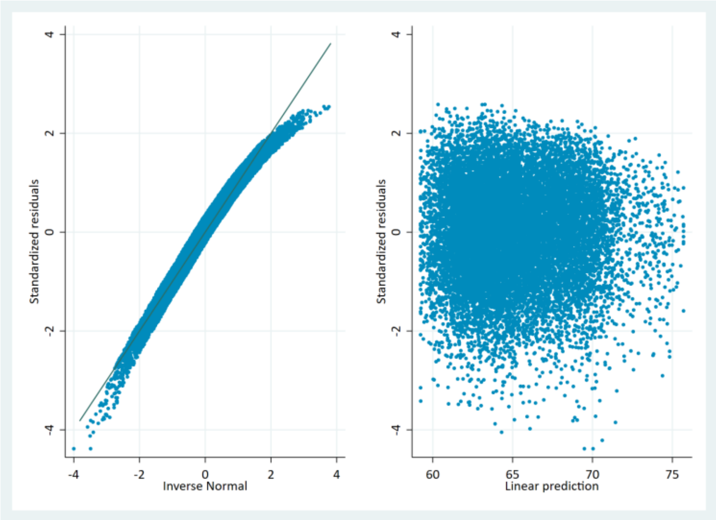
(a) FDR



(b) Corsi

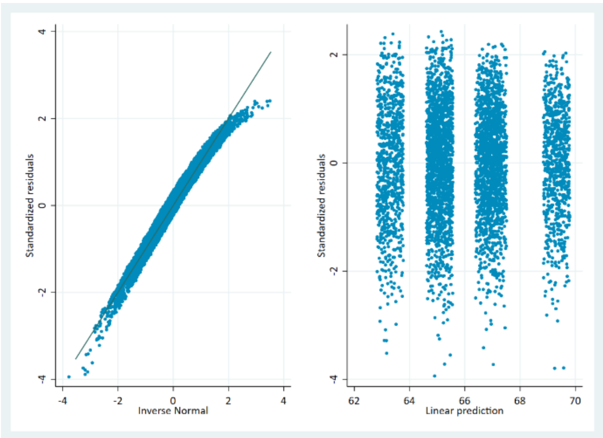


(c) BDR

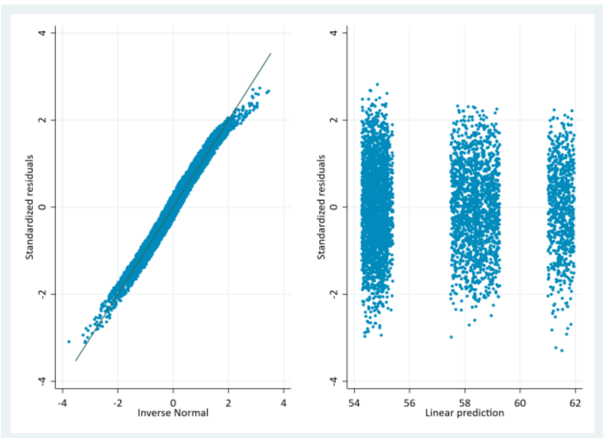


2. SEP

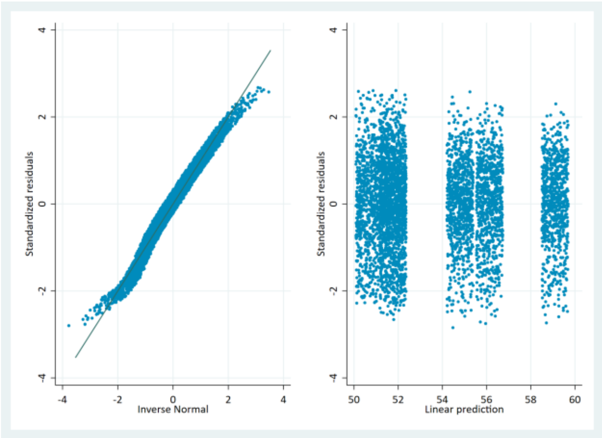
(a) FDR



(b) Corsi

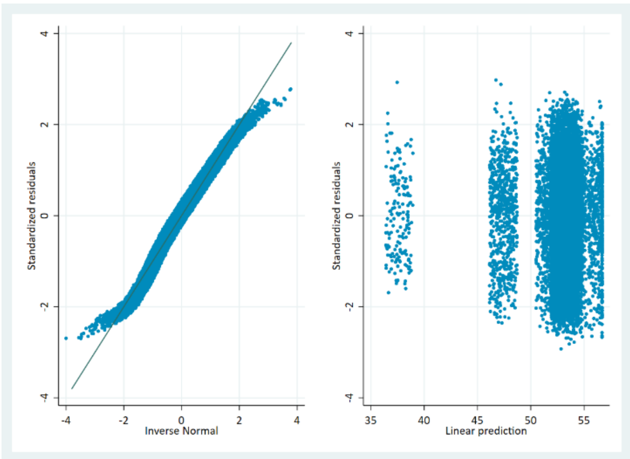


(c) BDR

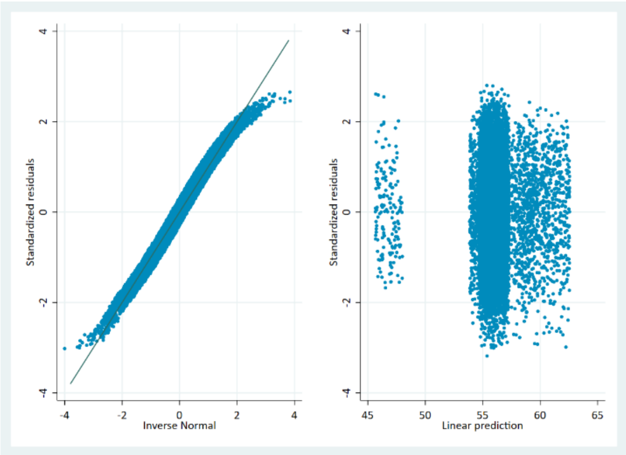


3. Ethnicity

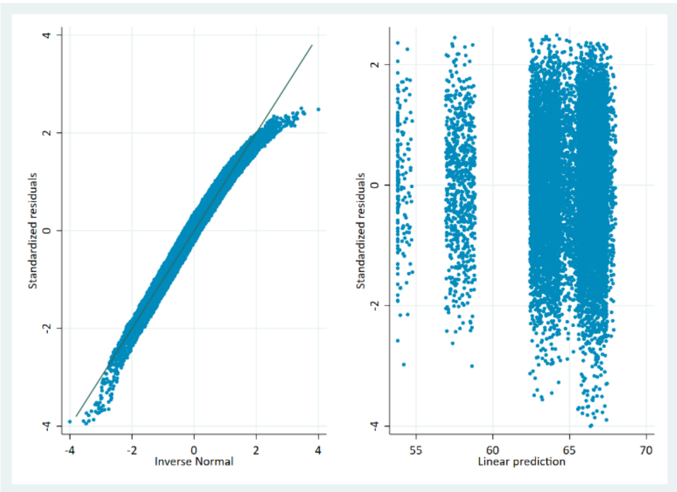
(a) FDR



(b) Corsi


Standardized residuals
Inverse Normal
Standardized residuals
Linear prediction

(c) BDR


Standardized residuals
Inverse Normal
Standardized residuals
Linear prediction

C2. Study 1: age analyses

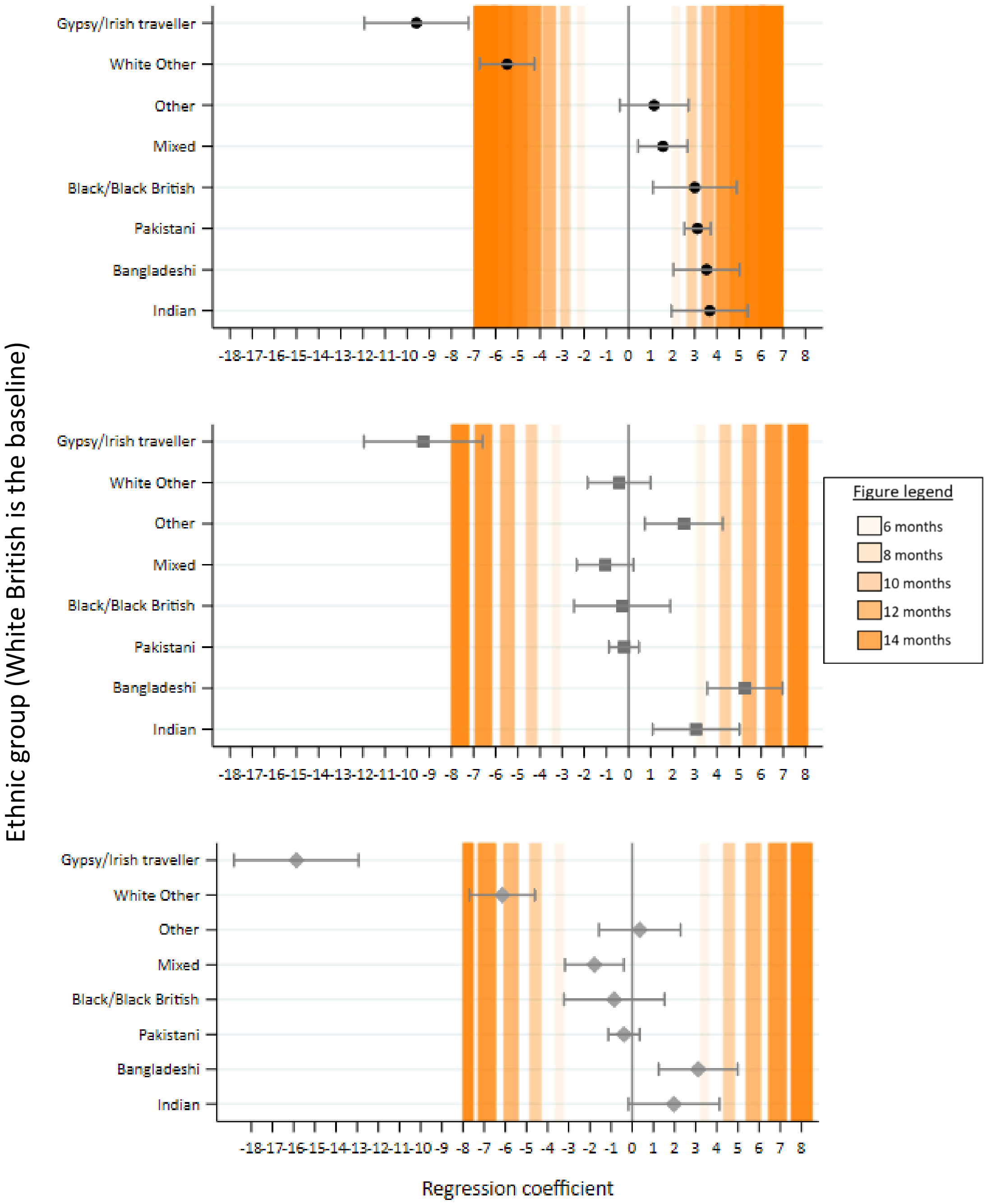
	FDR (n = 15,087)			Corsi (n = 14,995)			BDR (n = 15,146)		
Age in months	*B* (95% CI)	t	p	*B* (95% CI)	t	p	*B* (95% CI)	t	p
1	.36 (.33 to .39)	24.36	<.001	.55 (.51 to .58)	33.58	<.001	.57 (.54 to .61)	31.79	<.001
6	2.14 (1.97 to 2.32)	24.36	<.001	3.28 (3.10 to 3.47)	33.58	<.001	3.44 (3.22 to 3.65)	31.79	<.001
8	2.86 (2.63 to 3.09)	24.36	<.001	4.37 (4.12 to 4.62)	33.58	<.001	4.58 (4.30 to 4.86)	31.79	<.001
10	3.58 (3.29 to 3.87)	24.36	<.001	5.47 (4.63 to 5.21)	33.58	<.001	5.72 (5.37 to 6.08)	31.79	<.001
12	4.29 (3.95 to 4.64)	24.36	<.001	6.56 (6.18 to 6.94)	33.58	<.001	6.87 (6.45 to 7.29)	31.79	<.001
14	5.01 (4.61 to 5.41)	24.36	<.001	7.66 (7.21 to 8.10)	33.58	<.001	8.02 (7.52 to 8.51)	31.79	<.001
16	5.72 (5.27 to 6.19)	24.36	<.001	8.75 (8.24 to 9.26)	33.58	<.001	9.16 (8.60 to 9.73)	31.79	<.001
18	6.44 (5.92 to 6.96)	24.36	<.001	9.84 (9.27 to 10.42)	33.58	<.001	10.31 (9.67 to 10.94)	31.79	<.001
24	8.59 (7.90 to 9.28)	24.36	<.001	13.12 (12.36 to 13.89)	33.58	<.001	13.74 (12.90 to 14.59)	31.79	<.001
F test	*F(1, 15085) = 539.39*			*F(1, 14993) = 1127.32*			*F(1, 15144) = 1010.73*		
Unadjusted R^2	*.04*			*.07*			*.06*		

C3. Study 1: list of socioeconomic groups from original LCA

Class	Description
Least socioeconomically deprived and most educated”	Women currently and previously employed Father non-manual employment Women and fathers highly educated Up to date with bills Mortgage Not subjectively poor Not receiving means tested benefits Not materially deprived
“Employed, not materially deprived”	Women currently employed Father manual and non-manual employment Women and father medium levels of education Up to date with bills Mortgage Not subjectively poor Not receiving means tested benefits Not materially deprived
“Employed, no access to money”	Women currently and previously employed Father manual and non-manual employment Women and father’s medium levels of education Moderate behind with bills Mortgage and private renting Moderate subjective poverty Moderate receipt of means tested benefits Materially deprived in particular can’t afford holidays, money to replace goods and savings
“Benefits and not materially deprived”	Women low current employment Father manual employment and self-employed Women and fathers low levels of education, fathers education high don’t know response Up to date with bills Owns house outright Not subjectively poor High receipt of means tested benefits Not materially deprived
“Most economically deprived”	Women low current employment Father manual employment and unemployed Women and fathers low levels of education, fathers education high don’t know response Behind with bills Private renting and social housing Subjectively poor Highest receipt of means tested benefits Materially deprived

[reproduced from Fairley et al., 2014]

C4. Study 1: Graph with Gypsy/Irish traveller children included



D. Further information for Chapter 5

D1. Study 2: Correlation matrices

Table 45. Correlation matrix

	HLE 24	HLE 36	working memory	Most dep	Benefits	Employed, mat dep	Employed not mat dep	Gender	Age	EAL	IMS
HLE_24	1	.	.	.	.	.	.	.	.	.	.
HLE_36	.795	1	.	.	.	.	.	.	.	.	.
working memory	-.065	.076	1	.	.	.	.	.	.	.	.
Most deprived	.144	.036	-.101	1	.	.	.	.	.	.	.
Benefits	-.251	-.266	-.086	-.322	1	.	.	.	.	.	.
Employed, mat dep	-.129	-.010	.055	-.191	-.317	1	.	.	.	.	.
Employed, not mat dep	.159	.154	.021	-.204	-.337	-.200	1	.	.	.	.

Gender	-.245	-.273	.032	-.034	-.024	.002	.029	1	.	.	.
Age	-.045	.006	.355	.007	-.055	-.007	.066	.009	1	.	.
EAL	-.396	-.322	-.027	-.028	.296	.002	-.282	-.020	-.03	1	.
IMS	-.258	-.404	-.020	.030	.200	.012	-.294	-.003	-.063	.513	1

[Note: many of these variables are binary and the correlations cannot be validly interpreted, but are provided here for completeness]

D2. Technical information on model estimation

This section describes how the SEM was specified; based on proposed guidelines to estimate a full SEM (Bollen and Noble, 2011; Kenny, 2011).

7.5.1.1 Step 1. Model Specification

The information necessary for model specification comes from subject matter experts and their knowledge of theory and prior research in this area, and can be presented in a path diagram. Figure 1 summarises the SEM path diagram, that summarises the theory and set of hypotheses. The path diagram is depicted by a set of geometric figures and arrows showing the types of variables (observed or latent) and the relations between them. Relations of dependency and correlations are represented in bidirectional curves (Amorim et al., 2010).

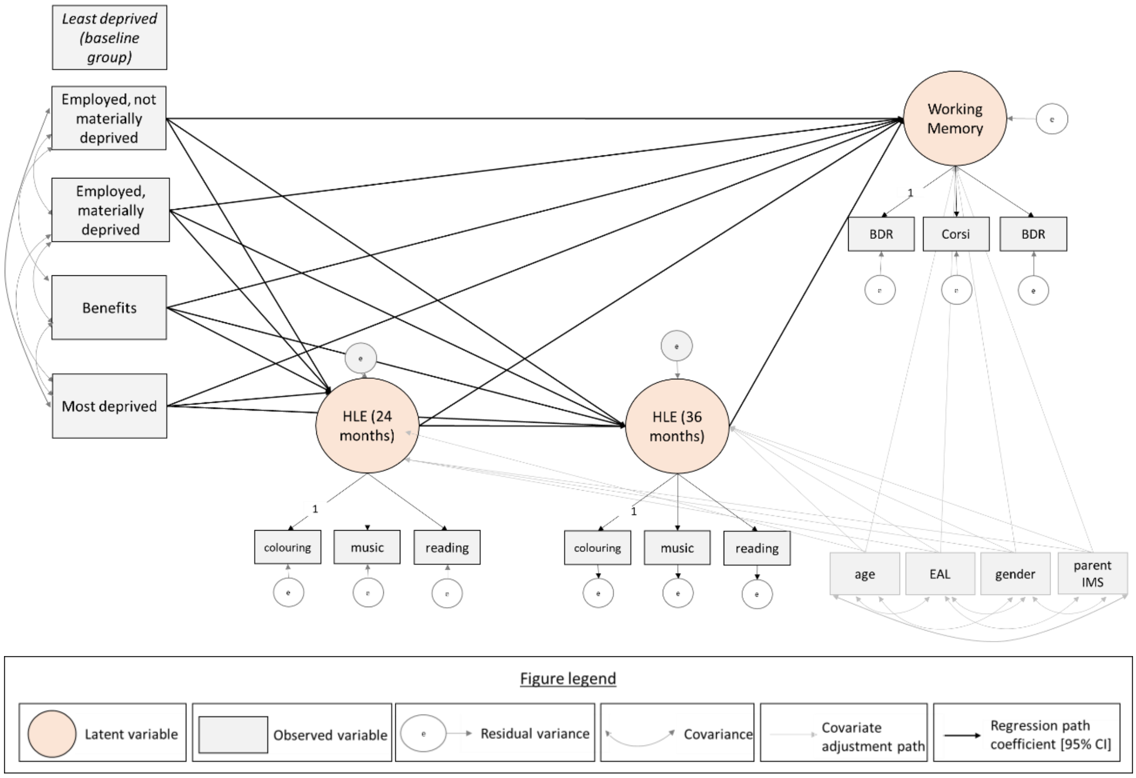


Figure 43. SEM path diagram

[Note: [1]Abbreviations: English as an Additional Language (EAL), parent immigrations status (parent IMS), Backwards Digit Recall (BDR), and Forwards Digit Recall (FDR). [2]SEP is fitted as a categorical variable with 'least deprived' as the baseline group, thus, dummy variables are used to model the associations].

7.5.1.2 Step 2. Identification of model

Model identification concerns whether a unique value for each and every unknown parameter can be estimated from the observed data (Wang and Wang, 2019, p.11). SEM assumes that the specified model is "identified" when there are more knowns than unknowns (or more observed variables than latent variables) (Kenny, 2011; Bollen and Noble, 2011). As a general rule, there need to be at least two indicators per latent variable and the indicators' errors need to be uncorrelated (Kenny, 2011).

There are two necessary conditions for identification. First, the number of data points (total number of observed variables) must not be less than the number of free parameters. The specified SEM (see Figure 1) has more observed variables than free parameters, and this assumption is met. Second, one of the factor loadings for each latent variable must be fixed to one, fixing the units of measurement of the latent variable (Wang and Wang, 2019). Mplus automatically fixes the value for the first observed variable within a latent variable, so this assumption will be met during model estimation.

7.5.1.3 Step 3. Estimation of measurement constructs

I first estimated the measurement components of the SEM and assessed the model fit for each of these. As specified in Section 1. 1. 1., EFA and CFA were conducted to find the most parsimonious measurement model for the HLE. To conduct the EFA, I modelled the data in MPlus specifying a 1, 2, and 3-factor model of the data using the oblique rotation method. Rotation maximises high item loadings and minimises low item loadings, therefore producing a more interpretable and simplified solution. Oblique rotation produces factors that are correlated, which is often seen as producing more accurate results for research involving human behaviours (Williams, Onsman, and Brown, 2010).

To assess how many factors to retain, I used the scree test; which involves examining the graph of the eigenvalues and looking for the natural bend or break point in the data where the curve flattens out. The number of datapoints above the “break” (not including the point at which the break occurs) is usually the number of factors to retain (Costello and Osborne, 2005). I also included a parallel analysis to assess how many factors to retain; which compares the eigenvalues generated from the data matrix to the eigenvalues generated from a simulated matrix created from random data of the same size, and then only factors with eigenvalues that are greater than the parallel average random eigenvalues should be retained (Hayton, Allen and Scarpello, 2004). Finally, interpretation involves examining which variables are attributable to a factor, and giving that factor a name or theme. At least two or three variables must load on a factor so it can be given a meaningful interpretation (Williams, Onsman and Brown, 2010).

To confirm the consistency of the structure of the home learning environment, I then conducted CFA in the second timepoint of the HLE data using the results from the EFA. The CFA allows a testing of the hypotheses of the structure of the HLE data (Costello and Osbourne, 2005).

7.5.1.4 Step 4. Full SEM estimation

The full measurement and structural SEM was estimated using Mplus. This will first be conducted without any covariates to check the model fit appears adequate, and then the full model with all covariates will be estimated (age, gender, English as an Additional Language, and parent immigration status). It was not desirable to include all of the potential covariates as specified previously in the Directed Acyclic Graph, as this may have resulted in overfitting the model. Overfitting or over adjusting a model refers to when instead of precisely describing the relationships between variables, a statistical model begins to describe the random error in the data. This occurs when an excessive number of variables are included in the model, increasing the complexity of the model (Schisterman, Cole and Platt, 2009).

Maximum likelihood estimates were used, which simultaneously estimates all model parameters by maximising the likelihood of sample data. When the outcomes are continuous, it assumes that the random variables follow a normal distribution (Maydeu-Olivares, 2017; Suhr, 2006).

7.5.1.5 Step 5. Assessment of Model fit

Model fit is a measure of how closely the relationships implied in the model fit with the relationships observed in the data. It is not necessary or plausible to assess all indices of model fit, however, it is recommended to report a variety of indices since they reflect different aspects of model fit and this will lead to more accurate conclusions (Wang and Wang, 2019, p. 21). Absolute model fit indices determine how well a model fits the sample data and depend on how well the model fits in comparison to no model at all. I report the following for absolute model fit:

- Model Chi-Square ($\chi 2$) statistic, which 'assesses the magnitude of discrepancy between the sample and fitted covariances matrices'. If $\chi 2$ provides an insignificant result at a 0.05 threshold, the model fit is considered adequate (Barrett, 2007; Wang and Wang, 2019, p. 17). The smaller the value of $\chi 2$, the better the fit of the model (Wang and Wang, 2019, p.17). However, the significance of $\chi 2$ is very sensitive to large sample sizes and it should therefore be interpreted alongside other model fit statistics (Barrett, 2007).

I report the following for comparative model fit:

- Comparative Fit Index (CFI): compares the specified model with the null model which assumes zero covariances among the observed variables (Bentler, 1990 in Wang and Wang, 2019, p.18). CFI values range from 0 to 1, where 0 indicates the worst fit and 1 indicates the best fit. A CFI value of .90 and above is considered acceptable (Wang and Wang, 2019, p. 18).
- Root Mean Square Error of Approximation (RMSEA): specifies the lack of fit of the specified model to the population. It adjusts for the model degrees of freedom, therefore providing a measure of the average lack of fit per degree of freedom. The values are: 0 = perfect fit, <.05 = close fit, .05 to .08 = fair fit and .08 to .10 = mediocre fit. (Wang and Wang, 2019, p. 19). A suggested cut-off is that RMSEA < .06 to be considered good model fit (Hu and Bentler, 1999 in Wang and Wang, 2019, p.19)
- Root Mean Square residual (RMR) and Standardised Root Mean Square Residual (SRMR): these values are the square root of the difference between the residuals of the sample covariance matrix and the hypothesised covariance

model. The SRMR is easier to interpret as it standardises the values, which range from 0 to 1. The lower the SRMR the better the model fit; a good model fit will obtain a value of less than .05 (Byrne, 1998; Diamantopoulos and Siguaw, 2000 in Hooper, Coughlan and Mullen, 2008), however values as high as 0.08 are also deemed acceptable (Hu and Bentler, 1999 in Hooper, D., Coughlan, J. and Mullen, 2008).

7.5.1.6 Step 6. Model re-specification

If model fit is poor, this may indicate that the model is a poor representation of the data. In this instance, the model can be re-specified, rather than examining and assuming that a single SEM is the best fit of the data. Any revisions should be guided by theory of the proposed causal mechanisms (Bollen and Noble, 2011; Wang and Wang, 2019, p.23). Any model re-specification would be detailed in the results, including any changes made and removal of any variables with poor model fit.

7.5.1.7 Step 7: Multi-group modelling

Once the measurement and structural SEM was established across ethnic groups, I explored the associations within the two main ethnic groups (White British and Pakistani) using multi-group modelling. Prior to multi-group modelling, measurement invariance across the two ethnic groups must be established. Measurement invariance establishes whether a variable measures the same concept in the same way across various sub-groups of respondents, and is therefore crucial prior to a multi-group model (Davidov et al., 2014; Putnick and Bornstein, 2016). Importantly, measurement equivalence does not mean there are no differences between the populations regarding a measured construct, but establishes that respondents from different groups that have the same position on a trait of interest should provide a similar response (Davidov et al., 2014). Measurement non-equivalence may arise due to translations of surveys within countries, people within countries belonging to different educational groups, people having different political orientations and viewing certain concepts differently, and a variety of other reasons. There are three types of measurement invariance to test:

- Configural invariance means that the same latent variables are measured by the same items in all groups in the same arrangement, and is used as a baseline for further invariance testing (Stride, 2017; Davidov et al., 2014).

- Metric invariance additionally requires that all loadings of items are the same across groups. If metric invariance is supported, we can conclude that the groups are interpreting the items in the same way, and if it is not supported, the measurement invariance may imply that some items are more important to the construct for one group than for the other (Campbell et al., 2008; Stride, 2017).

- Scalar invariance implies that both factor loadings and indicator intercepts are the same across groups, allowing a meaningful comparison of latent means across all groups. If scalar invariance is supported, we can conclude that the two groups use the response scale in a similar way, and if it is not supported, the invariance may imply systematic differences in the average item responses between groups that are not due to differences in the mean level of latent variables (Parker and Nagengast, 2016; Campbell et al., 2008; Stride, 2017). However, some have debated the importance of scalar invariance, arguing that it is an unrealistic ideal, and finding true scalar invariance with these strict tests of invariance is very difficult (Parker and Nagengast, 2016; Davidov et al., 2014).

Each of the increasingly constrained invariance models is nested within the previous models, so the change in fit is assessed by comparing fit indices between the configural, metric, and scalar invariance models. Typically, model comparisons are made by examining the change in $\chi 2$. However, additional indices have been recommended for comparing models, as $\chi 2$ is sensitive to large sample sizes (Stride, 2017; Campbell et al., 2008; Davidov et al., 2014). If measurement invariance holds, the $\chi 2$ difference tests would indicate non-significance, and the additional model fit indices will be consistent across the configural, metric, and scalar invariance models.

Once measurement invariance in established, multigroup modelling can take place. The multi-group model tested the strength of relationships between socioeconomic position and working memory across different ethnic groups, treating ethnic group as a moderating rather than an exposure variable (Byrne, 2013). Multi-group modelling begins with the estimation of two models: one in which all parameters are allowed to differ between groups (an unconstrained model), and one in which all parameters are fixed to those obtained from analysis of the pooled data across groups (a constrained model). We call the first model the "unconstrained" model since all parameters are free to vary, and the second the "constrained" model since each path, regardless of its group, is constrained to a single value determined by the entire dataset. A χ^2 difference test between the two models was conducted and if the two models are not significantly different then it can be assumed that there is no variation in the path coefficients by group. If they are significantly different, there is a need to understand which paths within the model are the same and which paths are different. This is achieved by sequentially constraining the coefficients of each path and re-fitting the model and comparing this to the fully constrained model with further χ^2 difference tests (Lefcheck, 2019).

7.5.1.8 Step 8. Model description

I fully described the path coefficients and model fit for the full SEM estimated without the multi-group estimation; this allows an examination of hypotheses (a) and (b). Second, I described the path coefficient's and model fit for the SEM estimated across the two ethnic groups using multi-group modelling. Significance was prespecified to be p<.05 for individual paths and p<.10 for the moderated paths in the multi-group model. The model coefficients will be described in a table and the final multi-group model will be depicted using both a table and a figure.

E. Further information for Chapter 6.

E1. Study 3: normality of data for analysis and post-estimation plots for ethnic density analysis

As there are two regressions run for (1) White British and (2) Pakistani participants, the data here regarding normality are presented for both of these groups.

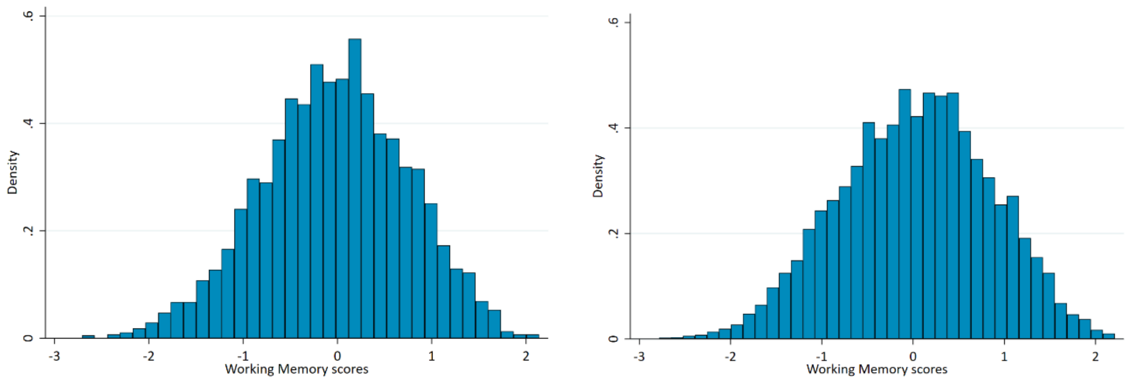


Figure 44. Histograms of working memory scores for White British (left) and Pakistani (right) participants

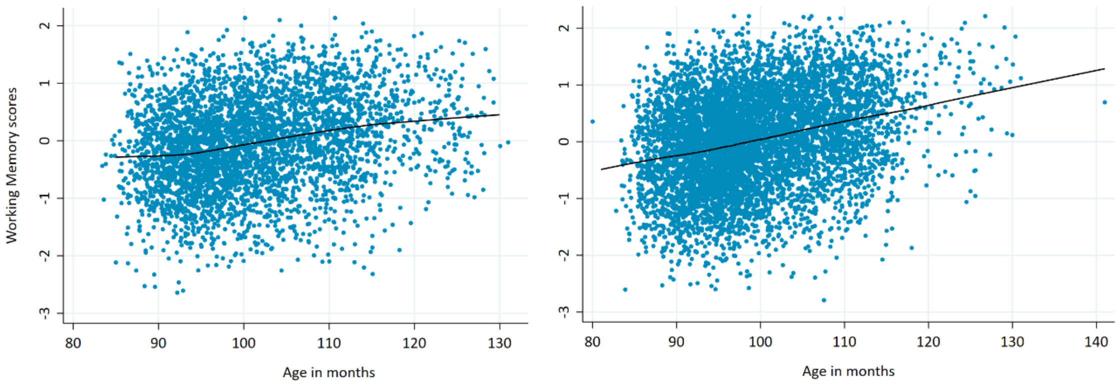


Figure 45. Linearity between continuous covariate age and outcome for White British (left) and Pakistani (right) participants

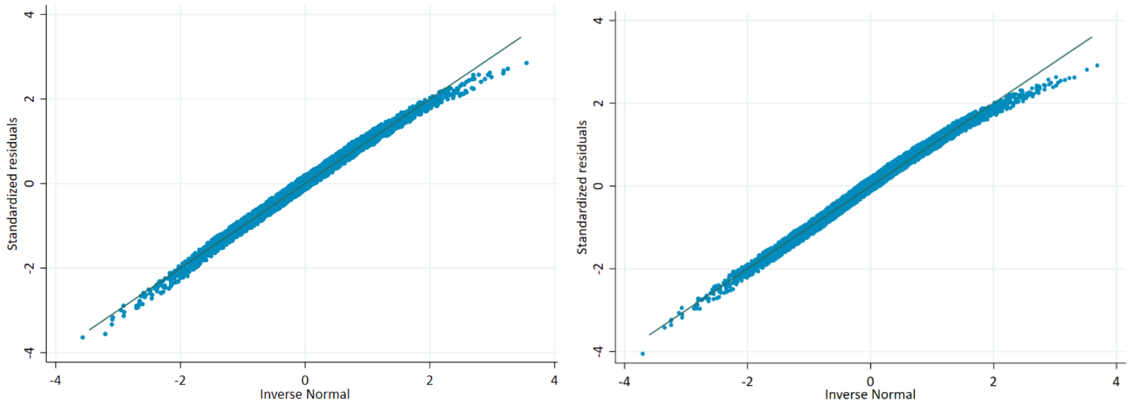


Figure 46. QQ-plot for White British (left) and Pakistani (right) participants

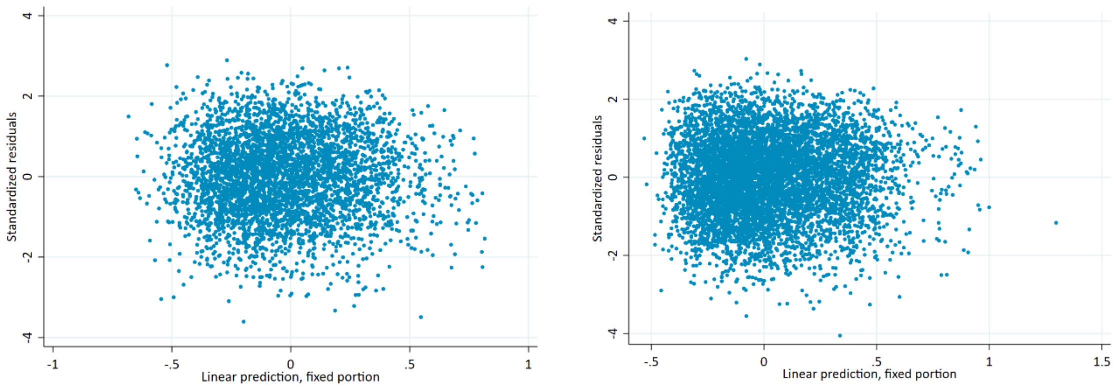
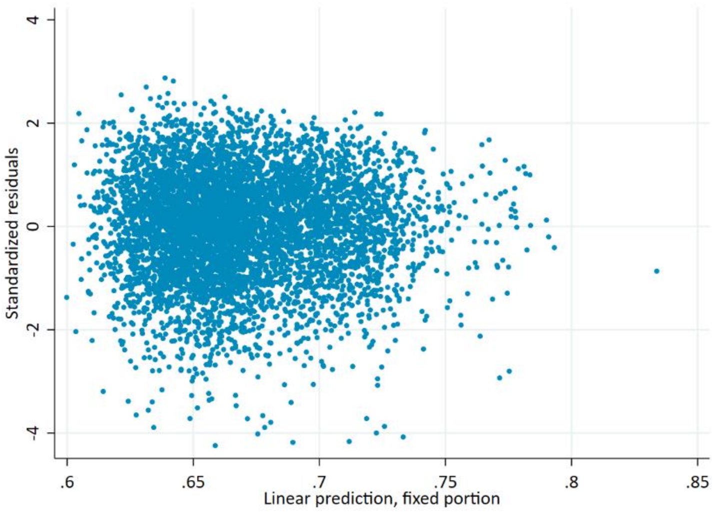
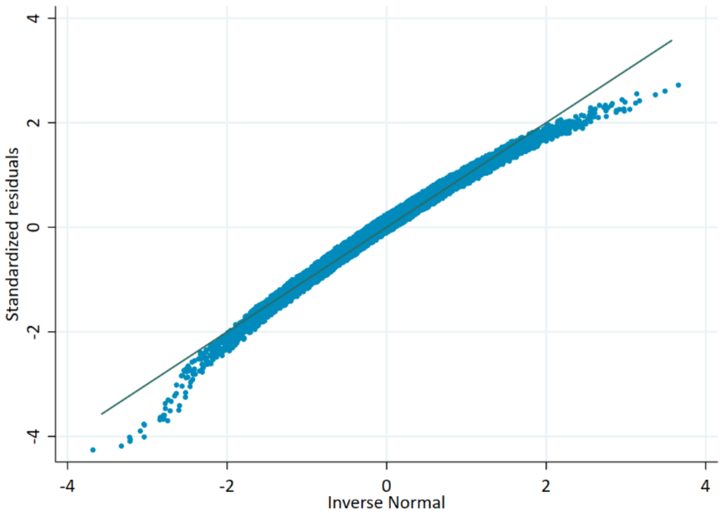


Figure 47. Homogeneity of variance for White British (left) and Pakistani (right) participants

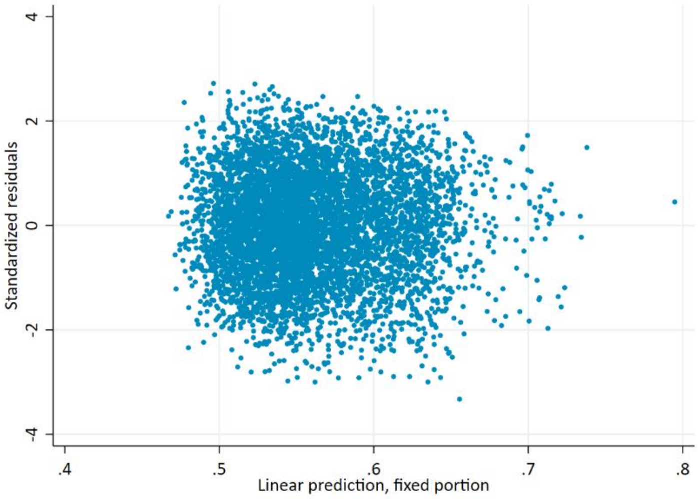
D1. Study 3: post estimation plots for Mosque and/or Madrassa analysis

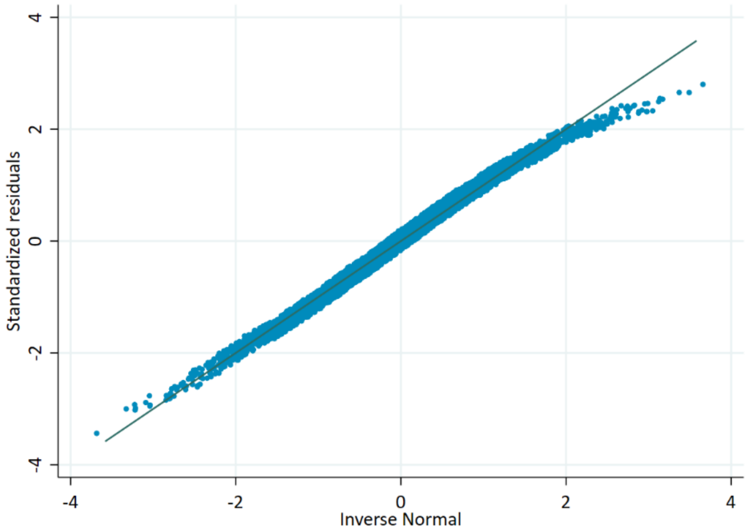
FDR



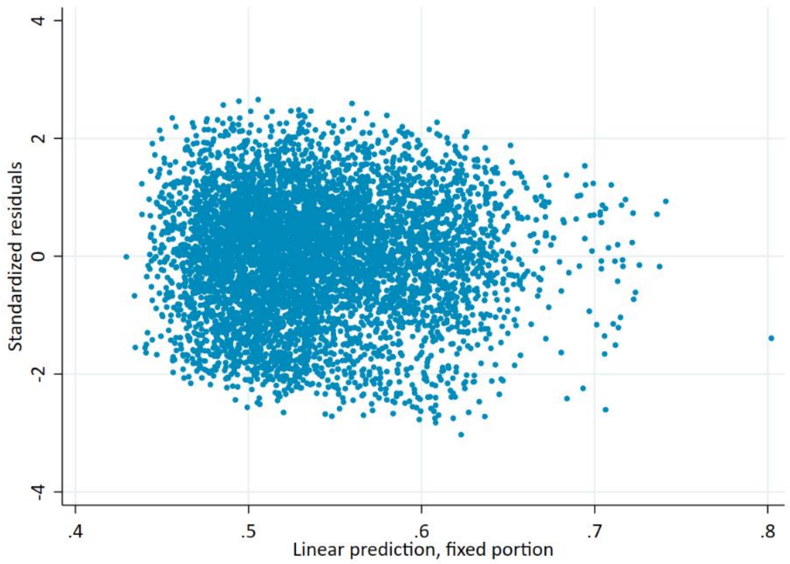


Corsi

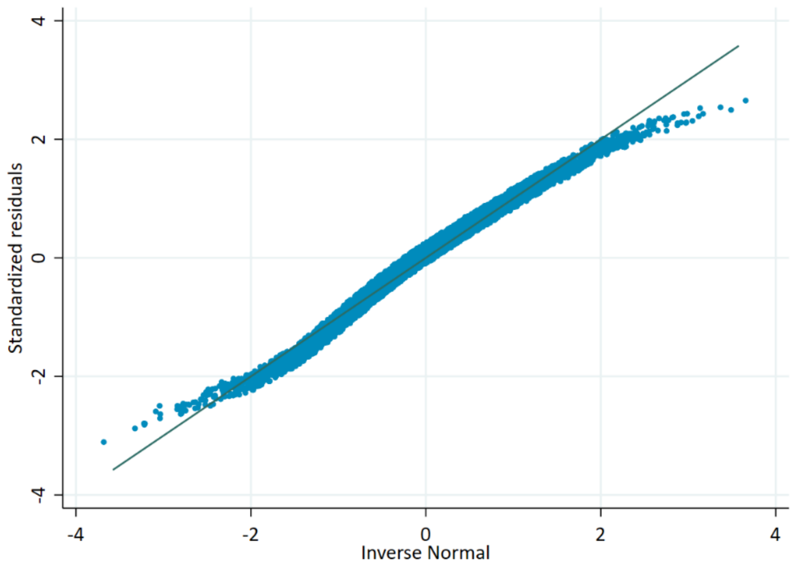

Standardized residuals
Linear prediction, fixed portion
4
2
0
-2
-4
.4
.5
.6
.7
.8


Standardized residuals
Inverse Normal
4
2
0
-2
-4
-4
-2
0
2
4

BDR



Standardized residuals
Linear prediction, fixed portion
4
2
0
-2
-4
.4
.5
.6
.7
.8



Standardized residuals
Inverse Normal
4
2
0
-2
-4
-4
-2
0
2
4

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